COLLABORATIVE AND CONTENT BASED FILTERING PERSONALIZED RECOMMENDER SYSTEM FOR BOOK

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COLLABORATIVE AND CONTENT BASED FILTERING PERSONALIZED RECOMMENDER SYSTEM FOR BOOK

ABSTRACT

Personalized recommendation systems provide end users with suggestions about information items, social elements, products or services that are likely to be of their interest based on users' details such as demographics, location, time, and emotion. Incorporating contextual information in recommendation system is an effective approach to create more accurate and personalized recommendations. Therefore, in this study, a Personalized Hybrid Book Recommender is proposed, which integrates several users' characteristics, namely their personality traits, demographic details and current location, together with review sentiments and purchase reason, to improve their book recommendations. The system is able to determine user's personality traits by utilizing the Ten Item Personality Inventory. The proposed recommender system would be evaluated using two metrics, that are, Standardized Root Mean Square Residual and Root Mean Square Error of Approximation. The proposed technique was evaluated by comparing it against baseline models and existing personalized recommendation systems. This study is able to show effectiveness of integrating user's contextual data (personality trait, demographic data and location) with product's features (review and purchase reason).

Keywords: recommendation system, context – aware, personality, demographic, location,

PENYARINGAN BERASASKAN KOLABORATIF DAN KANDUNGAN YANG DIPERIBADIKAN UNTUK SISTEM PENGESYORAN BUKU

ABSTRAK

Sistem pengubahsuaian yang dicadangkan memberikan pengguna akhir cadangan tentang maklumat item, unsur sosial, produk atau servis yang mungkin merupakan minat mereka berdasarkan butiran pengguna seperti demografi, lokasi, masa, dan emosi. Menggabungkan maklumat kontekstual dalam sistem pengubahsuaian adalah pendekatan yang berkesan untuk mencipta cadangan yang lebih tepat dan disesuaikan. Oleh itu, dalam kajian ini, Pengubahsuaian Hibrid Pengesyoran Buku Dicadangkan, yang mengintegrasikan beberapa ciri-ciri pengguna, iaitu ciri personaliti mereka, butiran demografi dan lokasi semasa, bersama dengan sentimen ulasan dan sebab pembelian, bagi meningkatkan cadangan buku mereka. Sistem ini dapat menentukan keperibadian pengguna dengan menggunakan *Ten Item Personality Inventory*. Sistem pengubahsuaian yang dicadangkan akan dinilai menggunakan dua metrik, iaitu, "*Standardized Root Mean Square Residual*" dan "*Root Mean Square Error of Approximation*". Kami akan menilai kualiti dan ketepatan teknik yang dicadangkan dengan membandingkannya dengan model asas. Kajian ini dapat menunjukkan keberkesanan dalam mengintegrasikan data kontekstual pengguna (sifat keperibadian, data demografi dan lokasi) dengan ciri produk (ulasan dan sebab pembelian).

Kata Kunci: sistem pengubahsuaian, konteks - kesedaran, keperibadian, demografi, lokasi

DEDICATION

To my beloved mother

Who taught me that the truth is everything in life

To my beloved late father

Who taught me how to be strong in life and always appreciate the given chance

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I would to acknowledge certain people who have helped in making this whole project a success. Without these people, I would not have been able to reach my targets within the constraints of time and quality.

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LIST OF SYMBOLS AND ABBREVIATIONS

BVM	:	Back Vector Machine
CB	:	Content-based Filtering
CF	:	Collaborative Filtering
DF	:	Demographic Filtering
DSR	:	Design Science Research
FFM	:	Five Factor Model
LBSM	:	Location-based Recommendation Using Sparse Geo-Social Networking Data
MediSem	:	Personalised Medical Reading Recommendation
NLP	:	Natural Language Processing
PHyBR	:	Personalised Hybrid Book Recommender
PLMTA	:	Personalised Location-based Mobile Tourism Application
TIPI	:	Ten Item Personality Inventory
TISP	:	Social Presence on Personalized Recommender System
RS	:	Recommendation System
SDLC	:	System Development Life Cycle

CHAPTER 1: INTRODUCTION

1.1 Overview

In past 10 years, there is a rapid rise in Internet usage globally. Countries worldwide have seen the unbelievable growth of Internet users (Einav et al., 2014). These users not only use the data accessible on the Internet but also generate a large amount of data through different activities, such as searching, browsing, submitting personal information, sharing digital items (e.g., music, e-book, photo etc.) and blogging etc. (Lian & Yen, 2014). Beside users, the number of websites on the world wide web is increasing exponentially too. Concurrently, technologies for collecting, distributing, processing, and analysing data have been advancing at a very fast speed. The collective results of all these advances are that a huge amount of data is produced every day (Einav et al., 2014; Pennacchiotti & Gurumurthy, 2016; Wang et al., 2015).

Internet transmission in the past years has forced an increasing number of organizations towards the Web to obtain more clients, because traditional transaction and communication methods are no longer viable. A recent research has determined that from 2011 to 2014, the intention of shopping rates have grown two-fold for at least half of the shopping categories. In such a situation, the total size of available data is increasing rapidly every day; newspapers are now publishing their articles and news online. All kinds of products are now accessible on e-commerce websites, music, movie and book can be purchased online and a huge growing number of people are using social networks (Kumar & Maan, 2014; Li & Karahanna, 2015; Qian et al., 2014).

1.2 Recommendation System

When it comes to dealing with lots of items or products, there is a need of a Recommendation System (RS) to help users discover what they may like. RSs are programs, software techniques and methods suggesting items to be of interest to a user (Figure 1.1) (Bakshi et al., 2014).

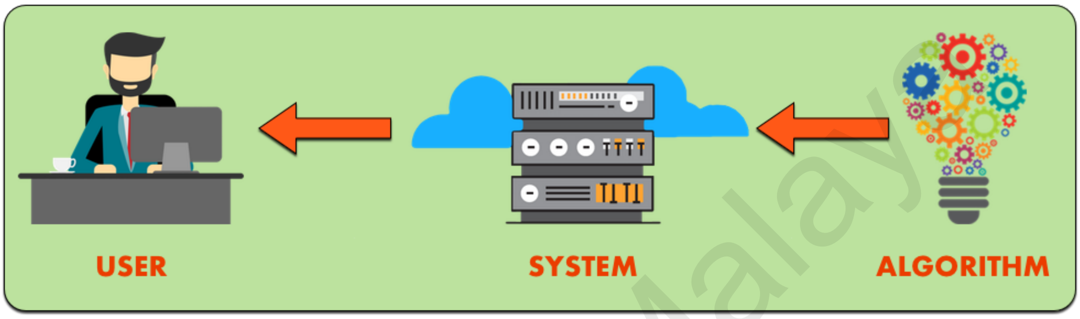


Figure 1.1: Recommendation System

As indicated in Figure 1.1, recommendation algorithm involves with many different decision-making processes, for example, which book to read, what movie to watch, what music to listen, or what item to purchase. Generally "Item" is used as a general term to demonstrate what the RS suggests to users. Usually a RS choose a particular type of item (such as movie, book, or music) to focus on and customizes its design, graphical user interface and the main recommendation algorithm technique to generate useful and effective recommendation and suggestions for the users. Primarily RSs are moving towards people who need personal assistance in making decision on choosing the interested item among overwhelming number of alternative items that system or website may offer (Kardan & Ebrahimi, 2013; Ricci, 2010).

Nowadays recommendations focus on providing personalized suggestions to users, so they receive diverse recommendations and suggestions (Cunico & Silva, 2017). In addition, there are some traditional RSs, which they provide non-personalized suggestions. These kind of recommendations are usually much easier to generate and are listed in newspapers or magazines. These non-personalized recommenders might be useful in some cases or situations, but they are not typically the main focus of RS researches (Pera et al., 2011; Qian et al., 2014)

RSs have been successfully applied to multiple domains and fields. E-commerce was one of the first domains which utilised RSs, because there was an essential need of replacing the salesperson with an electronic shopping assistant (Su et al., 2017; Zhao, 2016; Bollich et al., 2016). As a salesperson does in a physical store, a RS does the same by identifying products based on user preferences (Li & Karahanna, 2015). For instance, when the user is search for a laptop, the recommender may suggest a variety of similar laptops or products related to the laptop, such as bags or external hard-disks.

Tourism industry is also one of the domains which RSs have been applied to and it is one of the biggest economic industries globally. Contextual information like weather, distance and season, have been integrated with user interests on places, such as restaurants or hotels, to generate meaningful and accurate recommendations (Gavalas et al., 2014; Lucas et al., 2013; Ricci, 2010).

Other well-known areas are the book, music and movie categories; music platforms like Spotify, movie portals like Netflix, and book portals such as Amazon, incorporate powerful RSs in their websites that can suggest music, books and movies (Oord et al., 2013; Kanetkar et al., 2014; Maria & Ng, 2013).

There are other domains in which RSs have been used, are the research and evaluation industry. RSs can be used to recommend research articles to a reader based on his reading history or what he/she published before. In such a case, the RS is able to examine the content of the research articles to generate useful recommendation results and to look for repeated tags or keywords that can be used to describe user preferences (Cheng et al., 2011; Desyaputri et al., 2013; Lu et al., 2015).

Another main area is the social network sector. Social network platforms (such as Facebook and Instagram) utilise RSs to recommend friends to the user (Pawar et al., 2017). The social network platform is used to determined relationships and connections (such as trust or distrust) between online users (Chechev & Koychev, 2014). Lastly, RSs can be used in scientific fields, where experience and education in the field are essential elements for providing useful and accurate suggestions, such as insurances or financial services (Gartrell et al., 2010; Qian et al., 2014).

1.3 Types of Recommender Systems

Generally, there are two types of RSs, traditional and context-aware, with each having multiple techniques and approaches (Adomavicius & Tuzhilin, 2015). These two systems will be elaborated briefly, but there will be more in depth in the next chapter (Literature Review).

1.3.1 Traditional Recommender Systems

Usually, RSs display a list of items or products (such as music, books, video, articles, etc.) to the user, which the user might be interested in. First, the RS needs to estimate the user's preferences, in order to generate the recommendation result (Guo et al., 2016). The traditional RSs would first collect data about user, either explicitly or implicitly

(Bobadilla et al., 2013). For instance, a book recommender platform might request the user to explicitly provide the rating for the books that he/she has read before (Kanetkar et al., 2014; Wani et al., 2017); a movie recommender may consider that if the user has watched a movie repeatedly, that is an implicit sign of interest for that movie (implicit data) (Bogers, 2010; Mishra et al., 2017). In some cases, the main mission of the RS is to foresee the interest of user on the items or products that the user did not used or purchased before. The RS recommend the products, which are determined to match the user's preferences (Kanetkar et al., 2014).

In the area of traditional RSs, Collaborative Filtering (CF) is the most popular technique for determining the user's preferences. CF suggests the items or products to user based on other similar users' interests. Usually, CF approaches generate recommendation based on explicitly acquired user's ratings and uses these ratings to calculate the similarity between users. Therefore, CF approaches are sometimes referred to as "user-to-user correlation". The CF approaches do not need domain knowledge , so they can be easily applied in fields where ratings are available (Tewari & Barman, 2016; Tinghuai et al., 2015; Wei et al., 2017).

Although, it needs to be understood that the RS with CF approach needs the user to rate an adequate number of products or items before it can accurately estimate the user's preferences. Therefore, Content-based Filtering (CB) is introduced that only focus on the similarities between items rather than users. It recommends the items based on similar items, which the user liked, purchased or viewed in the past (Lu et al., 2015; Mathew et al., 2016). The CB approach calculates the similarity based on the content or description of the items or products. For instance, when the user gives a high rating for a book that belongs to business genre, the RS tries to suggest other books from the same genre (Mathew et al., 2016). Because of the early improvements made in terms of information retrieval, many CB systems can only recommend products that have textual information (Lu et al., 2015). CB methods require both product details and user feedbacks. However, in some scenarios, it is hard to obtain the details of an item (Lu et al., 2015; Gao et al., 2015; Su et al., 2017).

1.3.2 Context-Aware Recommender Systems

Many researches have recognised the significance of contextual information in many domains, such as personalising e-commerce platforms, mobile computing, data retrieval, management, and marketing. (Adomavicius & Tuzhilin, 2015; Asabere, 2013; Huang, 2016). Among the huge number of researches that have been done in the domain of RSs, most of the existing studies have focused on suggesting items, which are most relevant to users' preferences without considering any extra information about contextual data like weather, location and time (Bogers, 2010; Adomavicius & Tuzhilin, 2015; Winoto et al., 2012).

Many research areas have been trying to define and describe the context from different aspects. In the domain of RSs, contextual data cover a very large set of information. Schlitz et al. (2009) describe context as:

"Where you are, what available resources are accessible, and who you are with." (p. 134)

Chen et al. (2013) tried to describe it as:

"Context is the set of surrounding states and settings that either defines a behaviour or in which an event occurs and is interesting to the user." (p. 100)

Adomavicius (2015) give a more particular definition:

"Context is any data that can be utilized to characterise the situation of an object." (p. 192)

The object can be any entity (such as a place or person), which is related to the relationship between an item and a user, considering the item and the user itself (Codina et al., 2016). Since currently there are many traditional RSs, it is therefore instinctive to just take a contextual approach and add it to a traditional RSs. Thus, it is feasible and easier to enhance the existing traditional RS to be a contextualised RSs, rather than developing a new system (Adomavicius & Tuzhilin, 2015).

Generally there are two types of context-aware RSs, (i) contextual pre-filtering and (ii) contextual post-filtering. Basically it depends on which phase the RSs use the contextual data. For instance, the RS with the pre-filtering approach utilises a pre-processing method, which can be used to contextualised the dataset of the traditional RS. It is about the current context that the dataset is being used to generate recommendation (Adomavicius & Tuzhilin, 2015). Then, the traditional RS is able to estimate the user's interest in the current context based on the chosen data. In another hand, the contextual post-filtering method is also utilising the traditional RS by ignoring the contextual data in the dataset at the initial stage, but using the contextual information to enhance recommendation result when it is generating the recommendation (Codina et al., 2016). The enhancement is done by either rearranging the items in the recommendation list based on their ranking or removing the unrelated items for the given context. However, in some cases, the RS is not able to gather extra information about the context directly (Hawalah & Fasli, 2014; Knijnenburg & Kobsa, 2013).

1.4 Personalized recommender systems

As users of RSs may have different needs in various situations and contexts, it is becoming increasingly important to consider contextual data when filtering information (Hawalah & Fasli, 2014). This resulted in the birth of personalized recommendations, focusing on various user contexts such as time of access (Wang & Shao, 2004), location of access (Braunhofer et al., 2014; Huang, 2016; Liu et al., 2013) and emotion/mood (Shan et al., 2009).

Recently, studies have revealed the significance of psychological aspects of users such as their personality traits and emotions during the decision-making process (Bollich et al., 2016; Pera et al., 2011; Hu & Pu, 2010). Generally, personality is defined as the continuing patterns of behaviour, feeling, motivation and thought, which are conveyed in different situations (Nunes et al., 2008; Zhang, 2016).

One of the most widely used models to determine users' personality is Big Five model, which is also known as the Five Factor Model (FFM) (Gerras & Wong, 2016). Big Five model illustrates the personality traits in five different dimensions (i.e. extraversion (E), agreeableness (A), conscientiousness (C), neuroticism (N) and openness (O)) based on a hierarchical organisation. Big Five is considered to represent the basic dimensions of user personality, as its dimensions are steady, cross-culturally applicable and have biological basis (McCrae & Costa, 1996). It is also one of the most widely used and recognized instruments in determining a user's personality (Braunhofer et al., 2013; Borghuis et al., 2017; Fernández-Tobias et al., 2016; Hengartner et al., 2016).

The early studies conducted on personalising RSs, shows that by utilising the user's personality characteristics, they can achieve higher recommendation accuracy (Asabere et al., 2017; Hu & Pu, 2009; Tkalčič et al., 2013). The RS is able to determine the personality of the user either explicitly (by asking user to take the personality test or questionnaire) or implicitly (by monitoring and observing user's behaviour and interaction) (Corr, 2016; Kosinski et al., 2013). For example, Bhosale et al. (2017) implicitly acquired users' personality traits through their Facebook profile info. However, some studies showed that explicitly acquiring user personality information would yields a better result and prediction accuracy (Bhosale et al., 2017; Borghuis et al., 2017; Fernández-Tobias et al., 2016; Ferwerda & Schedl, 2014; Hengartner et al., 2016).

1.5 Motivation

The aim of this study is to cover a comprehensive research about personalized RS and improving recommendation quality by focusing on different angles and every angle introduces lots of opportunities to enhance the personalisation of RSs. In particular, this study is motivated by the following factors:

a) Due to the increasing number of online shoppers, researchers are building recommendation engines specifically for ecommerce with having a large variety of products from different categories (Einav et al., 2014; Flanagin et al., 2014; Li & He, 2017). Thus it is very important to consider that the RS need to be scalable to recommend different types of items or products and not to be a domain specific RS (Tananchai, 2017; Wang et al., 2016; Wani et al., 2017). In this research, book is chosen because of its attribute complexity (such as title, author, publisher, published date, synopsis and etc.) and thus it is easy to be scaled to support other products such as movies or music.

b) User preferences can be related to the place where he/she is during the recommendation process (Liu et al., 2013). In other words, users who are living in the same context (city, state or country) tend to share similar interests (Bao et al., 2015; Gao et al., 2015). Thus, location in RS is an important factor, but it is usually utilised in tourisms apps (Lee et al., 2017; Memon et al., 2015; Ravi & Vairavasundaram, 2016; Santos et al., 2016; Takahashi et al., 2017). It is a great contribution to find out the effect of the location factor in recommending other items (such as book) than just places of interest.

c) Previous studies have focused on factors or contextual features to provide improved recommendations, such as emotion or mood (Kim et al., 2015; Shan et al., 2009; Winoto & Tang, 2010), geographical location (Braunhofer et al., 2014; Kim et al., 2015; Koceski & Petrevska, 2012), personality trait (Ferwerda & Schedl, 2014; Hengartner et al., 2016), demographic (Safoury & Salah, 2013; Zhao et al., 2016; Zhao et al., 2014), product reviews (Chen et al., 2015; Korfiatis & Poulos, 2013; Qian et al., 2014) and etc. Most of the studies utilizes a specific feature however Cantador et al. (2013) showed that one contextual feature can be used in multiple domains and this is a great motivation for our study to evaluate a hybrid-feature personalized recommendation.

d) Researchers are focusing on extracting meaningful and useful data from textual information related with items (Hawalah & Fasli, 2014). Furthermore, item's metadata, review and description can be used to analyse and extract relative concepts and meaning beneath the natural human text (Haugen et al., 2017). This sort of information can be extracted in different ways like understanding weak and strong points of an item, determining most interesting products and exploring semantic relationships between users (Haugen et al., 2017; Yu et al., 2014).

1.6 Problem Statement

The main aim of using personalization techniques is to generate customized recommendations based on user preferences and interests (Gavalas et al., 2014; Gao et al., 2010). As users may have different needs in various situations and contexts, it is becoming increasingly important to consider contextual data when filtering information (Hawalah & Fasli, 2014). Therefore, it is advantageous to utilise users' contextual features in the recommendation process, such as emotion or mood and location (Kim et al., 2015; Shan et al., 2009; Winoto & Tang, 2010; Braunhofer et al., 2014; Kim et al., 2015; Koceski & Petrevska, 2012). These features however, have been underutilized in RSs, for instance, location is usually used to recommend travel points to tourists with improved accuracy. Studies using location to recommend bools for example have yet to be conducted, hence the current work intends to explore the use of location in book recommendations.

The use of contextual features for personalized recommendations have showed promising results (Colomo-Palacios et al., 2017; Huang, 2016; Koenig et al., 2015), however, most studies tend to favour a specific domain for identified features, for example, mood, time and emotion are often explored in music/movie domain, whereas location in tourism. Contextual features need not be domain specific as shown by Cantador et al. (2013), where correlations were found between users' personality traits across multiple domains. For example, users who scored high on Openness (i.e. personality) prefer educational books and country music. This suggests that a feature that is used to determine users' preferences for product A, can be used to determine their preference for product B. The current study hence posits that various features can be used in an integrated manner to improve book recommendations. Additionally, studies that integrated personality in RSs are also limited (Asabere et al., 2017; Liu et al., 2015; Shen et al., 2016; Zhang et al., 2017). The scarcity of such studies motivates our study here.

Aside from user's contextual features, product features such as reviews, description, etc. play important roles in improving recommendations as well (Achakulvisut et al., 2016; Chen et al., 2017; Musto et al., 2016). The CB approach relies on product's description or content to provide recommendation and the basic step of generating recommendation is to find the similarity in user's profile (that contains user's interests and preferences) with items' attributes (Achakulvisut et al., 2016; Musto et al., 2016). The result shows the accuracy of predicting of the user's level of interest in choosing those recommended items (Musto et al., 2016). Usually, characteristics that describe the item, are obtained from its metadata or the textual description that is attached to the item (Lu et al., 2015). However, the textual information obtained from the item's metadata is usually very short and not really enough to estimate the user interest correctly. Moreover, it involves natural language uncertainty when it is learning from the extracted textual information (Achakulvisut et al., 2016; Chen et al., 2017; Musto et al., 2014). The traditional keyword-based profiles are not able to take further step beyond the usage of syntax-based structures to estimate users' interests due to having some inherited problems such as polysemy (i.e. the relationship of one single word with two or more distinct definitions), named entity recognition, multi-word expressions and disambiguation (Belém et al., 2017; Hong et al., 2017). Recent studies have begun utilizing sentiment analysis and Natural Language Processing (NLP) tools to perform analysis on the acquired textual information to improve recommendations (Antunes et al., 2016; Hong et al., 2017; Kermany & Alizadeh, 2017), however such studies are lacking as well.

Recently, the growing number of studies on semantic technology has encouraged more researchers to apply it to the domain of CB recommenders (Tabara et al., 2016). Studies conducted on semantic techniques have showed the transformation from a keyword-based representation of user and item profile to a concept-based representation (Antunes et al., 2016; Cunico & Silva, 2017). The semantic technologies and NLP are the most important elements of recent studies in the domain of CB RS that try to perform deep content analytics on the acquired textual information (Antunes et al., 2016; Hong et al., 2017; Kermany & Alizadeh, 2017). The review shows that despite the number of studies on personalized RSs, a lot more can be accomplished to improve the recommendations (Martinez-Cruz et al., 2015; Nirwan et al., 2016; Zhang et al., 2017).

1.7 Research Aim and Objectives

Personalized RSs have now become important tools of making accurate predictions for products or services during a live interaction. generally, personalisation is defined as the way wherein products, items and information can be customised in a specific manner to meet the particular and unique needs of an individual person (Nagarnaik & Thomas, 2015). There has been much work done on improving personalization by studying user behaviour. However researchers believe that there is still a lot to be done to obtain a more accurate RS (Martinez-Cruz et al., 2015; Nirwan et al., 2016; Zhang et al., 2017).

The study aims to extend the literature by addressing the mentioned gaps by proposing a personalized RS that integrates several user's and product's features in order to improve the recommendation accuracy. The RS was tailored to support book recommendations; hence, it is aptly named as Personalized Hybrid Book Recommender (hereinafter referred to as PHyBR). The specific objectives and their respective research questions (RQ) are as follows:

i. To identify user and product contextual features that can be used to personalised recommendation.

RQ1: *What suitable contextual features can be used to improve recommendations?*

RQ2: *How can the contextual features used to generate personalised recommendation?*

the RQs above are about designing of PHyBR's recommendation engine, in which specific contextual-features were first identified in order to improve recommendation accuracy. The processes involved also include the integration of several filtering mechanisms, as would be described in Chapter 3 in this study.

ii. To develop an enhanced hybrid personalized RS based on the identified user and product contextual features.

RQ3*: How to integrate the features to improve recommendations?*

RQ4: *How to efficiently use multiple context features to find similar users?*

RQ5: *What fulfilling mechanism can be used to improve the recommendation accuracy?*

All the RQs above revolve around the development of recommendation engine that integrate identified context features to improve personalized recommendation. The developed RS need to understand and know more about user's preferences and utilized CF filtering methods to have the higher chance to meet user's interest. Furthermore, it should empower CB's approach via great tools (i.e. Semantic Technologies) to exploit the similarity between items.

iii. To assess the effectiveness of the proposed technique in recommending relevant items.

RQ6: *What would be the optimal mechanism(s) to evaluate PHyBR?*

The final RQ is related to the evaluation of the recommendation strategy whereby experiments were conducted to assess and compare PHyBR in several different scenarios. The implementation and assessment results are presented in Section 3 and 4, respectively.

1.8 Dissertation Structure

The structure of dissertation is illustrated in the Figure 1.3 below:

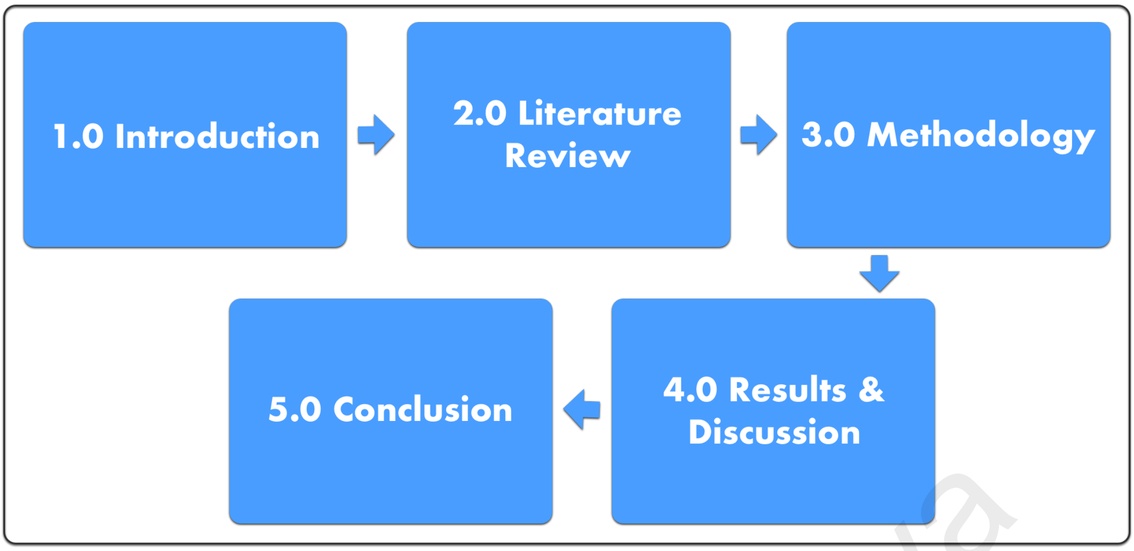


Figure 1.2: Dissertation structure flow

In this study, **Chapter 1** highlights the overall research requirements; covering from problem statement, research aim, objectives. A brief background about personalized RSs was presented; followed by the issues that existing recommendation algorithms are facing. By analysing the issues, the main objectives and motivation were listed to start this research.

Chapter 2 studies the background of previous conducted studies relevant to this study. It consists of the advantages and disadvantages of the techniques proposed in previous studies. Chapter 2 also attempts to explain more on (a) personality-based recommendation algorithms; (b) demographical recommendation algorithms; (c) geographical recommendation algorithms; (d) natural language processing; (e) semantic analysis. A comparative summary is also discussed.

Chapter 3 describes the proposed methodology, design and procedures for the proposed model. The implementation of the proposed model is covered in detail. A methodology that improves recommendations by manipulating several contexts (i.e. personality, demographics, location, purchase reasoning and user reviews). This model can be categorized into three main parts: registration, user profiling and recommendation, which will be elaborated in details later in chapter 3.

Chapter 4 provides discussion and analysis about the accuracy of the proposed technique. It is evaluated using two metrics; they are: Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). Both of which reveals the proposed technique's performance and compares it with the baseline models in terms of the recommendation accuracies.

Lastly, **Chapter 5** finalises the study, discussing about the achieved objectives, listing the study's contributions and summarizing the research work. The perspective and proposed future studies are also elaborated in this final chapter.

1.9 Summary

In this chapter, the basic understanding of the proposed research was presented in brief. First, it introduced the RS, how it works and how many elements it consist of. In addition, it described basic types of RSs with their functionalities. Then the problem domain was mentioned that was explored from existing methods and techniques, summarised in the problem statement section. Based on the existing problems and issues, the objectives and goals of this study were concluded. This study's research methodology was briefly explained as well. In addition, the contributions of this work is listed together with the factors that motivated us to start this research. In the next chapter, we will study the background of RSs and go through the existing RSs by listing their problems and key findings.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

Recommendation Systems (RSs) are tools and suggestion methods for products or items for the users. “Item” is the term used to determine what is being recommended to users by system (Dai et al., 2014; Majid et al., 2013; Wang et al., 2015; Wei et al., 2017). An RS’s focus is on a particular type of item (such as movies, books, music, or news) and its planning, its graphical user interface, and the main suggestion method to prompt the recommendations, are all made to provide effective and meaningful recommendations for that particular sort of product (Hawalah & Fasli, 2014; Nirwan et al., 2016).

RSs are initially utilised for individuals who do not have enough competence or personal experience to evaluate the potentially very large number of alternative items that RSs may provide (Martinez-Cruz et al., 2015; Musto et al., 2016). For instance, Amazon.com utilises an RS to customise the online shopping experience for each user (Maria et al., 2011). In personalised recommendation usually different users receive diverse suggestions (Musto et al., 2014). Additionally, there are also traditional RSs that provide non-personalized suggestions. These kind of RSs are easier to develop and are usually utilised in news feed Web sites (such as online newspapers or magazines). Usual suggestions contains the top ten selections of movies, books and etc. These types of non-personalized recommender are not usually addressed by recent RS research, even though they could be effective and meaningful in some occasions (Bobadilla et al., 2013; Wani et al., 2017).

RSs development started from an simple process of monitoring and observation. Usually users tend to rely on suggestions that other users provide for their daily and routine decisions (Hariri et al., 2015; Zhang, 2016). For example it is common to rely on what one's peers recommend when selecting a book to read; employers count on recommendation letters in their recruiting decisions; and when selecting a movie to watch, individuals tend to read and rely on the movie reviews that a film critic has written and which appear in the newspaper they read (Zhou et al., 2015).

In trying to utilise these patterns or actions, the initial RS approaches leverage suggestions generated by the group of end users specially for the target user (Colomo-Palacios et al., 2017). In other words, the list of suggestions are made based on what other users with similar interest and preferences had liked before (Cheng & Shen, 2014). This is how the CF approach works on suggesting items, its reason is that when the user behaviour history matches other users' behaviours in the past, the new suggestion based on those similar users might be relative and meaningful (Guo et al., 2016; Ravi & Vairavasundaram, 2016).

In the recent years, RSs have enabled the researchers to find alternative ways of dealing with data overload issue (Guan et al., 2016). Eventually, an RS overcomes this issue by suggesting the user with some items that he/she might not have seen it before but it would meet his/her preferences (Hawalah & Fasli, 2014; Liu et al., 2015; Liu et al., 2016). A RS suggest new items or services to the user by utilising difference sort of information and knowledge about the target user, other similar users, available items or users' behaviours stored records. Then the system provide the user with the list of suggested items that the user might be interested or not. A good RS stores the user behaviour and feedbacks to enhance the suggestion algorithm. So next time, the RS would suggest the new items based on only the items that the user was interested in before (Adomavicius & Tuzhilin, 2015; Hong et al., 2017; Sedhain et al., 2014).

AS mentioned before, The RS research domain is new compared to other classical studies in the domain of information system tools and techniques. RSs is known as an discrete study area in mid 90s (Luo et al., 2014). The following facts shows that the interest in RS domain has considerably grown:

i. RSs have a vital contribution in popular websites such as Netflix, Amazon, Google, TripAdvisor, IMDb and YouTube. additionally numerous broadcasting and internet-based firms are also fitting RSs in the services they provide for their users (Colomo-Palacios et al., 2017; Guan et al., 2016; Smith & Linden, 2017). For instance Amazon, the online electronic commerce company, has spent a considerable amount of resourced to improve the accuracy of its RS (Gomez-Uribe & Hunt, 2016).

ii. There are exclusive workshops, conferences and dedicated sessions to RSs which are often held in the conferences in the fields of databases, information systems and adaptive systems (Beilin & Yi, 2013; Belém et al., 2017). In universities there are exclusively courses related to RSs and tutorials in this regard are highly favoured at computer science conferences; and lately number of books which addressing RSs methods are published (Romero & Ventura, 2013; Wang et al., 2016).

2.2 Goals of Recommender Systems

The main objective of RS is to help the e-commerce Web sites to increase their sales (Li & Karahanna, 2015; Zhao, 2016). By recommending carefully selected items to users, RSs bring relevant items to the attention of users (Xin et al., 2014). This increases the sales volume and profits for the merchant. Although the primary goal of an RS is to increase revenue for the merchant, this is often achieved in ways that are less obvious than might seem at first sight (Handler, 2015). In order to achieve the broader business-centric goal of increasing revenue, the common operational and technical goals of RSs are as follows:

1. **Relevance:** The most obvious operational goal of an RS is to recommend items that are relevant to the user at hand (Gil et al., 2016; Huang, 2016). Users are more likely to consume items they find interesting. Although relevance is the primary operational goal of an RS, it is not sufficient in isolation (Kardan & Ebrahimi, 2013). Therefore, more goals are listed below, which are not quite as important as relevance but are nevertheless important enough to have a significant impact.
2. **Novelty:** RSs are truly helpful when the recommended item is something that the user has not seen in the past (Hawalah & Fasli, 2014; Singh & Boparai, 2016). For example, popular movies of a preferred genre would rarely be novel to the user. Repeated recommendation of popular items can also lead to reduction in sales diversity (Chen et al., 2013; Panniello et al., 2014).
3. **Serendipity:** A related notion is that of serendipity, wherein the items recommended are somewhat unexpected, and therefore there is a modest element of lucky discovery, as opposed to obvious recommendations (Jenders et

al., 2015; Sugiyama & Kan, 2015). Serendipity is different from novelty in that the recommendations are truly surprising to the user, rather than simply something they did not know about before (Zheng, 2014). It may often be the case that a particular user may only be purchasing items of a specific type, although a latent interest in items of other types may exist which the user might themselves find surprising (Jenders et al., 2015). Unlike novelty, serendipitous methods focus on discovering such recommendations (Kotkov et al., 2016). For example, if a new Indian restaurant opens in a neighbourhood, then the recommendation of that restaurant to a user who normally eats Indian food is novel but not necessarily serendipitous. On the other hand, when the same user is recommended Ethiopian food, and it was unknown to the user that such food might appeal to her, then the recommendation is serendipitous. Serendipity has the beneficial side effect of increasing sales diversity or beginning a new trend of interest in the user (Sugiyama & Kan, 2015; Zheng, 2014). Increasing serendipity often has long-term and strategic benefits to the merchant because of the possibility of discovering entirely new areas of interest (Jenders et al., 2015). On the other hand, algorithms that provide serendipitous recommendations often tend to recommend irrelevant items. In many cases, the longer term and strategic benefits of serendipitous methods outweigh these short-term disadvantages (Kotkov et al., 2016).

4. **Diversity:** RSs typically suggest a list of top-k items (Yu et al., 2016). When all these recommended items are very similar, it increases the risk that the user might not like any of these items (Feng et al., 2014). On the other hand, when the recommended list contains items of different types, there is a greater chance that the user might like at least one of these items (Chen et al., 2013; Chen et al.,

2016). Diversity has the benefit of ensuring that the user does not get bored by repeated recommendation of similar items (Adomavicius & Kwon, 2014; Chen et al., 2016; Yu et al., 2016).

Aside from these concrete goals, a number of soft goals are also met by the recommendation process both from the perspective of the user and merchant (Feng et al., 2014). From the perspective of the user, recommendations can help improve overall user satisfaction with the Web site (Chen et al., 2010). For example, a user who repeatedly receives relevant recommendations from Amazon.com will be more satisfied with the experience and is more likely to use the site again (Smith & Linden, 2017). This can improve user loyalty and further increase the sales at the site (Martinez-Cruz et al., 2015). At the merchant end, the recommendation process can provide insights into the needs of the user and help customize the user experience further (Zhao, 2016). Finally, providing the user an explanation for why a particular item is recommended is often useful. For example, in the case of Netflix, recommendations are provided along with previously watched movies. As it can be observed in the following sections, some recommendation algorithms are better suited to providing explanations than others (Meyffret et al., 2013; Tinghuai et al., 2015).

There is a wide diversity in the types of products recommended by such systems (Colombo-Mendoza et al., 2015; Panniello et al., 2014; Su et al., 2017; Zhang, 2016). Some recommender systems, do not directly recommend products (Cantador et al., 2013; Su et al., 2017). Rather they may recommend social connections, which have an indirect benefit to the site by increasing its usability and advertising profits

(Zhou et al., 2015). In order to understand the nature of these goals, some popular examples of RSs will be discussed in this chapter, which showcase the broad diversity of RSs that were built either as research prototypes, or are available today as commercial systems in various problem settings (Gomez-Uribe & Hunt, 2016; Smith & Linden, 2017).

2.3 Recommender Systems Function

In the previous section, RSs were defined as software tools and techniques providing users with suggestions for items a user may wish to utilize (Colomo-Palacios et al., 2017; Tejeda-Lorente et al., 2014). Now it is needed to refine this definition illustrating a range of possible roles that an RS can play. First of all, the role played by the RS must be distinguished on behalf of the service provider from that of the user of the RS. For instance, a travel recommender system is typically introduced by a travel intermediary (e.g., Expedia.com) or a destination management organization (e.g., Visitfinland.com) to increase its turnover (Expedia), i.e., sell more hotel rooms, or to increase the number of tourists to the destination (Lu et al., 2015; Yu et al., 2016), whereas, the user's primary motivations for accessing the two systems is to find a suitable hotel and interesting events/attractions when visiting a destination (Lu et al., 2015).

In fact, there are various reasons as to why service providers may want to exploit this technology:

- ***Increase the number of items sold:*** This is probably the most important function for a commercial RS, i.e., to be able to sell an additional set of items compared to those usually sold without any kind of recommendation (Ashrafa et al., 2016; Azaria et al., 2013; Doshi et al., 2016; Vargas & Castells, 2014). This goal is achieved because the recommended items are likely to suit the user's needs and wants. Presumably the user will recognize this after having tried several recommendations. Non-commercial applications have similar goals, even if there is no cost for the user that is associated with selecting an item. For instance, a content network aims at increasing the number of news items read on its site. In general, it can be said that from the service provider's point of view, the primary goal for introducing an RS is to increase the conversion rate, i.e., the number of users that accept the recommendation and purchase an item, compared to the number of simple visitors that just browse through the information (Ashrafa et al., 2016; Doshi et al., 2016; Vargas & Castells, 2014).

- ***Sell more diverse items:*** Another major function of an RS is to enable the user to select items that might be hard to find without a precise recommendation (Chen et al., 2016; Feng et al., 2014; Vargas & Castells, 2014). For instance, in a movie RS such as Netflix, the service provider is interested in renting all the DVDs in the catalogue, not just the most popular ones (Colombo-Mendoza et al., 2015). This could be difficult without an RS since the service provider cannot afford the risk of advertising movies that are not likely to suit a particular user's taste. Therefore, an RS suggests or advertises unpopular movies to the right users (Colombo-Mendoza et al., 2015).
- ***Increase the user satisfaction:*** A well designed RS can also improve the experience of the user with the site or the application (Liang et al., 2006; Park et al., 2006). The user will find the recommendations interesting, relevant and, with a properly designed human-computer interaction, he will also enjoy using the system. The combination of effective, i.e., accurate, recommendations and a usable interface will increase the user's subjective evaluation of the system. This in turn will increase

system usage and the likelihood that the recommendations will be accepted (Jiang et al., 2010).

- ***Increase user fidelity:*** A user should be loyal to a Web site which, when visited, recognizes the old customer and treats him as a valuable visitor (Behl et al., 2016; Cui, Hu, et al., 2016). This is a normal feature of an RS since many RSs compute recommendations, leveraging the information acquired from the user in previous interactions, e.g., her ratings of items (Hays & Singer, 2012; Yang et al., 2016). Consequently, the longer the user interacts with the site, the more refined the user model becomes, i.e., the system representation of the user's preferences, and the more the recommender output can be effectively customized to match the user's preferences (Behl et al., 2016; Hu, et al., 2016; Cui, et al., 2016).
- ***Better understand what the user wants:*** Another important function of an RS, which can be leveraged to many other applications, is the description of the user's preferences, either collected explicitly or predicted by the system (Chen et al., 2016; Qian et al., 2014; Yu et al., 2016). The service provider may then decide to re-use this knowledge for a number of other goals such as improving the management of the item's stock or production (Ekstrand et al., 2014). For instance, in the travel domain, destination management organizations can decide to advertise a specific region to new customer sectors or advertise a particular type of promotional message derived by analysing the data collected by the RS (transactions of the users) (Hu, et al., 2016; Ekstrand et al., 2014).

There are some important motivations mentioned above as to why e-service providers introduce RSs. But users also may want an RS, if it will effectively support their tasks or goals. Consequently an RS must balance the needs of these two players and offer a service that is valuable to both (Liang et al., 2006).

As these various points indicate, the role of an RS within an information system can be quite diverse. This diversity calls for the exploitation of a range of different knowledge sources and techniques and in the next section, some core techniques and models is presented that are used to identify the right RS (Chen et al., 2016; Feng et al., 2014; Vargas & Castells, 2014).

2.4 Models of Recommender Systems

The basic models for RSs work with two kinds of data, which are (i) the user-item interactions, such as ratings or buying behaviour, and (ii) the attribute information about the users and items such as textual profiles or relevant keywords (Domingues et al., 2013; Wei et al., 2017; Yu et al., 2016). In the following, the most popular models of RSs are presented in details.

2.4.1 Collaborative Recommender Systems

CF models use the collaborative power of the ratings provided by multiple users to make recommendations (Wei et al., 2017). The main challenge in designing CF methods is that the underlying ratings matrices are sparse (Bao, 2012). Consider an example of a movie application in which users specify ratings indicating their like or dislike of specific movies. Most users would have viewed only a small fraction of the large universe of available movies. As a result, most of the ratings are unspecified. The specified ratings are also referred to as observed ratings. Throughout this thesis, the terms "specified" and "observed" will be used in an interchangeable way. The unspecified ratings will be referred to as "unobserved" or "missing" (Qian et al., 2014).

The basic idea of CF methods is that these unspecified ratings can be imputed because the observed ratings are often highly correlated across various users and items (Sedhain et al., 2014;Yang et al., 2014). For example, consider two users named Alice and Bob, who have very similar tastes. If the ratings, which both have specified, are very similar, then their similarity can be identified by the underlying algorithm. In such cases, it is very likely that the ratings in which only one of them has specified a value, are also likely to be similar. This similarity can be used to make inferences about incompletely specified values (Yu et al., 2016). Most of the models for CF focus on leveraging either inter-item correlations or inter-user correlations for the prediction process. Some models use both types of correlations. Furthermore, some models use carefully designed optimization techniques to create a training model in much the same way a classifier creates a training model from the labelled data. This model is then used to impute the missing values in the matrix, in the same way that a classifier imputes the missing test labels (Guo et al., 2016; Maria Soledad Pera et al., 2011). There are two types of methods that are commonly used in CF, which are referred to as memory-based and model-based methods:

1. ***Memory-based methods:*** Memory-based methods are also referred to as neighbourhood-based CF algorithms. These were among the earliest CF algorithms, in which the ratings of user-item combinations are predicted on the basis of their neighbourhoods (Ghazarian & Nematbakhsh, 2015). These neighbourhoods can be defined in one of two ways:
   - ***User-based collaborative filtering:*** In this case, the ratings provided by like-minded users of a target user A are used in order to make the recommendations for A. Thus, the basic idea is to determine users,

who are similar to the target user A, and recommend ratings for the unobserved ratings of A by computing weighted averages of the ratings of this peer group. Therefore, if Alice and Bob have rated movies in a similar way in the past, then one can use Alice's observed ratings on the movie Terminator to predict Bob's unobserved ratings on this movie. In general, the k most similar users to Bob can be used to make rating predictions for Bob. Similarity functions are computed between the rows of the ratings matrix to discover similar users (Al-Shamri, 2014; Koren & Bell, 2015). Studies used this filtering approach to recommend interesting items to a user depending on alike-minded users called neighbours (Bellogín et al., 2014; Wang et al., 2016).

- ***Item-based collaborative filtering:*** In order to make the rating predictions for target item B by user A, the first step is to determine a set S of items that are most similar to target item B. The ratings in item set S, which are specified by A, are used to predict whether the user A will like item B. Therefore, Bob's ratings on similar science fiction movies like Alien and Predator can be used to predict his rating on Terminator (Bilge & Kaleli, 2014; Li et al., 2016). Similarity functions are computed between the columns of the ratings matrix to discover similar items (Li & He, 2017). For instance, Bilge & Kaleli (2014) designed an RS that first explored and analysed the user-item matrix to determined relationships between multiple different items, and then use these relationships to generate recommendation results for users.

The advantages of memory-based techniques are that they are simple to implement and the resulting recommendations are often easy to explain (Koren & Bell, 2015). On the other hand, memory-based algorithms do not work very well with sparse ratings matrices (Li et al., 2016). For example, it might be difficult to find sufficiently similar users to Bob, who have rated Gladiator. In such cases, it is difficult to robustly predict Bob's rating of Gladiator. In other words, such methods might lack full coverage of rating predictions. Nevertheless, the lack of coverage is often not an issue, when only the top-k items are required (Koren & Bell, 2015).

2. ***Model-based methods:*** In model-based methods, machine learning and data mining methods are used in the context of predictive models (Aggarwal, 2016). In cases where the model is parameterized, the parameters of this model are learned within the context of an optimization framework. Some examples of such model-based methods include decision trees, rule-based models, Bayesian methods and latent factor models. Many of these methods, such as latent factor models, have a high level of coverage even for sparse ratings matrices (Jiang et al., 2015; Liu et al., 2014). For example, Jiang et al. (2015) proposed an RS that utilises user interesting topics, such as societal, cultural, or landmark, are obtained from the geo-tag restricted textual description of images via the user-model instead of only from geographical locations.

The design of recommendation algorithms is influenced by the system used for tracking ratings. The ratings are often specified on a scale that indicates the specific level of like or dislike of the item at hand (Koren & Bell, 2015). It is possible for ratings to be continuous values, such as in the case of the Jester joke recommendation engine, in which the ratings can take on any value between -10 and 10 (Benkaouz et al., 2016). This is, however, relatively rare. Usually, the ratings are interval-based, where a discrete set of ordered numbers are used to quantify like or dislike. Such ratings are referred to as interval-based ratings. For example, a 5-point rating scale might be drawn from the set $\{-2, -1, 0, 1, 2\}$, in which a rating of -2 indicates an extreme dislike, and a rating of 2 indicates a strong affinity to the item. Other systems might draw the ratings from the set $\{1, 2, 3, 4, 5\}$ (Ghazarian & Nematbakhsh, 2015; Koren & Bell, 2015; Zhou et al., 2015).

Figure 2.1 Example of 5-point interval ratings

The number of possible ratings might vary with the system at hand. The use of 5-point, 7-point, and 10-point ratings is particularly common (Koren & Bell, 2015). The 5-star ratings system, illustrated in Figure 2.1, is an example of interval ratings. Along each of the possible ratings, the semantic interpretation of the user's level of interest is indicated (Jiang et al., 2015). This interpretation might vary slightly across different merchants, such as Amazon or Netflix. For example, Netflix uses a 5-star ratings system in which the 4-star point corresponds to "really liked it," and the central 3-star point corresponds to "liked it." Therefore, there are three favourable ratings and two unfavourable ratings in Netflix, which leads to an unbalanced rating scale. In some cases, there may be an even number of possible ratings, and the neutral rating might be missing. This approach is referred to as a forced choice rating system (Gomez-Uribe & Hunt, 2016; Maria Soledad Pera et al., 2011).

Figure 2.2 Example of ordinal ratings

One can also use ordered categorical values such as {Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree} in order to achieve the same goals . In general, such ratings are referred to as ordinal ratings, and the term is derived from the concept of ordinal attributes (Koren & Sill, 2013). An example of ordinal ratings, used in Stanford University course evaluation forms, is illustrated in Figure 2.2.

2.4.2 Content-Based Recommender Systems

In CB recommender systems, the descriptive attributes of items are used to make recommendations. The term "content" refers to these descriptions. In content-based methods, the ratings and buying behaviour of users are combined with the content information available in the items (Gao et al., 2015; Lu et al., 2015; Yao et al., 2015). For example, consider a situation where a user has rated the movie Terminator highly, but there is no access to the ratings of other users. Therefore, CF methods are ruled out.

However, the item description of Terminator contains similar genre keywords as other science fiction movies, such as Alien and Predator. In such cases, these movies can be recommended to him (Pera & Ng, 2013).

In CB methods, the item descriptions, which are labelled with ratings, are used as training data to create a user-specific classification or regression modelling problem. For each user, the training documents correspond to the descriptions of the items he has bought or rated. The class (or dependent) variable corresponds to the specified ratings or buying behaviour. These training documents are used to create a classification or regression model, which is specific to the user at hand (or active user). This user-specific model is used to predict whether the corresponding individual will like an item for which her rating or buying behaviour is unknown (Lu et al., 2015).

CB methods have some advantages in making recommendations for new items, when sufficient rating data are not available for that item (Achakulvisut et al., 2016). This is because other items with similar attributes might have been rated by the active user. Therefore, the supervised model will be able to leverage these ratings in conjunction with the item attributes to make recommendations even when there is no history of ratings for that item (Musto et al., 2016).

However, CB methods do have several disadvantages as well (Guo et al., 2016; Su et al., 2017):

i. In many cases, CB methods provide obvious recommendations because of the use of keywords or content. For example, if a user has never consumed an item with a particular set of keywords, such an item has no chance of being recommended. This is because the constructed model is specific to the user at hand, and the community knowledge from similar users is not leveraged. This phenomenon tends to reduce the diversity of the recommended items, which is undesirable (Guo et al., 2016).

ii. Even though CB methods are effective at providing recommendations for new items, they are not effective at providing recommendations for new users. This is because the training model for the target user needs to use the history of her ratings. In fact, it is usually important to have a large number of ratings available for the target user in order to make robust predictions without overfitting (Lu et al., 2015).

Therefore, CB methods have different trade-offs from collaborative filtering systems.

2.4.3 Knowledge-Based Recommender Systems

Knowledge-based recommender systems are particularly useful in the context of items that are not purchased very often (Arnett et al., 2015; Zhang et al., 2016). Examples include items such as real estate, automobiles, tourism requests, financial services, or expensive luxury goods (Aggarwal, 2016). In such cases, sufficient ratings may not be available for the recommendation process. As the items are bought rarely, and with different types of detailed options, it is difficult to obtain a sufficient number of ratings for a specific instantiation (i.e., combination of options) of the item at hand. This problem is also encountered in the context of the cold-start problem, when sufficient ratings are not available for the recommendation process. Furthermore, the nature of consumer preferences may evolve over time when dealing with such items (Colombo-Mendoza et al., 2015). For example, the model of a car may evolve significantly over a few years, as a result of which the preferences may show a corresponding evolution. In other cases, it might be difficult to fully capture user interest with historical data such as ratings. A particular item may have attributes associated with it that correspond to its various properties, and a user may be interested only in items with specific properties. For example, cars may have several makes, models, colours, engine options, and interior options, and user interests may be regulated by a very specific combination of these options. Thus, in these cases, the item domain tends to be complex in terms of its varied properties, and it is hard to associate sufficient ratings with the large number of combinations at hand (Zhang et al., 2016).

Such cases can be addressed with knowledge-based recommender systems, in which ratings are not used for the purpose of recommendations. Rather, the recommendation process is performed on the basis of similarities between customer requirements and item descriptions, or the use of constraints specifying user requirements. The process is facilitated with the use of knowledge bases, which contain data about rules and similarity functions to use during the retrieval process. In fact, the knowledge bases are so important to the effective functioning of these methods that the approach takes its name from this fact. The explicit specification of requirements results in greater control of users over the recommendation process (Arnett et al., 2015). In both CF and CB systems, recommendations are decided entirely by either the user's past actions/ratings, the action/ratings of his peers, or a combination of the two (Nirwan et al., 2016). Knowledge-based systems are unique in that they allow the users to explicitly specify what they want (Colombo-Mendoza et al., 2015). This difference is illustrated in Table 2.1.

Table 2.1: The conceptual goals of various recommender systems

Method	Conceptual Goal	Input
Collaborative	Give me recommendations based on a collaborative approach that leverages the ratings and actions of my peers/myself.	User ratings + community ratings
Content-based	Give me recommendations based on the content (attributes) I have favoured in my past ratings and actions.	User ratings + item attributes
Knowledge-based	Give me recommendations based on my explicit specification of the kind of content (attributes) I want.	User specification + item attributes + domain knowledge

Knowledge-based recommender systems can be classified on the basis of the type of the interface (and corresponding knowledge) used to achieve the aforementioned goals:

1. **Constraint-based recommender systems:** In constraint-based systems, users typically specify requirements or constraints (e.g., lower or upper limits) on the item attributes. An example of such an interface is illustrated in Figure 2.3. Domain-specific rules are used to match the user requirements to item attributes. These rules represent the domain-specific knowledge used by the system. Such rules could take the form of domain-specific constraints on the item attributes (Felfernig et al., 2015). Furthermore, constraint-based systems often create rules relating user attributes to item attributes (e.g., "Older investors do not invest in ultra-high-risk products."). In such cases, user attributes may also be specified in the search process (Murphy et al., 2015). Depending on the number and type of returned results, the user might have an opportunity to modify their original requirements (Felfernig et al., 2015). For example, they might relax some of their constraints when too few results are returned, or they might add more constraints.

This search process is interactively repeated until the user arrives at her desired results (Zhang et al., 2016).

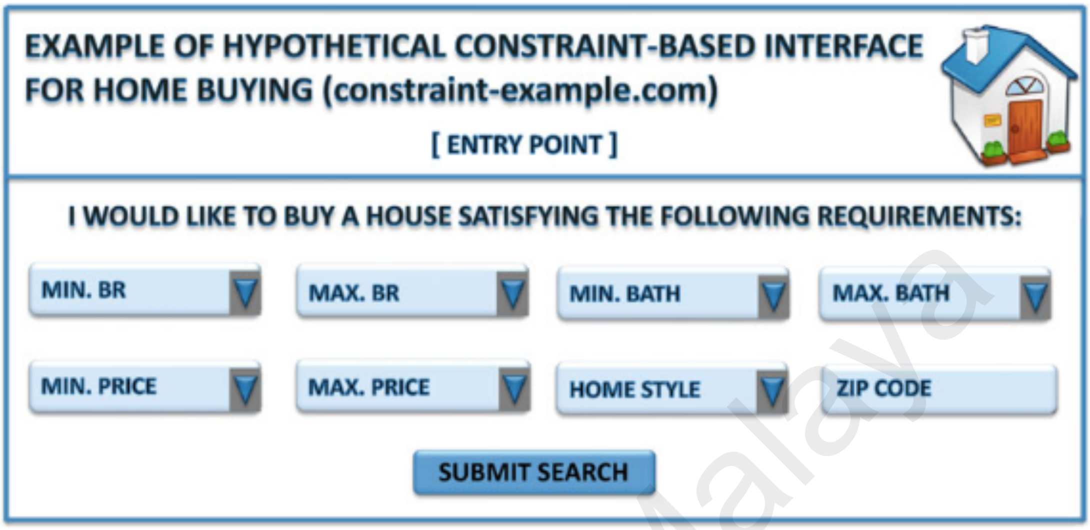


Figure 2.3: A hypothetical example of an initial user interface for a constraint-based recommender

2. **Case-based recommender systems:** In case-based recommender systems, specific cases are specified by the user as targets or anchor points (Musto et al., 2015). Similarity metrics are defined on the item attributes to retrieve similar items to these cases (Sauer, 2016). An example of such an interface is illustrated in Figure 2.4.

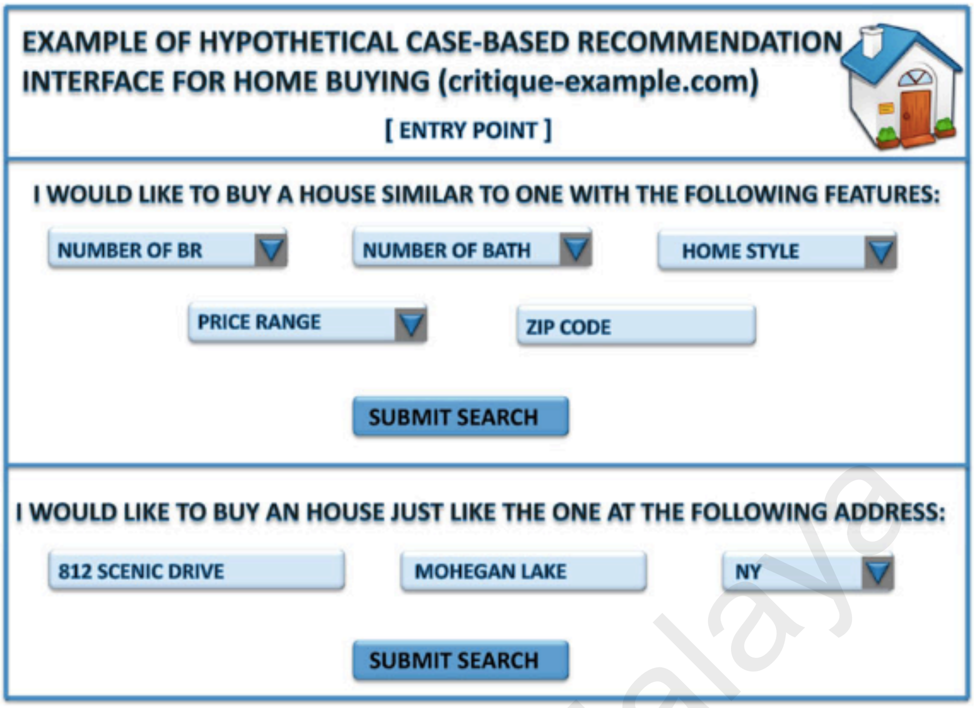


Figure 2.4: A hypothetical example of an initial user interface for a case-based recommender

The similarity metrics are often carefully defined in a domain-specific way. Therefore, the similarity metrics form the domain knowledge that is used in such systems. The returned results are often used as new target cases with some interactive modifications by the user (Wu et al., 2015). For example, when a user sees a returned result, which is almost similar to what they want, they might re-issue a query with that target, but with some of the attributes changed to the user's liking. This interactive process is used to guide the user towards items of interest (Musto et al., 2015).

Note that in both cases, the system provides an opportunity to the user to change their specified requirements. However, the way in which this is done is different in the two cases. In case-based systems, examples (or cases) are used as anchor points to guide the search in combination with similarity metrics. Critiquing interfaces are particularly popular for expressing feedback in such systems, where users iteratively modify one or more attributes of a preferred item in each iteration. In constraint-based systems, rules or constraints are used to guide the search. The form of the guidance may often take the form of search-based systems, where users specify their constraints with a search-based interface (Gemmis, et al., 2015).

It is noteworthy that both knowledge-based and CB systems depend significantly on the attributes of the items. Because of their use of content-attributes, knowledge-based systems inherit some of the same disadvantages as CB systems (Aggarwal, 2016). For example, just like CB systems, the recommendations in knowledge-based systems can sometimes be obvious because the use of community (i.e., peer) ratings is not leveraged. The main difference is that content-based systems learn from past user behaviour, whereas knowledge-based recommendation systems recommend based on active user specification of their needs and interests (Zhang et al., 2016). Therefore, in most of the recommendation literature, knowledge-based recommenders are considered to be a distinct category from CB recommenders. These distinctions are based both on the goals of such systems and the kind of input data used (Aggarwal, 2016).

2.4.4 Demographic Recommender Systems

In Demographic Filtering (DF), the demographic information about the user is leveraged to learn classifiers that can map specific demographics to ratings or buying propensities (Bobadilla et al., 2013). An early RS, referred to as Grundy, recommended books based on the library of manually assembled stereotypes (Rich, 1979). The characteristics of the user were collected with the use of an interactive dialogue. It has observed that the demographic groups from marketing research can be used to recommend items (Rich, 1979). Another work (Teo, 2001) makes Web page recommendations on the basis of the demographic characteristics of users that have rated a particular page highly. In many cases, demographic information can be combined with additional context to guide the recommendation process (Zhao et al., 2016).

DF is a stereotypical system as it categorizes users based on their demographic attributes. Later, DF uses the user opinions for the items of the system as a basis for recommendations. Formally, DF has M users, U $= \{u_1, \ldots, u_M\}$, having N demographic attributes, D $= \{a_1, \ldots, a_N\}$. Usually, DF collects demographic attributes during the registration process using questionnaire about the user demographic data and the user's characteristics. Through interacting with the system, the user is asked explicitly or implicitly to rate K items, S $= \{s_1, \ldots, s_K\}$, such as news, Web pages, books, movies, or CDs. Initially, each user u_i may rate a subset of items S_i. The declared rating if available of user u_c for an item S_k is denoted by $r_{c,k}$ (Zhao et al., 2016).

After constructing the user profile, DF calculates the similarity value between the current active user and the remaining training users using a suitable similarity measure. This value indicates how closely the two users in consideration resemble each other. Accordingly, a set of neighbours is selected for this active user from the ranked list of the training users. After that DF assigns a predicted rating to all the items seen by the neighbourhood set and not by the active user. The predicted rating, $pr_{x,k}$, indicates the expected interestingness of the item S_k to the user u_x. The predicted rating, $pr_{x,k}$, is usually computed as an aggregate of the ratings of $u_x s$ neighbourhood set for the same item S_k (Zhao et al., 2016):

$$pr_{x,k} = \frac{\sum_{u_y \in N_x} \mathrm{sim}(u_x, u_y) \times r_{y,k}}{\sum_{u_y \in N_x} |\mathrm{sim}(u_x, u_y)|} \qquad \text{Eq. 1}$$

where N_x denotes the set of neighbors for u_x who have rated item S_k.

DF does not require a list of ratings for user profiling that are required by other RSs like CF and CB. This makes DF strong against "new user" problem. More interestingly, DF follows the same way that recommendations are made in real life. Moreover, DF is easy, quick, and straight forward as the profiling fields are always very few compared to ratings. This is very important when the number of users is very large. For other RSs, the system accuracy relies largely on the number of ratings because the larger the number of ratings the system get from the user, the higher the quality of its recommendations. This is not the case for DF, because the profile is fixed for long time once the profiling attributes are obtained from the user (Zhao et al., 2016). Later in Section 1.6 (Personalized Recommendation), there will be some existing studies and researches which have used DF to enhanced their recommendation system.

On the other hand, the basic disadvantage of DF lies in its sensitivity to security and privacy issues especially for e-commerce applications. Usually, online users are reluctant to share a big amount of personal information with a system due to their security. Due to their privacy, some users assume that disclosing demographic data breaks the anonymity of these systems (Kanetkar et al., 2014; Zhao et al., 2014).

2.4.5 Location-Based Recommender Systems

As the smartphone popularity is increasing, users are often happy to be provided with location-based suggestions (Wang et al., 2016). For instance, a user might wish to discover nearby restaurant while traveling, based on his/her latest history of browsing or ratings of other visited restaurants (Ashrafa et al., 2016). Usually, RSs that suggest places of interest, have an aspect of location developed into it. Foursquare is an example of such platform that suggest different sorts of interesting places such as museums or restaurants (Liu et al., 2016). In general, location-based RSs have two spatial locality classifications:

i. ***User-specific locality:*** the user's interests and preferences are linked with his/her geographical location (Chen, 2013; Schedl & Schnitzer, 2014). For instance, a user from California may not read a book similar with someone from Texas and that means, users from different locations might have same preferences.

ii. ***Item-specific locality:*** Item's location can have a direct effect on the user's preference. For instance, a customer might not travel a long distance to have meal in a restaurant, so the restaurant's location is attractive to the nearby customers (Braunhofer et al., 2014; Majid et al., 2013; Ravi & Vairavasundaram, 2016).

The travel locality and preference locality have different algorithms in RSs. The travel locality is tied with the context of the user, whereas the preference locality are designed in a self-learn manner and need to be able to learn more about the user as the user uses the system. Therefore, researchers have observed the growth in usage of GPS-enabled RSs that are utilised in various domains (Liu et al., 2016; Ratsameethammawong & Kasemsan, 2010). Recent studies and researches have focused on integrating location as a contextual features with their recommendation to have more personalized recommendation and further in this chapter they will be described in details (Section 1.6).

2.4.6 Semantics-Aware Recommender Systems

As it is mentioned before, CB RSs produce recommendations based on items' textual information (such as user review or description) (Garrido & Ilarri, 2014; Hong et al., 2017; Tabara et al., 2016). During the initial process of CB recommendation, the RS needs to retrieve sufficient information from user's profile and then tries to match the user's preferences with items' attributes. The outcome result is the list of relative items that the user might be interested with high level of accuracy (Tabara et al., 2016).

Usually, the textual information of the item can be used to describe the item's attributes. Therefore, CB approach extracts these attributes to match it with corresponding user's profile attributes. Sometimes the obtained information is not enough to be matched with user's preferences. In addition, it might be confusing to extract data from some provided textual information such as user's reviews, due to having the language ambiguity (such as "polysemy", "synonymy", "multi-word expressions", "named entity recognition" and "disambiguation"). Thus, RSs utilise some external tools to extract relative information from the textual data (Antunes et al., 2016; Garrido & Ilarri, 2014).

Semantic technologies are becoming very popular due to the issue of language ambiguity. Therefore, having different open source tools (such as "Wikipedia", "DBpedia", "Freebase", and "BabelNet") become very handy (Alzu'bi et al., 2015). Studies conducted on semantic techniques have showed the transformation from a keyword-based representation of user and item profile to a concept-based representation (Antunes et al., 2016; Cunico & Silva, 2017). The semantic technologies and Natural Language Processing (NLP) are the most important elements of recent studies in the domain of CB RS that try to perform deep content analytics on the acquired textual information (Antunes et al., 2016; Hong et al., 2017; Kermany & Alizadeh, 2017).

Semantic techniques are classified into top-down and bottom-up approaches (Colomo-Palacios et al., 2017). Top-down approaches rely on the integration of external knowledge, such as machine readable dictionaries, taxonomies or ontologies (with or without value restrictions and logical constraints), for annotating items and representing user profiles in order to capture the semantics of the target user information needs (Colomo-Palacios et al., 2017; Rodriguez-Garcia et al., 2014). The main motivation behind top-down approaches is the challenge of providing recommender systems with the linguistic knowledge and common sense knowledge, as well as the cultural background which characterize the human ability of interpreting documents expressed in natural language and reasoning on their meaning (Colomo-Palacios et al., 2017).

On the other hand, bottom-up approaches exploit the so-called geometric metaphor of meaning to represent complex syntagmatic and paradigmatic relations between words in high-dimensional vector spaces. According to this metaphor, each word (and each document as well) can be represented as a point in a vector space (Colomo-Palacios et al., 2017). The peculiarity of these models is that the representation is learned by analysing the context in which the word is used, in a way that terms (or documents) similar to each other are close in the space (Bontcheva & Rout, 2014). For this reason bottom-up approaches are also called distributional models. One of the great virtues of these approaches is that they are able to induce the semantics of terms by analysing their use in large corpora of textual documents using unsupervised mechanisms, as evidenced by the recent advances of machine translation techniques (Bontcheva & Rout, 2014).

2.4.7 Social Recommender Systems

New generation of RSs are based on some elements such as structures of social network and social tags, or it can be a integration of few social elements (Sedhain et al., 2014). Generally, social network platforms gain lots of attention because of its popularity nowadays (Tewari & Barman, 2016; Yang et al., 2016). In the following sub-sections, the different types of social RSs is presented.

2.4.7.1 Product and Content Recommendations with Social Influence

RSs are generating suggestion for different sort of items and content by utilising the social network platforms (Tang et al., 2013). The viral marketing utilises the RS to recommend content or items based on the current influential related entities in the society (Muchnik et al., 2013). this domain of RS is based on influence analysis in communities. In such a domain, the main task of the RS is to define the existing influencers and relatively tries to produce suggestions (Aral & Walker, 2014). For instance, the RS can try to look for the influential users in social network platforms such as Facebook and then explores the trending topics and based on those trending topics, it generates recommendation result (Aral & Walker, 2014).

2.4.7.2 Trustworthy Recommender Systems

Some social network platforms (such as Slashdot or Epinions) utilise the trust between their users to generate suggestions. The users are able to determine their trust towards other online users (Chechev & Koychev, 2014; Yang et al., 2016). For instance, a user might define another user to be his trusted friend by writing a positive review of that particular user, or the user may explicitly denote another user as a trusted online friend. These kinds of information help the RS to make better suggestions based on target user's trusted friends (Zou et al., 2015). Recent studies showed that trust-based recommendation yields better result as the user feels the recommendation is somehow generated by his/her trusted friends (Zou et al., 2015).

2.4.8 Hybrid Recommender Systems

The researches need to be careful when they are dealing with different types of RSs, because every RS might need different types of input, depending on which scenario the RS works better (Nagarnaik & Thomas, 2015). For instance, CF approaches work on user ratings (Aggarwal, 2016; Ronen et al., 2014; Wei et al., 2016), knowledge-based RSs that work well on user's activities in the knowledge bases context (Sauer, 2016), and CB approaches depend on the item's attached textual information and users ratings (Chen et al., 2017; Lu et al., 2015; Mathew et al., 2016). In addition, DF methods utilise the users' demographic data to generate recommendations (Zhao et al., 2016). It is important to note that each one of these RSs have their weaknesses and strengths (Nagarnaik & Thomas, 2015). For instance, knowledge-based RS in comparison with other types of RSs, perform better when there is not sufficient amount of information available (this RS can be used to overcome cold-start issue) (Bobadilla et al., 2012).

However, CF approach would perform much better when there is enough information available about users (Aggarwal, 2016).

Some studies showed that different types of RSs can be utilised to perform the same task when there are different types of available inputs (Kanetkar et al., 2014). Therefore there is an opportunity to use hybrid approach in such a case, which multiple types of RSs are combined to improve the recommendation result (Kanetkar et al., 2014; Singh & Boparai, 2016). Hybrid RSs are closely related to the domain of Ensemble-based RSs that different types of algorithms is integrated to build a new stronger approach. Ensemble-based RS integrates different approaches to utilises information from various sources and this would lead to improve the effectiveness and accuracy of the RS's final result (Chen et al., 2014; Zhang et al., 2017).

2.5 Personality and Recommender Systems

In the past 10 years, a growth in number of RSs is observed which have utilised user-oriented methods to improve their recommendation results. the conducted researches investigated different aspects of user's psychology such as his/her personality, pattern of thoughts or emotions (Chen et al., 2016; Ferwerda & Schedl, 2014). It is important to take note that the main task of RSs is to provide better options for their users and by utilising user's personality, it is easier to understand his/her preferences. Some studies showed a great improvement when they consider user's personality approach integrated with traditional rating RSs (Lops et al., 2015). It is shown that by using personality in a RS's algorithm, it performed better and yields a better quality of suggestion result (Tkalcic & Chen, 2015). Therefore, during the process of building a personalised RS, first need to understand the user's aspects such as personality trait, mood, emotion and pattern of thoughts (Kazai et al., 2016). This is the reason why need to consider user-oriented information, so the RS can differentiate each individual better and groups them under different classifications (Cremonesi et al., 2013; Kavu et al., 2017).

It is meaningful to differentiate each users based on their personality that can be used in a very wide range of RSs (Yu et al., 2016). For instance, user's interest on music is very relative with his/her personality type (Lu & Tseng, 2009). Studies illustrated that each type of human personality has its own unique interests and preferences. This shows that in domain of RS, the understanding of user's personality is important and need to recommend items in a personalised manner (Chen et al., 2013). Personality has been introduce to help CF to improve exploring user-similarity and added a new field to the user's profile in RS. As long as the RS obtain the users' personality, it can group the users in different personality group and look for the similar users within the specific group of users (Asabere et al., 2017; Chen et al., 2016).

The domain of psychology defines personality as collection of information about each individual's emotion, pattern of thoughts, attitude, interpersonal and behaviour. RS can utilise these collection of information about users and try to explore each user's personality detail for enhancing the personalised recommendation algorithm (Cremonesi et al., 2013; Tkalcic & Chen, 2015). In order to utilise the user's personality attributes in computer-based algorithms, the RS need to convert it to some feature vectors that can be quantified (Tkalcic et al., 2016). The traditional studies provides a very long and comprehensive set of questionnaires for the users to obtain the parameters of their personality data, which was a barrier for users that everyday used the RSs. (Nirwan et al., 2016). The NEO Personality Inventory and International Personality

Item Pool (IPIP) are such long questionnaires that were used by traditional RSs (Hengartner et al., 2016). Recent conducted researches have been exploring ways to obtain these parameters of personality in an implicit manner, which will not ask the user directly to fill-up the long questionnaires, For instance, social network platforms (such as Instagram, Facebook and Twitter) and other user generated textual information (such as review and emails) (Cantador et al., 2013; Majid et al., 2013; Pera et al., 2011).

2.5.1 Basic concept of personality

According to Cantador et al (2013), personality traits are so important because they can be used to differentiate the individuals by their personal attitudes, behaviours, motivations and emotions. Therefore, personality can be used in the domain of RSs to enrich the user's profile with essential data. In addition, it is important to take note that the user's personality cannot be changed easily, so it is independent from user's context.

Old Greeks were the first researchers that conducted studies to differentiate humans with their personalities and classified the individuals' personalities into four categories: (i) Sanguinic, (ii) Choleric , (iii) Phlegmatic and (iv) Melancholic (Tsoucalas et al., 2017). In the following section, there are listed three popular personality models that currently are utilised to estimate the personality traits of users.

2.5.1.1 The Myers-Briggs Model of Personality

In year 1990, Katharine Cook Briggs and Isabel Briggs Myers constructed and developed a psychological personality test called Myers-Briggs Type Indicator (MBTI). MBTI divides the personality traits into four dimensions: Introversion–Extraversion, Sensation–Intuition, Thinking–Feeling, and Judging–Perceiving. Respondents are classified into one of 16 personality types based on the largest score obtained for each bipolar scale (Tananchai, 2017). For instance, a person scoring higher on Introversion than Extraversion, Intuition than Sensation, Feeling than Thinking, and Judging than Perceiving would be classified as an Introverted, Intuitive, Feeling, and Judging.

2.5.1.2 The Hogan Development Survey Model Of Personality

The Hogan Development Survey (HDS) assesses user's characteristics that are likely to arise during difficult times such as stress, pressure and etc. HDS categorizes users based on eleven personality traits: Excitable, Sceptical, Cautious, Reserved, Leisurely, Bold, Mischievous, Colourful, Imaginative, Diligent and Dutiful. The 11 personality traits are subsequently broken down into three components, each of which represents themes of interpersonal tendencies: (1) ''moving away from people'' (Excitable, Cautious, Sceptical, Reserved and Leisurely), reflecting those who are insecure and move away from people to manage this; (2) ''moving against people'' (Bold, Mischievous, Colourful and Imaginative), reflecting those who are competitive and confident, and move against others through intimidation and manipulation in order to manage their insecurities; and (3) ''moving towards people'' (Diligent and Dutiful), reflecting those who are conformist and obedient, who move towards others to gain approval in order to manage their insecurities (Hogan & Hogan, 1997).

The HDS is a multi-dimensional measure of dysfunctional dispositions, which was specifically developed for use in the workplace. It describes the dark side of personality that emerges in times of increased strain and can disrupt relationships, damage reputations, and derail peoples' chances of success. (Church et al., 2016; Grijalva et al., 2015; Prokopy et al., 2015; Saleh & Hu, 2016).

2.5.1.3 The Five Factor Model of Personality

The origin of Five Factor Model of personality (FFM) is from the lexical speculation that it is vital to observe the important things in people's life, because in the long run those things end up part of their language (Seibert & DeGeest, 2017). Some studies focused on the user's language to explore and retrieve his/her personality traits (Borghuis et al., 2017; Elahi et al., 2013). However, FFM is based on the five important factors (i.e. agreeableness, extraversion, openness to experience, neuroticism and conscientiousness) (Seibert & DeGeest, 2017).

Openness to Experience (O), regularly alluded to only as Openness, portrays the qualification between creative, imaginative individuals and logical, routine individuals. People with high score of Openness are regularly unconventional, noncompliance and are exceptionally mindful of their sentiments. They can effortlessly think in deliberation. Individuals with low score of Openness try to have similar preferences. They favor straightforward and direct considering over complex, equivocal and unobtrusive. The sub-factors are creative ability, creative intrigued, emotionality, adventurousness, judgment skills and radicalism (Chmielewski & Morgan, 2013; Seibert & DeGeest, 2017).

Conscientiousness (C) involves the manner, which people try to restraint, coordinate and control their inspiration and driving forces. Individuals with high scores of Conscientiousness tend to be judicious while those with lower scores of Conscientiousness try to be imprudent. The sub-elements are efficiency, loyalty, achievement-striving, self-discipline and carefulness (Chmielewski & Morgan, 2013; Seibert & DeGeest, 2017).

Extraversion (E) elaborates the high level of socialising attitude and in the absence of high score value of Extraversion, it shows the lack of socialising and engagement with surrounding people. The Extraversion's sub-elements are joyfulness, assertiveness, friendliness, gregariousness, excitement-seeking and happiness. Outgoing individuals with high level of Extraversion try to respond with eagerness and frequently have positive feelings. In the other hand, introverted individuals with low level of Extraversion try to be calm, low-key and withdrawn in social activities (Chmielewski & Morgan, 2013; Seibert & DeGeest, 2017).

Agreeableness (A) indicates person contrasts in relationship with participation and social balance. the Agreeableness has some sub-elements such as believe, profound quality, benevolence, participation, humility and sensitivity (Chmielewski & Morgan, 2013; Seibert & DeGeest, 2017).

Neuroticism (N) alludes to the inclination of encountering opposing sentiments. Individuals with high level of Neuroticism are sincerely open-minded. They always try to reply honestly to generally impartial boosts. They are regularly in a awful disposition that unequivocally influences their reasoning and settlement. Individuals with low level of Neuroticism are quiet, psychologically steady and free from tireless terrible temperament. The Neuroticism's sub-elements are uneasiness, outrage, discouragement, immoderation, self-consciousness and powerlessness (Chmielewski & Morgan, 2013; Seibert & DeGeest, 2017).

Table 2.2 summaries the FFM's factors with their corresponding sub-elements.

Table 2.2: Examples of adjectives related to the FFM (Seibert & DeGeest, 2017)

Factor	Adjectives
Extraversion (E)	Active, assertive, energetic, enthusiastic, outgoing, talkative
Agreeableness (A)	Appreciative, forgiving, generous, kind, sympathetic, trusting
Conscientiousness (C)	Efficient, organized, planful, reliable, responsible, thorough
Neuroticism (N)	Anxious, self-pitying, tense, touchy, unstable, worrying
Openness (O)	Artistic, curious, imaginative, insightful, original, wide interest

In comparison with other personality models, FFM is the most comprehensive and popular method do determine the personality model (Seibert & DeGeest, 2017). Although MBTI is very popular in the business sector (Gerras & Wong, 2016), but it has been subject to sustained criticism by professional psychologists. The main problem is that it displays what statisticians call low "test-retest reliability" (Tondello et al., 2016; Wechsler et al., 2018). In other words, if a user repeats the tests t after only a five-week gap, there is a 50% chance that the user will fall into a different personality category. This issue has limited the researches to utilise this personality model in their academic work (Bughi et al., 2017; Tondello et al., 2016; Wechsler et al., 2018). On the other hand, The HDS is developed for use in the workplace. Unlike other personality models, the HDS is specifically concerned with personality characteristics that may cause an individual to derail or be unsuccessful at certain tasks and it is utilised mainly by studies on derailment risks and leadership (Church et al., 2016; Grijalva et al., 2015; Prokopy et al., 2015; Saleh & Hu, 2016).

Over the years, FFM has been put to use in various circumstances with high success rates being reported by multiple academic researchers who could independently verify the model’s predictive accuracy (Borghuis et al., 2017; Hengartner et al., 2016; Keyes et al., 2015; Leutner et al., 2017). The important factor that separates the FFM from others is that it is not based on the theory of any one particular psychologist, but rather on language, the natural system that people use to understand one another (Hao et al., 2016). Thus, FFM is selected to be used in this research to determine the users’ personality traits.

There are a number of assessment instruments researchers use to measures FFM’s five traits such as NEO Personality Inventory (NEO-PI), Big Five Inventory (BFI), Ten Item Personality Inventory (TIPI) and etc. (Butkovic et al., 2015; Hengartner et al., 2016). TIPI is utilised in this research because the questionnaire contains only 10 questions (Appendix A) and the goal is to produce a short and useful checklist that would help to effectively and efficiently calculate the five dimensions in a very short time (Chiorri et al., 2015; Oshio et al., 2014).

2.5.2 Relationship between Personality and User Preferences

A number of studies showed that personality relates strongly with user preferences (Braunhofer et al., 2015; Cantador et al., 2013; Nunes et al., 2008; Tkalcic et al., 2016). Some conducted researches illustrated that users' personality or identity relates unequivocally with their interests and preferences. Users with diverse identities try to benefit diverse sorts of substance, independent of the domain. Such a data is exceptionally important when developing an RS for a particular domain (Cantador et al., 2013). In a study, Gosling et al. (2003) investigated how music inclinations are correlated to user's personality traits (based on the FFM model). They developed four types of music classifications that are (i) energetic & rhythmic, (ii) intense & rebellious,

(iii) reflective & complex, and (iv) upbeat & conventional. The personality traits Openness is related to the reflective & complex class that is open to have new experience. The the intense & rebellious class is also connected with Openness to have new experience. Need to take note that in spite of the fact that this class carries music with negative feelings, yet it is not referring to Agreeableness or Neuroticism. In addition, the upbeat & conventional class is emphatically close to the personality type of Agreeableness, Extraversion and Conscientiousness. At last, they explored that the energetic & rhythmic class is connected with two personality types (i.e. Agreeableness and Extraversion) (Gosling et al., 2003).

In another research, Rentfrow et al. (2011), expanded their proposes RS to cover more domains such as book, movie, music, magazine and TV series. They defined five categories for their content that are: cerebral, communal, thrilling, aesthetic and dark. The FFM factors are not directly related with these five defined categories and based on this study, one category can be related to more than one FFM factors. For instance, the category of communal is having a positive relationship with Agreeableness, Extraversion and Conscientiousness, while not having any sort of connection with other factor such as Neuroticism. In addition, they have discovered that the cerebral category does not have any relationship with any of the FFM factor and did not fall into any personality trait domain (Rentfrow et al., 2011).

In the similar research, Butkovic et al. (2015) explored the relationship between personality traits and music and they examined that two personality traits (i.e Extraversion and Openness) are able to be relative to the music preferences. This study showed that users who have scored high in Extraversion values tend to like more trending and popular music, whereby, users who have Openness personality try to listen to different and diverse styles of music (Butkovic et al., 2015).

Cantador et al. (2013) conducted a research to explore the relationships between user's personality with his/her interests in multiple domains (such as books, movies, music and TV series). They completed the experiment and have proved that there is an enormous number of possible relationship that the user's personality can have with his/her preferences in various cross domains (Cantador et al., 2013).

Odić et al. (2013) conducted an experimental research based on a contextual RS (movie dataset) to investigate the possibility of having relationship between categories of movie and user's personality traits in various social context. They experimented multiple patterns, for instance, users with different types of personality traits watching their interested movie categories in different social context (such as watching with friends vs. alone). This experiment did not have 100% accuracy, because users with Conscientiousness and Openness personality traits did not express their feelings and the system could not capture their full emotions (Odić et al., 2013).

2.5.3 Personality Acquisition

During the design phase of personalised RSs, researchers have the major issue for finding a way of acquiring personality traits. Basically, all the acquisition methods are grouped into (i) explicit methods and (ii) implicit methods (Finnerty et al., 2016).

The explicit methods have the higher accuracy of estimating the user's personality trait but need to take note that these methods are time consuming and disturbing

(Finnerty et al., 2016). Therefore, it is meaningful to utilise these methods in researches and studies to achieve higher accuracy with less noise (Braunhofer et al., 2015).

On the other hand, implicit methods provide a modest alternative way of obtaining user's personality traits. As it is mentioned before, these methods do not yield very accurate result in comparison with explicit methods (Finnerty et al., 2016).

2.5.3.1 Explicit Personality Acquisition

International Personality Item Pool (IPIP) is a broadly utilized questionnaire for evaluating the FFM components. The IPIP's inventory contains 50 to 100 questions, usually 10 to 20 questions per factor (10 or 20) (Skowron et al., 2016). Generally, when number of questions increases, it gives a higher chance to estimate the personality trait correctly, in spite of the fact that it takes time for the use. Besides, it has been approved in terms of cross-cultural contrasts and interpreted in numerous languages (Finnerty et al., 2016).

Hellriegel and Slocum (2010) defined a questionnaire, which the user only needs to answer five questions for each personality trait, therefore, there are total number of twenty-five questions in the questionnaire to estimate the five parameters. The average value of total five answered scores would be the corresponding score value for the particular personality trait (Slocum Jr & Hellriegel, 2010). John and Srivastava (1999) built a very comprehensive questionnaire called Enormous Five Stock (BFI) that contains 44 questions, by which it has eight or nine questions to estimate each personality trait. For instance, the questions for personality trait of Openness are "is original, comes up with new ideas", "is curious about many different things", "is ingenious, a deep thinker", "has an active imagination", etc.. The BFI is considered as a verified estimation of personality parameters (John & Srivastava, 1999).

2.5.3.2 Implicit Personality Acquisition

Quercia et al. (2011) provided the results of their research that illustrates solid relationships between users' particular FFM personality traits and the parameters retrieved from their micro-blogs. Quercia et al. utilized a set of information about 335 users that each user's record contains user's FFM identity variables and the individual micro-blogs. The study retrieved multiple highlights from the micro-blogs and classified them into several categories: "listeners", "popular", "highly-read" and "influential". Each category illustrated a solid relationship with one of the FFM personality traits. Quercia et al. utilised a machine learning method to take one step further and estimate the FFM personality traits (Quercia et al., 2011).

Chittaranjan et al. (2013) took a very interesting approach to utilise the usage of portable device (user's phone) for determining FFM factors. They utilised the detailed information of user's SMS, call and application-usage as factors for estimating the FFM parameters. They noticed that these obtained information express much about user's personality and characteristics. The authors improved the personality trait prediction by utilising the Back Vector Machine (BVM) (Chittaranjan et al., 2013).

In a similar domain research, Shen et al. (2013) proposed an approach to predict user's personality based on his/her emails. They only retrieved common aggregated information from the content of emails (such as common daily words, email's subject, sentiment analysis's result and styles of writing). The authors used these features to estimate the personality traits of the email's owner and the prediction process has three productive models, (i) sequential model, (ii) survival model and (ii) joint model. In sequential model, the system takes the user's personality trait first and after that check if it is needed to select a feature, but in survival model, the system lets every personality factor to indecently choose a feature. However, the joint model combines all the personality factors as a individual integrated factor and then decide which feature matches this new integrated factor. Based on the experimental evaluation with a dataset of 100,000 emails, the best model is survival model that have better estimation accuracy and performance. The other models did not perform well for some personality traits such as Extraversion and Agreeableness. The conducted research shows that each personality trait can be defined distinctively and independently from each other. However, it is important to know that it is hard to estimate some users' personality traits. For instance, a person with Conscientiousness factor intend to write short email, or an individual with Agreeableness factor like to start his/her email with polite words such as please, good morning and good wishes (Shen et al., 2013).

Recently due to the huge growth of the online users in social platforms, researches have tried to explore the relationship between users' online behaviour on social platforms and their personality factors (Bontcheva & Rout, 2014; Cantador et al., 2013). For example, Amichai-Hamburger & Vinitzky (2010) discovered a vital relationship between individual personality trait with his/her Facebook. The authors tested this approach with 237 users within university. the research obtained the user's personality explicitly, by asking them directly to answer the personality questionnaire. Then it performed the algorithm on collected data to calculate the relationship between the users' personality and their Facebook accounts. the experiment's result illustrated some findings such as users who have Extroversion personality trait tend to have more friends, or individuals with high score of Neuroticism personality tend to post personal sensitive data like photos. In addition, it interesting to know that users with high level of Openness, use Facebook as a tool to communicate with other users (Amichai-Hamburger & Vinitzky, 2010).

2.6 Personalized Recommendation systems

Recently, studies have revealed the significance of psychological aspects of users such as their personality traits and emotions during the decision-making process (Bollich et al., 2016; Hu & Pu, 2010; Pera et al., 2011). Personality refers to the enduring patterns of thought, feeling, motivation and behaviour that are expressed in different circumstances (Nunes et al., 2008; Zhang, 2016).

CF is one of the most popular used method to personalize the recommendations based on similar users (Yang et al., 2016). The technique has been shown to work on explicit data (e.g. rating) (Mishra et al., 2017; Ruiz et al., 2016; J. Wei et al., 2017), and also on implicit data such as users' purchasing history, personality trait, demographic, location, time, weather and etc. (Guo et al., 2016; Liu et al., 2016; Tewari & Barman, 2016).

Demographic information has a great impact on our daily life decisions that shows, it can be used to find similar group of people who have the similar demographic details such as similar gender or age (E. B. Santos et al., 2014). However, many online systems try to obtain these data either by asking the user explicitly or monitoring their behaviour and interactions (implicitly). DF can be one of the main filtering methods that enhance the recommendation accuracy and that is the reason why RSs try their best to have these demographic information (Zhao et al., 2016). Demographic information are user's related data such as nationality, income, gender, age, occupation and etc. (Safoury & Salah, 2013). For instance, movie RSs leverage on age groups, when the recommendation is first produced based on the age of the user and then can be filtered by other factors such as income or gender. In advertising domain, the gender is the main factor that needs to be considered, female and male customers have totally different shopping requirements (Zhao et al., 2014).

Based on our conducted research, there is a finding that only an small number of studies used DF alone, but many of the studies used DF as the integrated filtering approach with other methods to overcome the limitation of those methods such as cold-start issue of CF (Chulyadyo & Leray, 2014; Kardan & Ebrahimi, 2013; Wani et al., 2017; Zhao et al., 2016). For example, Braunhofer et al. (2015) presented a Context-Aware RS, which exploits the user demographic data to provide personalized recommendation. This RS utilised the demographic information to overcome the cold-start issue and it benefited its users. Furthermore, it allows the users who have rated very small number of items in the RS, to have the chance to receive recommendation results.

Some researchers have integrated DF with their hybrid model-based RSs to improve the effectiveness of their recommendation and to have better chance to meet users' preferences. They mostly used DF in movie RSs, which they categorise the movies based on users' demographic attributes. For example, the user who has the demographic details of female and student, receives documentary types of movies as recommendation (Safoury & Salah, 2013). Safoury and Saleh (2013) also introduced a solution that utilizes the new user's demographic information and not his/her ratings. This would be a great solution when the RS has no information about user's ratings and it can still suggest with only considering his/her demographic data. In another hybrid RS, Junior et al. (2014) engaged demographic information to explore and examine the real world contextual limitation in recommendation domains. Ghazanfar and Prugel-Bennett (2010) presented a hybrid RS that was consisted of different filtering methods such as CF, CB and DF. This study showed that by combining these approaches, they could resolve the weaknesses and limitations of each approach.

Sedhain et al. (2014) utilised the user's demographic information to find other similar users inside a social network platform. They combined DF with CF to overcome the cold-start issue by utilising a matrix algebra system, which uses users' additional data and information when their purchase histories are not available. In experiment phase, they used a dataset (from Kobo Inc.) that consists of purchase records of 30,000 users, 80,000 e-books. Sedhain et al. (2014) illustrated that by utilising Facebook page likes, they can improve recommendation by 3-fold, as well as solving the cold-start issue.

Social media sites have become tremendously popular in recent years and it present new opportunity to further improve the accuracy of RSs (Gao et al., 2015; Yang et al., 2014; Zhou et al., 2015). CF-based social RSs generated by trusted group of users (i.e. friends) are considered more relevant than other users (Chechev & Koychev, 2014; Tewari & Barman, 2016; Yang et al., 2016). In 2014, Qian et al. conducted a study about using three social elements, namely: interpersonal interest similarity (similar preferences that are shared between friends in social networks), interpersonal influence (interpersonal influence that friends have on each other) and personal interest, to generate the recommendation. The RS can utilise the personal interest to provide an accurate recommendation for its experienced users. The authors used different types of relationships in the RS algorithm: user-item and user-user. The user-item relationship is the mapping between users and items like rates, reviews and purchasing history. The user interest is obtained through his rating behaviour. However, the user-user relationship is about the circle of friends (social circle). The study showed that in social networks, friends have a great influence on each other, and they can be grouped in social circles with similar interests (Qian et al., 2014).

As for studies that have specifically looked into recommending books, Pera et al. (2011) developed PBRecS, an RS that recommends based on the individual preferences and social interactions. PBRecS provides suggestions that are based on two factors: the relationship between social platform users and the information the RS gathers in social platform such as tags and descriptions. This study verified that the accuracy of its proposed RS was improved based on the obtained information from LibraryThing. The authors showed that by using social-network (such as Amazon and LibraryThing) information, it is possible to enhance the quality of book suggestions (Pera et al., 2011). This study proved a hypothesis that a user would be in interested in suggestions, which produced by "trusted" users or friends greater than suggestions that are generated based on unknown or "not trusted" users. A recent study showed that book RSs perform better when users are grouped into smaller clusters as their online activities and behaviours can be observed more effectively (Gil et al., 2016). Therefore, recommendations are improved when they are provided based upon other users with whom a person has similarities with in real life, such as living in the same place or studying in the same university (Gil et al., 2016; Zhao et al., 2016).

Recently the mobile devices are rising and this gains the researchers attention to utilise this new invention for developing mobile RSs that give a better experience to their users, such as suggesting items which are related to the users' contexts. The mobile RSs can be applied in different domains to recommend various items or services such as vacation package (Colomo-Palacios et al., 2017), movie (Bogers, 2010) or personalised Web content (Hawalah & Fasli, 2014). In addition to items and users, the RS need to consider their context or environment attributes while generating the list of recommendations (Adomavicius & Tuzhilin, 2015; Colombo-Mendoza et al., 2015). For instance, a travel RS generates a personalised vacation recommendation based on the contextual information (such as weather, time and location) that provides suggestions, which have higher chance to meet users preferences (Gavalas et al., 2014; Lamsfus et al., 2015). In addition, the same thing might happen when an e-commerce Web site recommends some items to the users, it needs to determine the right items to be delivered on the right time and situation (Neuhofer et al., 2015). In particular, a user may prefer to receive the recommended books about recent world news on weekdays and during weekends he might prefer fiction and romantic types of books (Adomavicius & Tuzhilin, 2015; Panniello et al., 2014; Neuhofer et al., 2015).

These perceptions are reliable with the discoveries in behavioural investigation on shopper decision making in business that have built up that choice making. In this manner, the level of shopper's preferences prediction depends upon the degree to which the recommender framework has joined the pertinent contextual data into a suggestion strategy (Huang, 2016; Winoto et al., 2012).

In the past 12-14 years, context-aware RSs' abilities have been created by scholastic analysts and have been used in multiple application domains such as movies, books, music and restaurants (Adomavicius & Tuzhilin, 2015; Bogers, 2010; Colombo-Mendoza et al., 2015), travel recommenders and tourist guides (Braunhofer et al., 2014; Colombo-Mendoza et al., 2015; Gavalas, Konstantopoulos, Mastakas, et al., 2014a; Hawalah & Fasli, 2014), general music recommenders (Z. Cheng & Shen, 2014; Domingues et al., 2013; Schedl et al., 2015; Schedl & Schnitzer, 2014), news recommenders (Gulla et al., 2014; Lommatzsch, 2014; Wang et al., 2015), shopping assistants (Panniello et al., 2014), In specific, mobile RSs are made of an imperative extraordinary case of context-aware recommenders, where contextual information is regularly characterized by time and location, and there is a huge number of written works devoted particularly to mobile RSs (Colombo-Mendoza et al., 2015).

It is critical to understand that, the information collection process is responsible to acquire data from user's context either by asking the user explicitly or just implicitly. This encourage infers that the choices of which relevant data ought to be pertinent and collected for an application ought to be done at the application planning phase and well in progress of the time when genuine suggestions are given (Musto et al., 2014; Qian et al., 2014).

Actually, not all accessible relevant components might be important or valuable for suggestion purposes (Adomavicius & Tuzhilin, 2015). In the case of a book RS, numerous sorts of information could possibly be retrieved by such a RS from buyers who purchased books, for instance: (i) reason and motivation of buying the book; (ii) arranged gathering place and time to read book; (iii) the author's location at the time when user purchases his book. Obviously a few sorts of relevant data can be more significant in a given situation than the other sorts of data. For instance, in this case, the location of the author is probably the much less pertinent as contextual data than the reason of purchasing a book (Lu et al., 2015).

Since the contextual factors relevancy might change dramatically from RS to RS, it is important to spend some times to determine and recognise the most useful set of factors that have effect in the RS's accuracy (Colombo-Mendoza et al., 2015). For illustration in mobile recommendation frameworks, usually there are four contextual data that are regularly taken: (i) physical information such as geographical location, time, weather and light condition, (ii) social information such as the user's relationship status, total number of trusted friends, is the user living alone or with family, (iii) interaction media information such as the model of his/her laptop/mobile/TV, media substance type (video/text/audio/etc.), modular information such as user's state of mind-perceptive abilities, temperament, involvement and life objectives (Bauman & Tuzhilin, 2014; Mylonas, 2016).

In expansion to utilising the manual approach, for instance, using domain information of the RS's expert or an industry master in a given specific field, there are various methods to examining the pertinence of a given sort of contextual data (Mylonas, 2016). In specific, various existing highlight selection methods from information mining, machine learning and measurements can be utilized in the information pre-processing stage and it would be based on existing appraisals information (Bauman & Tuzhilin, 2014; Colombo-Mendoza et al., 2015). One technique of choosing the relevant contextual information that need to be utilized in a

RS, is proposed by Adomavicius et al. (2015) that a great extent of contextual traits need to be selected at first by the domain specialists as feasible relevant for the RS. At that point, after obtaining the information, users' rating data and the contextual data, different sorts of factual tests identifying needs to be utilised which of the chosen attributes of the context are really critical in the sense that they in fact influence user experiences, as showed by remarkable deviations in appraisals over distinctive values of a relevant trait. For instance, t-tests may be utilised pairwise to check on the off chance that great climate vs. awful climate, morning time vs. night time or studied a book alone vs. with a companion altogether influence the book reading experiences (as demonstrated by factually critical changes in rating conveyances). This is the great example of screening every one of the beginning steps to consider contextual aspects and selecting those that are not useful in a specific RS (Núñez-Valdéz et al., 2012).

Baltrunas & Ricci (2014) proposed another method to measure the relevancy of contextual attributes. They built a survey-based tool that inquires the users to judge what their inclinations would be in a wide assortment of theoretical (i.e., envisioned) contextual circumstances. This permits to gather wealthier contextual inclination data in a brief period of time, assess the effect of each contextual attribute on each user's preferences based on the gathered information, and incorporate into the proposed context-aware framework as it were those variables that were appeared to be vital. Indeed in spite of the fact that the collected information incorporates as it were theoretical relevant inclinations, which it is the user's preferences for products or items that user envisioned consuming beneath certain contextual situations. The researchers illustrated that the proposed context-aware RS was seen to be more successful by users as compared with the non-context-aware RS (Baltrunas & Ricci, 2014).

Context has a very wide concept and it needs to be concentrated on those domains, which are specifically related to RS (such as information mining, databases, e-commerce personalisation, data retrieving and structuring and mobile context-aware systems and showcasing) (Adomavicius & Tuzhilin, 2015).

In the information mining domain, context is in some cases characterized as occasions that define the life phases of a user and it can cause an alter in his/her preferences, feelings, and esteem for a company (Majid et al., 2013). In domain of context there are many examples such as getting married or divorce, giving birth to a child, getting a new job or retiring from a job. Information about this kind of relevant data assists (i) exploring designs and patterns related to the specific context by considering merely pertinent information. For instance, the relative information to the friend's wedding, or (ii) choosing the related data, the results of information mining, which are appropriate to the specific context, such as the explored patterns and designs that are relative to the enrolling of an individual (Colomo-Palacios et al., 2017; Majid et al., 2013; Sauer, 2016).

Panniello et al. (2014) used the purchase intention from users in an e-commerce platform as contextual data. Diverse intentions may lead to diverse sorts of conduct. For instance, a user may purchase from the same online account distinctive items for diverse reasons, such as purchasing a self-help book for moving forward his individual work abilities, purchasing a book as a present, or buying an electronic gadget for playing games. To make agreement with diverse intentions, Panniello et al. (2014) built a partitioned profile of a user for each buying context, and these partitioned profiles are utilized for developing isolated models anticipating the user's conduct in particular contexts and sections. Such relevant division of user is valuable and the result showed that the proposed framework is superior over diverse e-commerce platforms (Panniello et al., 2014).

Context in the writing works related to the context-aware frameworks, is characterized as the geographic location of the user, the surrounding objects, the personality of the personality of individuals nearby the user, and the adjustment in these mentioned components (Huang, 2016). Geographic location is one of the most vital contextual attribute of the user, which infers broad information about an individual's preference, behaviour and conduct. Therefore, it gave us the chance to know more about the the users in real physical world and as well as their online behaviours and interactions (Bao, 2012). Other components have been included to this denotation in a subsequent manner. For example, Brown et al. considered the time, date, weather and season. In another work, Ryan et al. (1999) included the physical body and mental levels of user's preferences. Dey et al. (2001) added the user's psychological status and widen the meaning to any data that can define and is related to the user's interaction with the system. A few researchers related the context attributes with the user (Dey et al., 2001; Franklin & Flaschbart, 1998), while other researchers focused on how context can be related to the recommendation framework (Rodden et al., 1998; Ward et al., 1997). Recently, researchers proposed new approaches for context-aware frameworks that can be used to improve the recommendation like hybrid algorithms for mobile RSs and visual models for graphical suggestions (Colombo-Mendoza et al., 2015; Colomo-Palacios et al., 2017; Khalid et al., 2014).

In spite of the fact that mobile RSs have been utilised in different domains (such as online shopping, publicising and substance provisioning), tourism is without a doubt the most swarmed field among them (Ricci, 2010; Braunhofer et al., 2014). One of the well-known study related to location is the study by Braunhofer et al. (2014), who proposed South Tyrol Suggest (STS), a revolutionary context-aware mobile RS that is used to recommend places of interest (POIs). the authors developed an Android-based application, which suggest POIs based on various contextual attributes (such as location, time, weather, day of week and user's emotional stage) in South Tyrol, Italy. It is an expanded grid factorization rating estimating approach. This RS is able to produce suggestions adjusted according to the current contextual circumstances. For instance, when it is raining, the RS suggests indoor places (such as historical centers, libraries and churches) and during great climate condition, it suggest outdoor places (such as parks, mountain climbs and lakes). This recommendation model has two findings: first, the recommendation algorithm effectively utilises climate when it is suggesting a POIs and this leads to achieve higher user interest and it fulfils the user satisfaction and experience; second, the dynamic learning component increments the number of obtained ratings of user together with the effectiveness of recommendation.

Nowadays, the academic community is focusing on the new recommendation factor that is purchase intention (Fang et al., 2016; Hennig-Thurau et al., 2012). The researchers are interested on exploring the elements that can define the user's willingness to buy the recommended item on e-commerce platforms (Fang et al., 2016). For instance, when a user browse the business genre in an online bookstore, despite from what he/she purchase before in the website, it is really important to know his/her motivation to purchase a business book and this really effect the suggestion result. In such a case, the user's purchasing motivation plays as the important factor that defines whether user would be interested in the recommended items or not (Cheng et al., 2011).

Some researchers showed that users' preferences in products or items may vary over time depending on their current location and situation (Chen, 2013; Hariri et al., 2015). For example, Chen (2013) developed a mobile application that uses location factor to trace a user within a real-library building, sections or places that he/she visits, to improve book recommendations. Usually in libraries, readers are searching or browsing for a specific book that is related to the particular domain of knowledge. The application allows the users to browse and search book collections through their mobile devices. Whenever the user chooses a book and walks to a specific area in the library to collect the book, the application stores his/her location. It utilizes the user's location to filter similar users by grouping the users who visited the same locations. This information is then used to generate book recommendations based on books read by similar users.

Fang et al. (2016) developed an online system that determined user's purchase intention by observing his online behaviour. According to this study, the user's behaviour is classified into four main actions: *view, buy, search, collect,* that combinatorically constructs the structure of user behaviour sequence that are utilised to estimate as their potential intention. In the case that users have the complicated behaviour and the users' preferences might change time to time (Gleeson et al., 2014), therefore, the authors focused on examining and determining users' interest based on his/her latest (30 minutes) interaction with the system. Once a user buy an item, the system will records all his/her interactions and activities that he/she perform before he purchased the item to analyse and understand his/her purchase intention. The view action among the four define actions, is the most corresponding action with the purchase intention. The user need to search and browse items but only view the details on a specific purpose. However, the evaluation result illustrated that utilising user's purchase intention would help to improve the recommendation accuracy.

When the system has enough information about the user's ratings, CF approach can work well. However, this is the shortcoming of CF method that it does not perform well when there is no sufficient rating data (due to not acquiring enough information from new users) (Mishra et al., 2017; Zhang et al., 2016), or it might be hard to motivate the users to express their interest on the recommended items as scalar rating (Lee et al., 2010; Ruiz et al., 2016). CB technique is introduced to overcome the CF limitation. This filtering method generate the recommendation based on the contents or descriptions of items. Items are defined as similar products, when they have the similar content. So, CB approach look for the similar items to item that the user purchased or liked before (Gao et al., 2015; Lu et al., 2015). Sometimes it recommends not just based on the content or description of the items, it can be the textual data generated by user, like tags (Tinghuai et al., 2015; Zhou et al., 2015) and social relationships (Bao et al., 2015; Bontcheva & Rout, 2014; Chechev & Koychev, 2014), to enhance the effectiveness of suggestion. Nevertheless, these CB methods cannot be used solely, particularly when the user has not much historical records and data.

CB RSs analyze the content of the items a user has previously evaluated (e.g., their textual description), in order to detect items that he/she has not considered yet and are similar to those he/she likes. Recently this domain of filtering gains lots of attention and it was because of emerging the use of semantic analysis and ontologies tools in CB RSs. These tools help the CB approach to perform better textual analysis on the items' descriptions to obtain more data and information about the items that would be useful to improve the RS's accuracy. This leads to the generation of a class of systems known in the literature as semantics-aware CB recommender systems, which have recently emerged. In their very recent survey, de Gemmis et al. (2015) proposed a high standard structure of a semantics-aware CB RS. In order to suggest the similar items to the user, this architecture processes all the items that a user visited before and store the data about items with similar content (de Gemmis et al., 2015).

In recent study, CB was used to improve recommendations based on a series of characteristics from a particular book to further recommend additional books with similar content (Mathew et al., 2016). In another research, Garrido & Ilarri (2014) proposed a lingual, ontological, and semantic enhanced book RS called Topic Map Recommender (TMR), which utilized the semantic tools and NLP to recommend books that meet each individual's preferences. TMR determined the conceptual "meaning" of the items' textual information (such as description and title) during the process of generating the recommendation result. It considered both the liked and disliked items in the recommendation process. However, TMR developed a conceptual map about each item that stores all the obtained information about the users' likes, dislikes and other interactions, so during the process of recommendation it also checks the similar items' conceptual maps. In order to obtain relative data to produce the conceptual maps, TMR utilises TM-Gen, a software that helps to explore and retrieve data from any sort of textual information and present the obtained data in the form of conceptual map. First, this tool breaks down the textual data into sentences and then scans through the provided sentences and points out the critical entities and keywords, and gives them a relevance score. Then, TMR integrates these retrieved entities and keywords to build the conceptual map. The last step is to build the user's profile based on his/her rating, browsing and purchasing history and tries to capture his/her preferences. In this way, TMR is able to build two different conceptual maps, one for the user's like and one for user's dislikes. Finally, TMR needs to generate the recommendation result based on the prediction of how likely the user will like or dislike the new recommended item. Generally, TMR illustrated that it is possible to utilise semantic techniques to improve the CB RS and it works with any sort of textual information such as reviews, descriptions, tags or title.

The semantic tools help to extract the embedded contextual data from the textual information. For instance, in the book review "I love to read this book during the weekend", "during the weekend" is the relative contextual attributes that define the user's context, the system knows that it can recommended similar books to the user during weekend and it would be his/her interest (Hariri et al., 2011; Li & Karahanna, 2015).

Hariri et al. (2011) presented that the user's interest toward a single hotel does not change when the user changes his/her context, but the user's interest changes in different context when he/she needs to select a hotel among different hotels. Thus, they focused to build a RS based on the review contexts and not like the traditional RSs, which utilises only the user's rating information. First, the RS classifies the type of traveling as the main contextual attributes and it has five classifications (i.e solo travel, couples, family, friends, and business). Then utilised Latent Dirichlet Allocation (LDA) approach (Ramage et al., 2009), that is "a supervised classification algorithm for multi-labelled text corpus based on topic modelling, to train a multi-class classifier that can determine the probability of each trip type being related to a review or the user’s current query". This classifier algorithm concentrates only on the users which have determined their travel types. It takes the reviews and tries to understand the semantic data and information that can be used to generate more accurate recommendation.

In a recent research, Wani et al. (2017) proposed a book RS that integrates CB and CF approaches. In CF approach, the system tries to find the similar users based on their purchase histories and reviews. The CB approach recommends items based on a comparison between the content of the items and a user profile. The content of each item is represented as a set of descriptors or terms, typically the words that occur in a document. The user profile is represented with the same terms and built by analysing the content of items which have been seen by the user. They proved that by using a hybrid technique, it is possible to overcome the drawbacks set by one recommendation technique and sum up advantages of different recommendation techniques to achieve a better recommendation accuracy.

Each of the mentioned studies concluded that they could improve the recommendation by utilizing techniques such as considering personality traits, user reviews, demographic, semantic or contextual data. Table 2.3 shows the summary of their solutions and key findings:

Table 2.3: Summary of Personalized Recommendation Systems

	Solution	Key Findings
Exploring demographic information in social media for product recommendation (Zhao et al., 2016)	It leverages the demographic information of both products and users extracted from social media for product recommendation.	• Obtaining both quantitative and qualitative evaluation results • Boosting product sales Improving the performance of recommendation result.
Social collaborative filtering for cold-start recommendations (Sedhain et al., 2014)	The authors used the demographic data of new user within a social network to find similar users for him.	Overcoming the cold-start issue by combining CF with DF and utilizing a generalized matrix algebra framework.
Personalized recommendation combining user interest and social circle (Qian et al.,2014)	This study provides more personalized recommendation by utilizing three social factors (personal interest, interpersonal interest similarity and interpersonal influence).	• Proving that friends in social networks have a great influence on each other. • Improving recommendation quality by grouping users in social circles with similar interests.
PBRecS: Personalized Book Recommendations Created by Using Social Media Data (Pera et al., 2011)	• It suggest books that appeal to users based on social interactions and personal interests. • The recommendations solely books that belong to a user's friends who share common interests with the user and the user trust them.	• verifying that by using social-media data the quality of books recommended by PBRecS is significantly higher than existing book recommenders.
Design and implementation of map reduce-based book recommendation system (Gil et al., 2016)	• Clustering users based on their online activities and behaviours improves the recommendation accuracy	• Recommendations are improved when they are provided based upon other users with whom a person has similarities with in real life.
RecomMetz: A context-aware knowledge-based mobile recommender system for movie showtimes (Colombo-Mendoza et al., 2015)	• a context-aware mobile recommender system based on Semantic Web technologies. • They considered three different kinds of contextual information (location, crowd and time).	• Achieved higher accuracy by integrating the location, time and crowd factors into a context-aware model. • Overcoming cold-start issue.
Experimental evaluation of context-dependent collaborative filtering using item splitting (Baltrunas & Ricci, 2014)	introduced and analysed a novel technique for context-aware CF that items experienced in two alternative contextual conditions are having different ratings.	• User's interest towards items/products changes in different context. • Providing the right item in right context has a direct effect in recommendation quality.
Personalized travel package with multi-point-of-interest recommendation based on crowdsourced user footprints	• A heuristic search-based travel route planning algorithm was designed to generate travel packages. • The application traces users "digital footprints" (visited	• Providing a personalized travel packages containing multiple points of interest and their visiting sequence by obtaining users' travel demands from mobile client.

(Huang, 2016)	locations) and tries to infer users' preferences.	
Comparing context-aware book recommender systems in terms of accuracy and diversity (Panniello et al., 2014)	• Generating the book recommendation list based on users' purchase intension.	• Diverse intentions may lead to diverse sorts of conduct. • Improving the recommendation novelty.
STS: A Context-Aware Mobile Recommender System for Places of Interest (Braunhofer et al., 2014)	• Personality, in terms of the Five Factor Model. • An active learning module that actively acquires ratings-in-context for POIs that users are likely to have experienced.	• To personalize recommendations and rating requests even for the new users, by leveraging their personality, which is known to be strongly correlated with their tastes and interests
An intelligent mobile location-aware book (Chen, 2013)	• Developing a mobile application that used location factor to recommend books to users.	• Improve the recommendation by using users' geographical location.
Recommender Systems Based on User Reviews: The State of the Art (Chen et al., 2015)	• They provide a comprehensive overview of how the review elements have been exploited to improve standard content-based recommending, collaborative filtering, and preference-based product ranking techniques.	• Classifies state-of-the-art ○ review-based user profile building ○ review-based product profile building
Learning word embeddings from wikipedia for content-based recommender systems (Musto et al., 2016)	• Developed a CB recommendation framework which uses textual features extracted from Wikipedia to learn user profiles.	• Solved high-sparsity issue • Showed better performance and quality compare to other well-performing algorithms such as CF and Matrix Factorization.
TMR: a semantic book recommender system using topic maps on the items' descriptions (Garrido & Ilarri, 2014)	• Proposed a semantic, ontological, and linguistic enhanced book recommendation system.	• Providing accurate personalized book recommendation by taking advantage of natural language processing (NLP) and semantic tools. • Showing a great improvement in CB field and it works in any context where the textual descriptions are available.
Making Recommendations Better: The Role of User Online Purchase Intention Identification (Fang et al., 2016)	• Developing an online system that determined user's purchase intention by observing his online historical behaviour.	• Proving the effectiveness of applying purchase intention in e-commerce RS. • Proposing a scenario-based approach to identify users' purchase intention.
Hybrid Book Recommendation System (Wani et al., 2017)	• Building a hybrid book RS that utilised CF and CB approaches to increase the recommendation accuracy.	• Finding the similar users based on their purchase histories and reviews. • Performing semantic analysis on the textual data of books content and user's profile.

2.7 Research Gap

It is greatly important to monitor user in different situations and contexts, to be able to provide personalized recommendations (Hawalah & Fasli, 2014). The existing studies tend to favour a specific contextual feature like location feature in the domain of traveling and tourism (Kim et al., 2015; Shan et al., 2009; Winoto & Tang, 2010; Braunhofer et al., 2014; Kim et al., 2015; Koceski & Petrevska, 2012). However, the location feature is being used in some book RSs, but just to trace the user in a public place such as university or library (Chen, 2013; Hahn, 2011). Studies using location to recommend books have yet to be conducted, hence the current work intends to explore the use of location feature together with demographic info and personality traits to cluster similar users.

Aside from user's contextual features, product features such as reviews, description, etc. play important roles in improving recommendations as well (Achakulvisut et al., 2016; Chen et al., 2017; Musto et al., 2016). However, products' textual information involve language ambiguity and recent studies showed that this issue can be overcome by applying sentiment analysis and NLP (Antunes et al., 2016; Hong et al., 2017; Kermany & Alizadeh, 2017). These tools are the most important elements of recent studies in the domain of CB RS that try to perform deep content analytics on the acquired textual information (Antunes et al., 2016; Hong et al., 2017; Kermany & Alizadeh, 2017). Current study is aiming to enhance the recommendation by considering product's contextual features (i.e. review and purchase reason). Moreover, studies that integrated different user's and product's contextual features in RSs are also limited (Asabere et al., 2017; Liu et al., 2015; Shen et al., 2016; Zhang et al., 2017).

2.8 Summary

In this chapter, RSs' concept, functionalities, types and background study were elaborated comprehensively. Furthermore, different RSs were analysed and listed their key findings and limitation. The possible enhancements that can be implemented to improve the accuracy of recommendation were discussed as well. Table 2.3 illustrates the overall summary of analysing mentioned personalised recommendation with their filtering methods.

According to the conducted literature review, incorporating contextual features would improve the RS. Thus, in this study, a hybrid book RS is presented, which integrates user's features (personality traits, demographic data and geographical location) with product's features (reviews and purchase intention). The outcome would be a more personalized recommendation with higher user interest accuracy. In the next section, PHyBR's software architecture and implementation are presented.

CHAPTER 3: METHODOLOGY AND IMPLEMENTATION

3.1 Overview

In Chapter 2, objectives, elements and functions of RSs and existing personalized RSs (with their solution and key findings) were discussed. In this chapter, the overall research methodology for enhancing personalized RS using integrated user and product contextual features is presented.

The research methodology and implementation, as a guide for the research, elaborates the specific strategies, methods and materials, used in the research to achieve the goals. In general, research methodology covers the procedure of presenting a solution, proposing new algorithm, implementation, and finally evaluation process and metrics. This chapter provides descriptive meaning of a system to develop, and analyse the proposed multiple contextual filtering methods which generates recommendation understanding multiple aspects of data and divergent expectation of user from the recommended result. Also we will discuss on how the processes of system design and implementation were conducted for recommending books. Through the design phase, the functions and processes involved in the system will be presented with more details.

3.2 Research Flow

Recently the RS domain becomes very popular and that leads to exploring different research strategies and approaches such as prototyping, case studies, testing, survey, evaluation and etc. (Sarwar et al., 2001; Herlocker et al., 2004). This study is focusing on developing an enhanced personalised recommender engine that produces customised suggestions by integrating user's contextual data (personality trait, demographic data and location) with product's features (review and purchase reason).

This study is based on the guidelines provided by the Design Science Research (DSR) – a "research that invents a new purposeful artifact to address a generalized type of problem and evaluates its utility for solving problems of that type" (Venable & Baskerville, 2012). In other words, this is a problem solving procedure based on the development and evaluation of technological artifacts such as new software, processes or systems (Hevner, 2007; March & Storey, 2008). DSR has been used in improving the effectiveness of organizations (Hevner, 2004), people's health and education (Pries-Heje et al., 2010; Seinet et al., 2011), and community interaction and well-being (Bilandzic & Venable, 2011).

Figure 3.1 depicts the main steps of the research, as research flow with four main phases. Phase 1 describes the main properties and weaknesses of existing solutions for the recommendation, which this study tries to address and present a solution for. Phase 2 expounds the standard flow or procedure of the platform to construct every necessary step to design the presented RS. In the third phase, the explanation on how the system prototype (PHyBR) has been developed is presented. The last Phase measures the effectiveness of the RS engine that needs to be assisted by the outcomes from the experiment and evaluation processes.

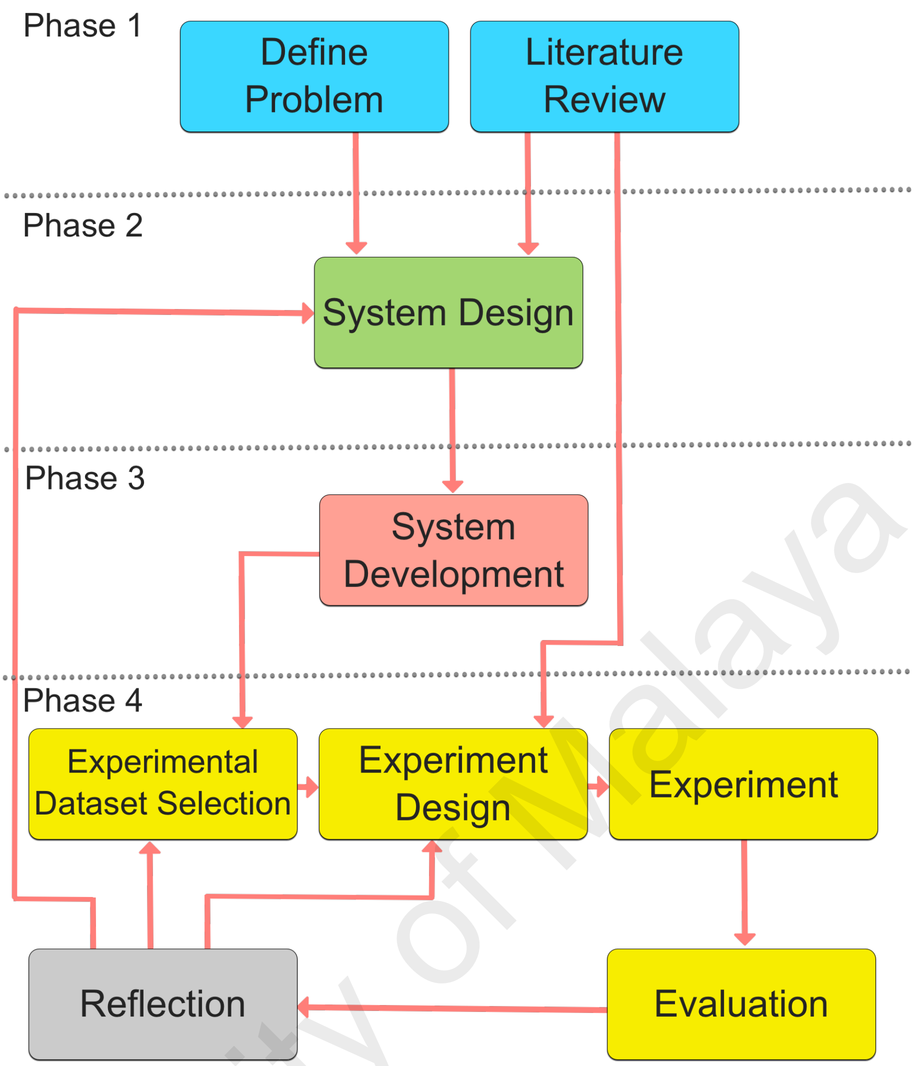


Figure 3.1: Research Flow

3.2.1 Phase 1: Research and Problem Definition

The goal of this phase is to determine the research questions and point out the gap in the study area, research range, objectives and goals of the research. In chapter 1, discussion was conducted pertaining to appropriateness and suitability of research topic, goals, scope, significance and limitations of research as well as research functional plans in starting the study. Chapter 2, the Literature Review is the main research approach and by analysing and studying the literature, it behaves as a main guidance in moving the research concentration and methodology. Literature review is conducted on the fundamentals of RS; its characteristics and advantages as well as studying different types of RSs and exploring their limitations.

Based on the research on existing approaches and defined problems, there are three objectives:

i. To identify user and product contextual features that can be used to personalised recommendation.
ii. To develop an enhanced hybrid RS based on the identified user and product contextual features.
iii. To assess the effectiveness of the proposed technique in recommending relevant items.

3.2.2 Phase 2: System Architecture And Design

3.2.2.1 System Architecture

In general, system architecture is the blueprint of the proposed system, which contains the overall structure and detailed behaviour of the system (Gillespie et al., 2017). In this section, the main architecture of our presented recommender, PHyBR, would be elaborated that generates personalized book recommendations by integrating users' personality traits and their demographic details together with their geographical location, review sentiments and purchase reason. The algorithm also performs sentiment analysis on reviews and natural language processing on purchase reason to have higher chance of meeting user's preferences.

Figure 3.2 depicts the overall PHyBR model, which can be categorized into three main parts, (1) registration, (2) user profiling and (3) recommendation. The model can be briefly described as follows:

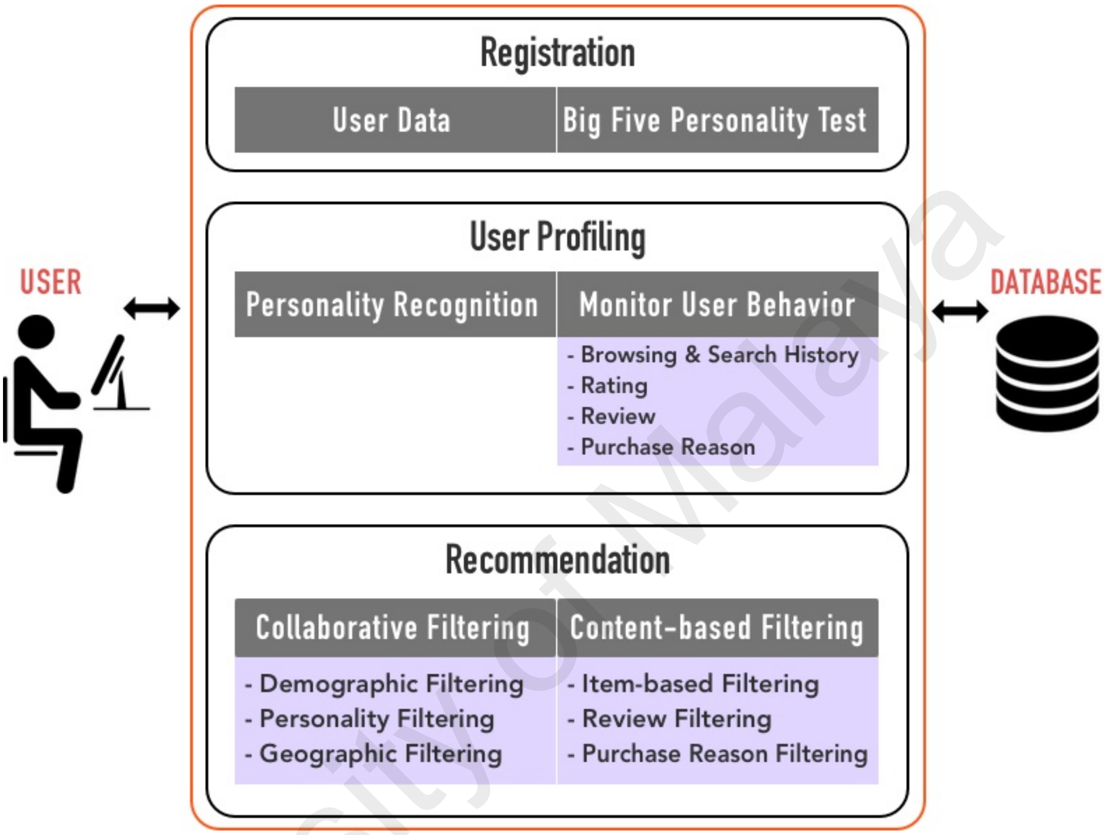


Figure 3.2: The PHyBR Model

i. A user provides his basic demographic details (i.e. age and gender), and answers the Big Five personality test. One of the most widely used models to determine users' personality is Big Five model, also known as the Five Factor Model (FFM), which is a hierarchical organization of personality traits in terms of five basic dimensions: extraversion (E), agreeableness (A), conscientiousness (C), neuroticism (N) and openness (O) (Keyes et al., 2015). Big Five is considered to represent the basic dimensions of user personality as its dimensions are steady, cross-culturally applicable and have biological basis (Giluk & Postlethwaite, 2015). Ten Item Personality Inventory (TIPI) is utilised to calculate the dimensions of the Big Five personality traits. The questionnaire contains only 10 questions (Appendix A) and its goal is to produce a short and useful checklist that would help to effectively and efficiently calculate the five dimensions in a very short time (Chiorri et al., 2015; Oshio et al., 2014).

ii. PHyBR performs user profiling based on the demographic data and personality trait, which is determined after he is finished with the TIPI test. PHyBR monitors user behaviour (such as his browsing, searching, reviews and purchase reason) and stores the data in the user profile. The user searches for the book by entering the book title, author name or book genre or any desired keyword as PHyBR performs natural language processing as well. The system stores the searched keywords for later use in the recommendation algorithm. The user is able to rate the book using the 5-star rating system, with 1 star shows the minimum level of interest and 5 stars showing the highest. When the user is about to purchase a book, he is asked to enter his purchase reason and justify factors that led him to buy the book. PHyBR also takes user's review after a book is purchased, and similar to purchase reason PHyBR performs the sentiment analysis on the review and stores it into the user profile. His positive or negative rating, purchase reason or review has a strong effect on his next search or recommendation result. PHyBR retrieves the current geographic location data from the device every time user launches the application and saves it as the last updated user's location. For example, if the user travels from City A to City B, the system will take the last visited place (State B) as the current place and will use it in the recommendation algorithm.

iii. PHyBR generates personalized book recommendation by combining two filtering approaches, Collaborative Filtering (CF) and Content-based Filtering (CB). The system first starts with CF by performing geographic filtering followed by personality and demographic filtering. It selects nearby users (within the same city), who have the same personality trait (i.e. Neuroticism, Conscientiousness, Extraversion, Agreeableness, or Openness) and age range. Then it executes CB, which looks up for books that similar users (output of CF method) have rated, written reviews or purchase reasons. The algorithm sorts the recommendation results based on the book's relevance weight that consists of most positive reviews, purchase reason and higher rating. In other words, books with small relevance weight will be displayed at the end of the recommendation list. In absence of nearby similar users during the early stage, PHyBR will perform the CB filtering, which maps the user's personality trait with the book genres (item-based, review and purchase reason filtering). This would prevent the system to have cold-start issue, because PHyBR can still generate recommendation based on personality-genres relationship.

3.2.2.2 Recommendation Logic

In this section, the PHyBR's recommendation logic is presented, which produces personalised book recommendation results utilising multiple filtering methods. As Figure 3.3 illustrates, there are two main filtering methods, namely, CF and CB, and each one of these filtering methods has three sub-filtering methods.

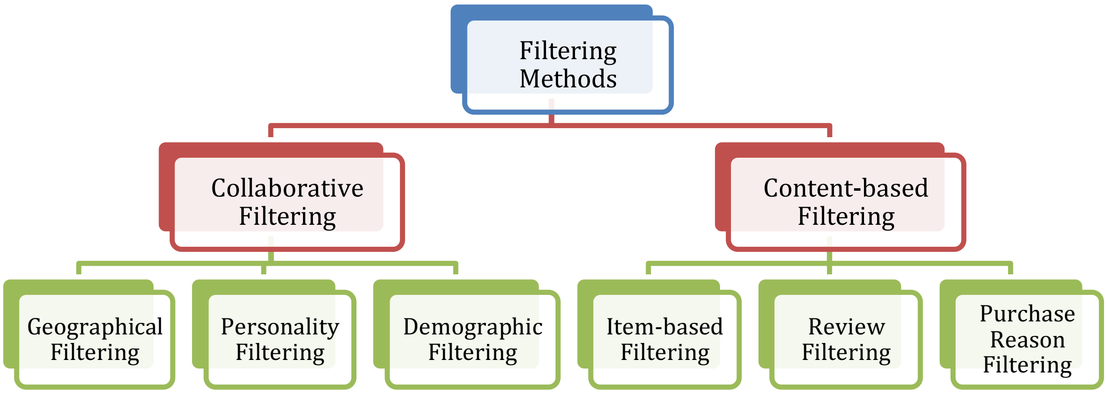


Figure 3.3: PHyBR's Recommendation Filtering Methods

Figure 3.4 shows the PHyBR's recommendation flow that it stars with CF filtering methods and then followed by CB methods. All these filtering methods will be elaborated in details in the following sections.

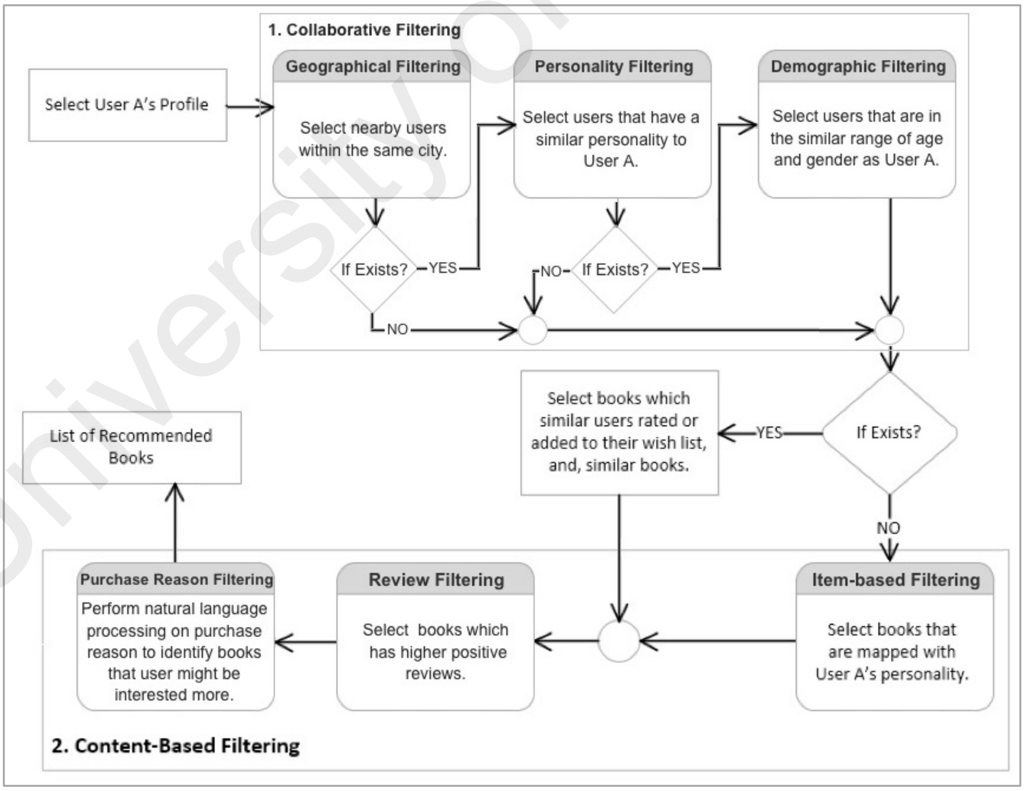


Figure 3.4: Processing Steps of PHyBR's Recommendation Logic

3.2.2.2.1 COLLABORATIVE FILTERING ALGORITHM

As Figure 3.5 shows, after PHyBR selects User A's profile, it performs the CF, which consists of three filtering methods:

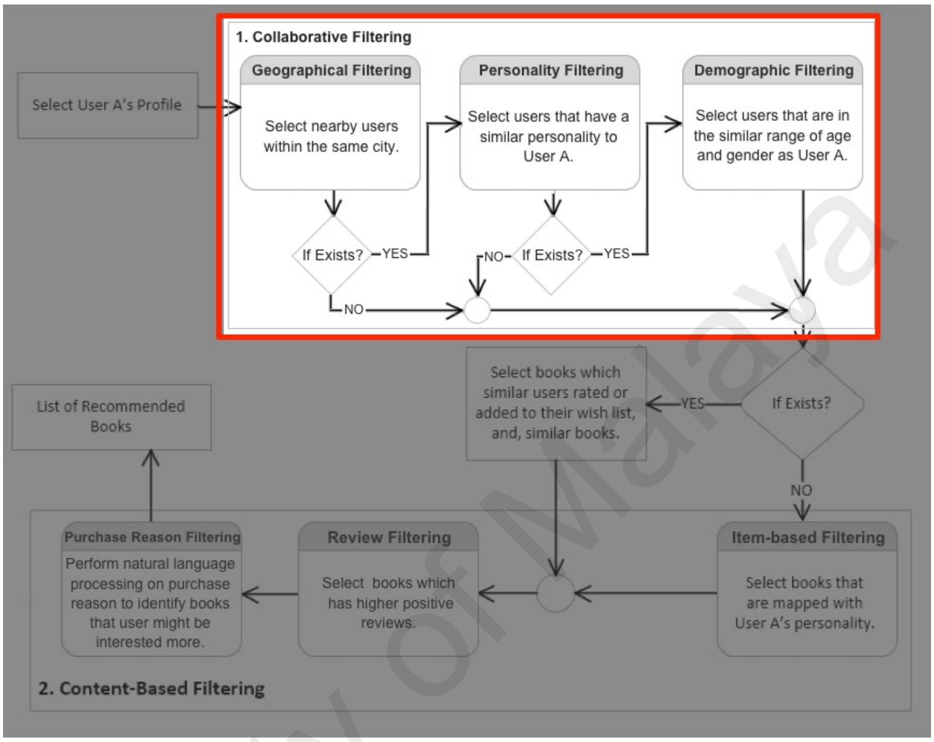


Figure 3.5: Collaborative Filtering Methods

GEOGRAPHICAL FILTERING METHOD

In the first step, PHyBR filters nearby users who are within the same city as User A (refer to Figure 3.6). The Haversine formula was applied to calculate the distance for finding the nearby users (Ratsameethammawong & Kasemsan, 2010), as depicted in Eq. 3.1, where d is the distance between two locations.

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \qquad \textbf{Eq. 3.1}$$

Every geographical location has a longitude and latitude that is used to specify the location on earth. φ_1 and φ_2 are the latitudes of the first and second location and λ_1 and λ_2 are the longitudes (Ratsameethammawong & Kasemsan, 2010). PHyBR obtains the latest geographical location every time a user uses the mobile application to ensure the algorithm uses the latest coordinates. PHyBR performs geographical filtering in the first step to create a manageable pool of users so it can apply the following filtering methods and this have a great effect on the algorithm's performance.

```
Algorithm GeographicalFilteringMethod (input_users,user_city)
    Var Empty List nearby_users;
     For Each user in input_users;
        If user->city equals to user_city;
            Append user to nearby_users;
        End If;
     Next user
Return nearby_users;
```

Figure 3.6: Geographical Filtering Algorithm Pseudo-Code

PERSONALITY FILTERING METHOD

After selecting the nearby users, PHyBR filters those who have similar personality traits as User A's. As the user takes the personality test during the sign up process, PHyBR determines their personality and saves the results in the user's profile. In this filtering method as Figure 3.7 shows, the algorithm retrieves the personalities of nearby users and compares them with User A's personality, and only takes the similar personalities. For example, if User A's personality trait is openness, this filtering method takes only the users that their personality traits are openness too.

```
Algorithm PersonalityFilteringMethod(input_users,user_personality)
    Var Empty List similar_users;
    For Each user in input_users;
        If user->personality equals to user_personality;
            Append user to similar_users;
        End If;
    Next user
Return similar_users;
```

Figure 3.7: Personality Filtering Algorithm Pseudo-Code

The cosine-based similarity was used to measure the similarity between users, as shown in Eq. 3.2 (A. Kumar et al., 2015):

$$\cos(\theta) = \frac{A \,.\, B}{\|A\|\|B\|} \qquad \textbf{Eq. 3.2}$$

By determining the cosine-based similarity, the system is effectively trying to find cosine value of the angle between the two users' personalities. Two users' personalities are determined as similar when the calculated cosine value is 1.

DEMOGRAPHIC FILTERING METHOD

Lastly, PHyBR filters the list of users by their demographic info to match the gender and age group of User A. PHyBR stores the user's demographic information after they are done with the sign up process. As Figure 3.8 illustrates, during this filtering method, the algorithm retrieves the demographic information of users, which were filtered during the last two steps, and now only takes those who fall under the same demographic gender and age group. There are three age groups: Teen (age <20), Young Adult (age 20-40) and Adult (age >40). Similar to personality filtering, the demographic filtering also used cosine-based similarity approach to measure the users' demographic comparison.

```
Algorithm DemographicFilteringMethod (input_users,user_age,user_gender)
    Var Empty List similar_users;
    For Each user in input_users;
        If user->gender equals to user_gender;
                If user->age is in user_age group;
                    Append user to similar_users;
                End If;
        End If;
    Next user
Return similar_users;
```

Figure 3.8: Demographic Filtering Algorithm Pseudo-Code

When these three filtering methods are completed, the list of similar users is finalized and PHyBR starts to analyse their browsing behaviour. A user's behaviour includes the visited books, rated books, search keywords and his book wish list. In order to map the book genres with personality traits, PHyBR used personality-based user stereotypes for the sixteen genres (Table 3.1) selected in each domain, distinguishing female and male users based on a previous study (Cantador et al., 2013).

Table 3.1: Personality-based user stereotypes in individual domain genres (Cantador et al., 2013)

BOOK GENRE	OPE	CON	EXT	AGR	NEU
comic	4.06	3.28	3.38	3.47	2.86
crime	3.83	3.44	3.43	3.47	2.99
drama	3.81	3.36	3.53	3.67	2.84
educational	4.02	3.66	3.57	3.66	2.74
fantasy	4.04	3.34	3.27	3.54	2.87
fiction	4.00	3.41	3.42	3.55	2.82
humor	3.90	3.40	3.62	3.56	2.78
mystery	3.91	3.53	3.51	3.61	2.76
non fiction	4.01	3.51	3.43	3.62	2.76
poetry	4.16	3.34	3.38	3.54	2.94
romance	3.89	3.52	3.49	3.60	2.85
scary	3.81	3.41	3.68	3.55	2.83
science fiction	4.13	3.42	3.25	3.51	2.81
self help	4.03	3.50	3.42	3.62	2.83
thriller	3.85	3.54	3.51	3.59	2.76
war	3.87	3.44	3.33	3.23	2.80

These stereotypes are vectors of five real values in the [1, 5] range that correspond to the average scores of the Big Five personality factors of users who had likes for the corresponding genres. For example, people with the personality trait "high degree of openness" tend to like poetry and science fiction (Cantador et al., 2013).

PHyBR selects the books based on similar users' browsing behaviour and personality traits; and then sorts them into a list based on popularity (how many times this book has been visited or added to wish list) and rating. The sorted list would be passed to CB algorithm for refinement.

3.2.2.2.2 CONTENT-BASED FILTERING ALGORITHM

As Figure 3.9 shows, PHyBR performs three kinds of CB filtering which are: (i) item-based filtering, (ii) review filtering and (iii) purchase reason filtering. In the condition that the CF algorithm generates the output (similar user's books), the CF algorithm will skip the item-based filtering and continues with second and third filtering methods. In the last two methods, PHyBR adds weight to the books by exploiting their reviews or purchase reason. Then it rearranges and resorts the recommended list.

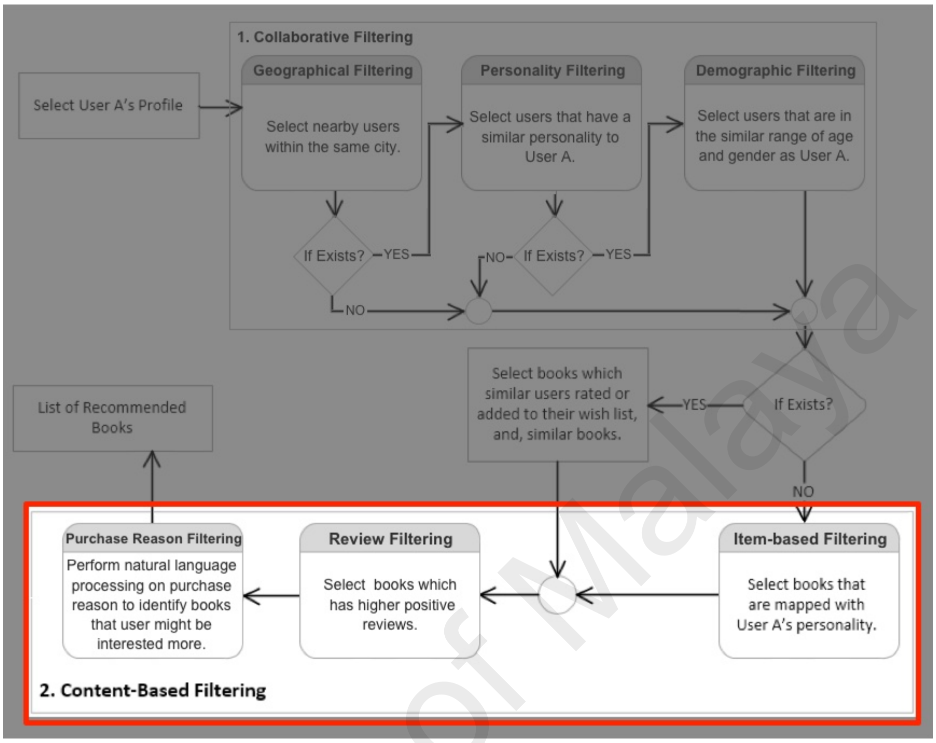


Figure 3.9: Content-Based Filtering Methods

ITEM-BASED FILTERING

In the case that PHyBR is unable to perform the CF algorithm due to lack of adequate information about users, it will perform item-based filtering, which maps the user's personality traits with book genres. In this stage PHyBR chooses the list of books that are matched to the user's personality traits and then sorts them based on the book's rating. This algorithm focuses on the recommended item (book) and the user (user's profile and behaviour history). Users interact with the system by searching for keywords or rating the books. The algorithm generates the recommendation in the following way (refer to Figure 3.10):

i. First the algorithm considers the user's profile by listing the books that match his personality and demographic group.

ii. Then, it filters the books that are similar with the books that the user has rated previously (i.e. books with ratings lower than 3 are not considered).

```
Algorithm ItemBasedFilteringMethod (user_personality,user_demographic)
    Var List mapped_books = retriveBooksMappedWithUser(user_personality,user_demographic);
    Var Empty List similar_books;
    For Each book in mapped_books;
        If book is similar to user's profile book history;
            Append book to similar_books;
        End If;
    Next book;
Return similar_books;
```

Figure 3.10: Item-Based Filtering Algorithm Pseudo-Code

For example, when PHyBR is unable to find any similar users for User A, it would start the item-based filtering method. First, it will grab all the books that matches his personality (i.e. openness). Then, it will check if User A has rated any books before, it will take the books that are in the same genres of those rates books.

REVIEW FILTERING

Every time a user writes a book review, PHyBR performs the sentiment analysis (MeaningCloud) on the review and stores it into the user profile. MeaningCloud is the popular cloud-based software that can be used to extract valuable information from any text source and it's functionalities is accessible via the cloud Application Programming Interfaces (APIs), as it is illustrated in Figure 3.11 (Dale, 2015; Sharma & Hoque, 2017).

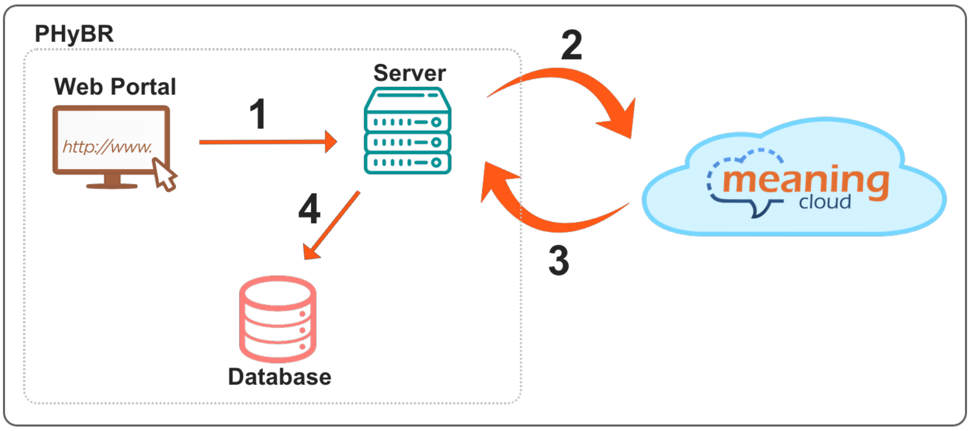


Figure 3.11: Requesting Sentiment Analysis From MeaningCloud

It indicates the polarity of text, whether the review is positive, neutral or negative. User positive or negative review has an effect on his next search or recommendation result. During this filtering process, PHyBR counts the number of positive reviews for each of the books and adds more weight to the book that has more positive reviews (as Figure 3.12 shows). This helps to sort the list and books with higher positive reviews will be moved to the top of the list.

```
Algorithm ReviewFilteringMethod(book_list)
    For Each book in book_list;
      If Total Number of  book->positive_review Greater Than Zero;
          Add on book->weight;
      End If;
    Next book;
    Sort book_list based on weight (descending order);
Return book_list;
```

Figure 3.12: Review Filtering Algorithm Pseudo-Code

According to Eq. 3.3, the adjusted Bayesian formula is used to calculate the weight of reviews and ratings (WR) (Chen et al., 2017):

$$WR = \left(\frac{v}{v+m}\right) \times R + \left(\frac{m}{v+m}\right) \times S \qquad \textbf{Eq. 3.3}$$

Where:

- v = number of reviews and ratings for the book
- m = minimum number of reviews and ratings required (currently 5)
- R = average rating for the book
- S = sum of all positive and negative reviews of the book

This formula is applied to every book in the list and once the WR is calculated, it would be added to the book weight. This helps to move the books with higher positive reviews and rating to the top of the recommendation list.

PURCHASE REASON FILTERING

This is the final filtering that PHyBR performs. It is one of the CB filtering methods that PHyBR applying to book's purchase reason. The principle is to use natural language processing on purchase reason to automatically identify books that a user might like. As Figure 3.13 demonstrates, this filtering process is divided into four steps.

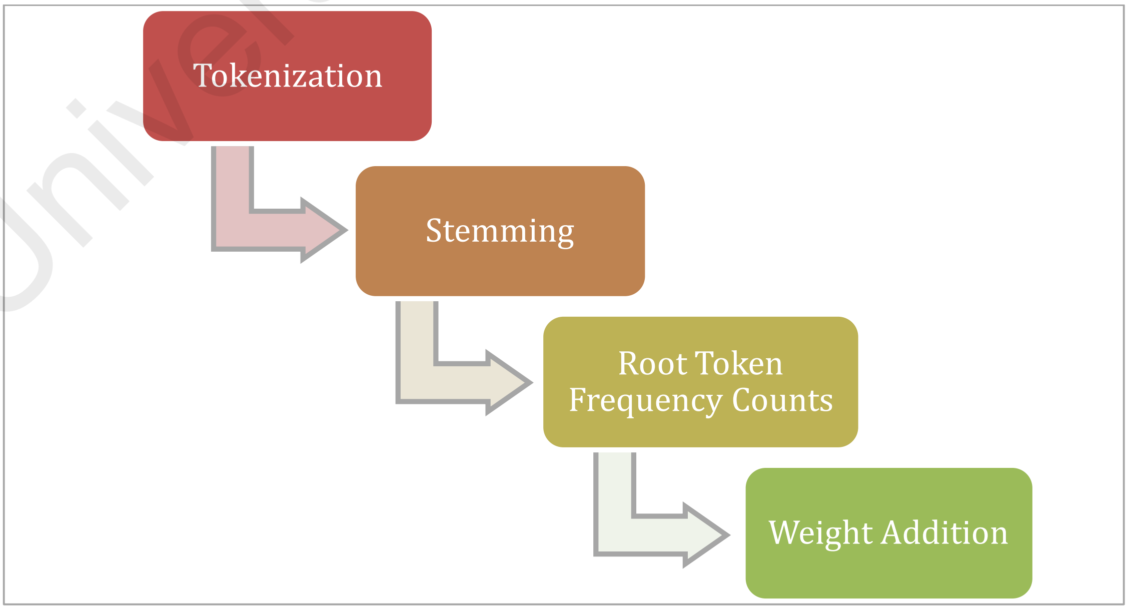


Figure 3.13: Purchase Reason NLP Process

Step 1. Tokenization:

This step is described as obtaining meaningful basic units from the user's purchase reason text. In text analysis, large strings of text can be expressed in tokens (Rehman & Kifor, 2015). These tokens often correspond to words. Therefore, a simple tokenization method to obtain tokens for the sentence "Motivational and inspiring stories" is by splitting them on whitespaces. This splitting results four tokens, i.e. "Motivational", "and", "inspiring", "stories" (Agerri et al., 2014).

Step 2. Stemming:

In this step PHyBR mapped every token to its root form. In the previous example, token "Motivational" in the mentioned sentence would be mapped to "Motive". In this step, the stemming process is implemented to find the root of an inflected word (Ibrahim & Salim, 2016).

Step 3. Root Token Frequency Counts:

This process is applied to all the purchase reasons of a book and resulting a list of root words. As Eq. 3.4 shows, CAPHyBR calculate the weight of purchase reason (WP) by matching the user's search history (K) with the list of root words (R) and adds more weight to the book for every match that occurs.

$$WP = |R \cap K| \qquad \textbf{Eq. 3.4}$$

Note that this step is only applied on generated list of books. Therefore, the frequency of most root tokens in a book purchase reason might be zero.

Step 4. Weight Addition:

Now, PHyBR adds more weight to the books that have more root token frequency counts. It sorts and rearranges the books according to their weights. This might help the user to discover a new book that contains the purchase reason.

Figure 3.14 shows the overall concept of purchase reason filtering method and how these four steps are combined together to perform the filtering. Finally, after PHyBR completed the purchase reason filtering, the list of recommended books is ready. It selects the top 15 books and displays them to the user.

```
Algorithm PurchaseReasonFilteringMethod(book_list)
    For Each book in book_list;
        For Each purchase_reason in book->purchase_reasons;
            Var additional_weight = Perform_NLP(purchase_reason);
            If additional_weight Is Greater Than Zero;
                Add on book->weight (+ additional_weight);
            End If;
        Next purchase_reason;
    Next book;
    Sort book_list based on weight (descending order);
Return book_list;
```

Figure 3.14: Purchase Reason Algorithm Pseudo-Code

There are five sample case studies provided in Section 1.3 (User Case Study).

3.2.2.3 System Design

System design describes the design for the process, module, database and interfaces that are in the system. The design of the system is to allow us to have an overview of the system to be developed (Van, 2013).

3.2.2.3.1 USE CASE MODEL

This section will describe the functionality of the proposed RS. The Use Case can be used to represent a unique set of user interaction with the proposed RS. It is a distinct, meaningful and useful component that helps to illustrate the list of functionalities. For instance, functions such as login, registration and recommendation, are being shown by utilising Use Cases. It is important to note that a Use Case might include another one or extent from the other Use Case and inherit all its functionalities (Hajri et al., 2015). There is one actor and seven use cases in PHyBR framework. Figure 3.15 indicates the use case diagram of the system and Table 3.2 contains the use case description.

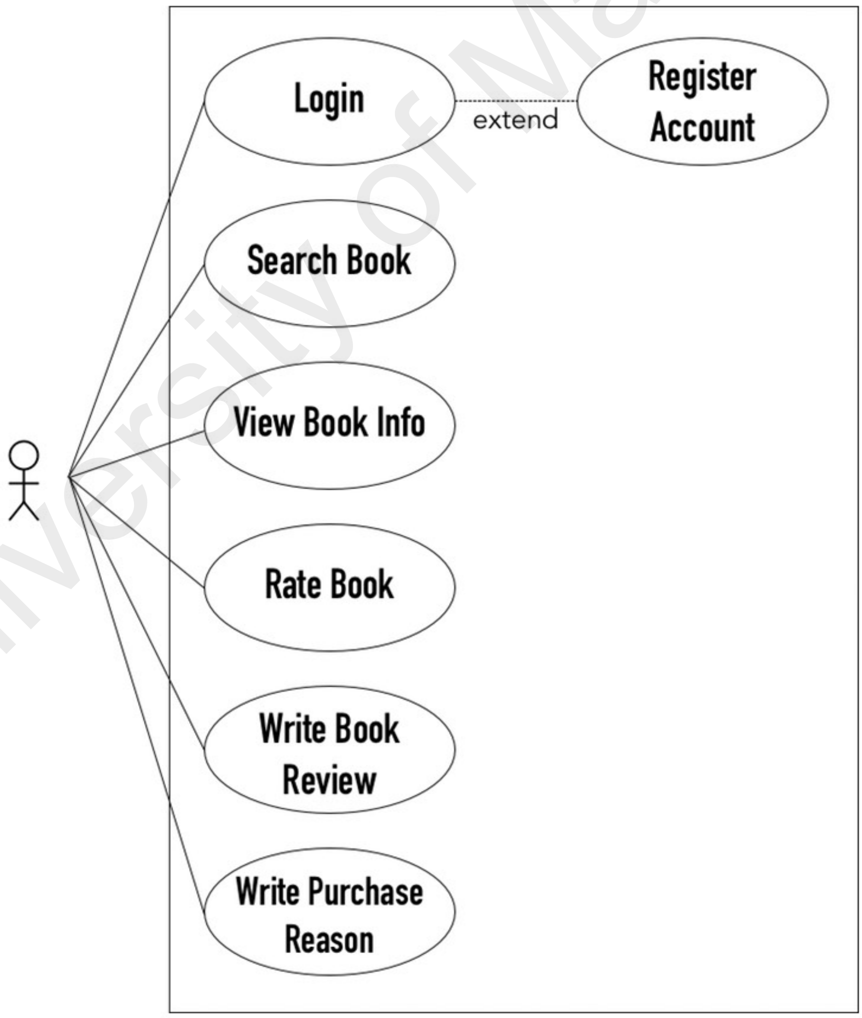


Figure 3.15: Use Case Model of PHyBR

As Table 3.2 shows, the user is able to perform activities such as login, registration account, search book, view book info, rate book, write book review and write book purchase. PHyBR monitors user’s activities and store his behaviour in the database to use these data when generating the recommendation result.

Table 3.2: Use Case Description

Use Case	Description
Login	Describe how registered user can log in to the system by entering their username and password. If the user is new, they will go to Register Account use case.
Register Account	Describe how new user can register a new account with the system. They will have to complete all the field in the registration form and personality test, and then click register to finish the process.
Search Book	Describe how registered user can search for book. The user is able to search book either by author’s name, book’s title or genre.
View Book Info	Describe how registered user can view details of a book. The user will click a book in the list and they can view the book’s title, author, rating and synopsis.
Rate Book	Describe how registered user can rate a book. They will pick any book and give rating from 1 to 5 stars.
Write Book Review	Describe how registered user write review for the chosen book.
Write Purchase Reason	Describe how registered user write his/her purchase intention for the chosen book.

3.2.2.3.2 DATABASE DESIGN

Database design is an important process before developing a system, the database design must be correct and appropriate to ensure that data can be stored properly without failure. It is important to have a well-designed database, because it helps to deliver more accurate and up-to-date data and information. (Mitrovic & Suraweera, 2016). A perfect design helps to obtain the essential goals when we are working with a database, so it is necessary to spend sometimes to learn the basic rules of well-designed database (Byrne & Shahzad, 2013). The database design consist of seven tables which are illustrated in Figure 3.16.

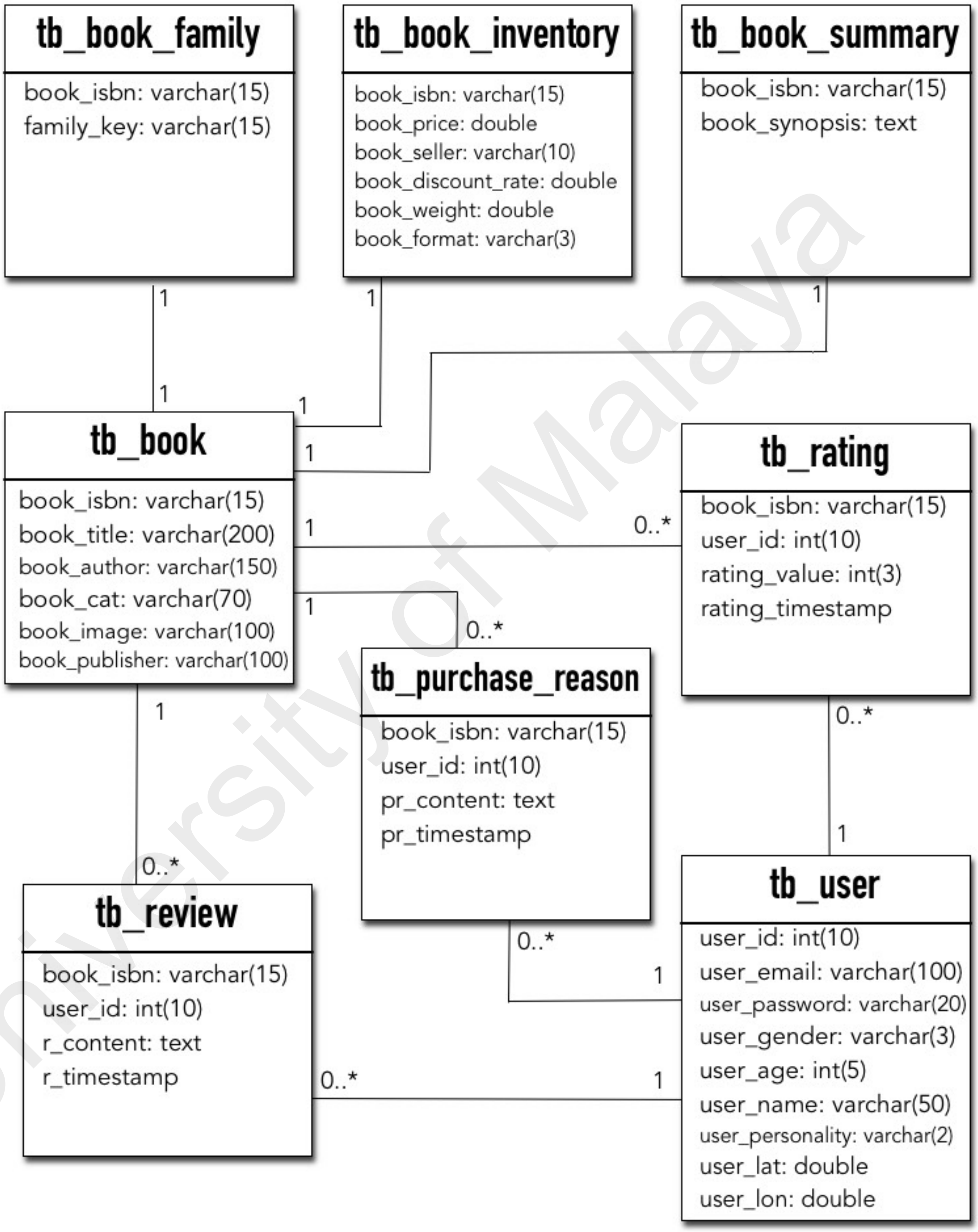


Figure 3.16: PHyBR's Database Design

The book's table (tb_book) is the main table, which is connected to almost all the tables in the database. It hold data about book such as author's name, book's title, genre, International Standard Book Number (ISBN), cover image and etc. The user table (tb_user) holds data about user (e.g. name, email, password, gender, age and etc.) that is able to rate (tb_rate), write purchase reason (tb_purchase_reason) and review (tb_review) for each book.

3.2.2.3.3 SEQUENCE DIAGRAM

Sequence diagram is an interaction diagram used to describe the flow of information between entities. It represent object and classes involved in the scenario of the particular use case and the order of exchanging messages and tokens between the objects (Tu et al., 2015). Figure 3.17 illustrates the flow of sequence of recommending books to the user.

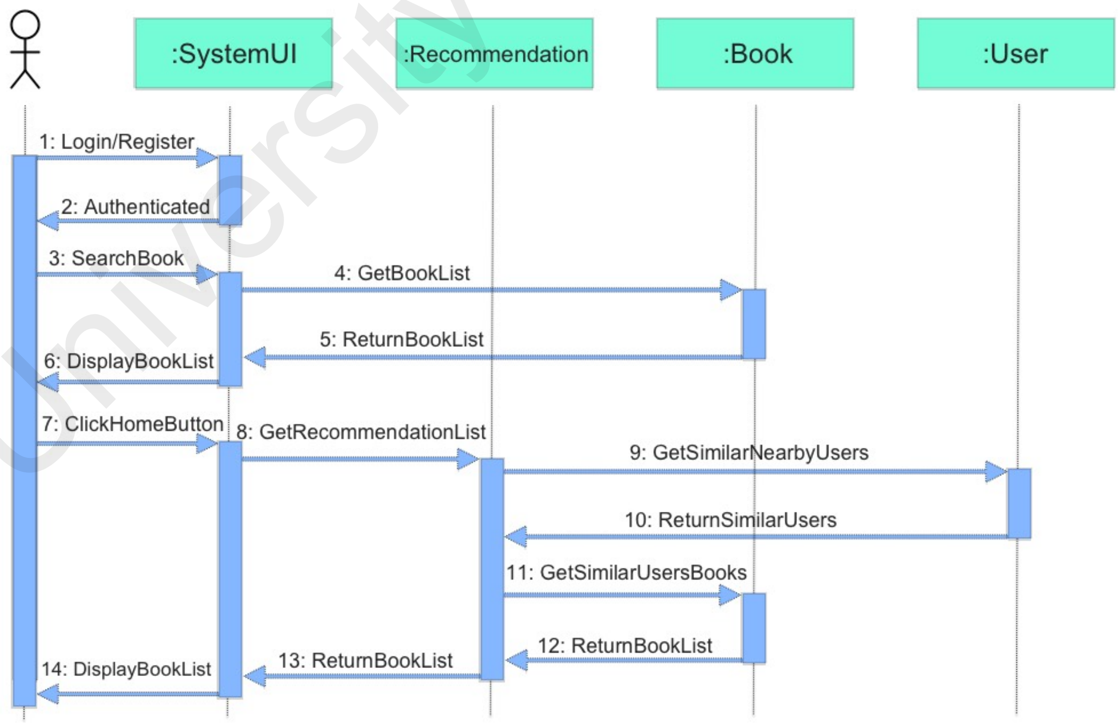


Figure 3.17: Sequence Diagram

The user is interacting with system's User Interface (UI) to perform each of the activities. First, he needs to login (or register, if it is the first time), and the system will authenticate him. He may search for any books by using a keyword (such as author's name, book's title and genre) and the recommendation object will return the list of books. He is able to rate a book, write review or purchase reason that would affect his later recommendation result. When the user is back to the Home page, the system generates the list of recommended books display it on the UI.

3.2.3 Phase 3: System development

This section talks about system development, which it is a standard procedure of converting the system design to the actual working platform and it involves the processes such as analysis, design, development, testing and debugging (Wasson, 2015). The System Development Life Cycle (SDLC) ensures end-state solutions in accordance to the requirements provided by the developer in support of goals and objectives. It represents a structured, systematic approach that aims at developing information systems. The SDLC incorporates a comprehensive checklist of rules and regulations governing IT systems (Valacich et al., 2015).

SDLC is used to develop our system prototype, because it would be easier to measure the progress of system development and the neat sequence of development phases and controls for extensive document and reviews to ensure the quality and maintainability (Berkling et al., 2009). As Figure 3.18 shows, the design process is used sequentially, in which progression is seen as flowing continuously toward a lower place, a process which will be passed through consists of five phases, namely Planning, Analysis, Design, Coding, Testing and Debugging (Mahalakshmi & Sundararajan, 2013). The flow is from top to bottom, and if there is any problem, the flow is reversed to go upward to do the correction (Arora & Arora, 2016).

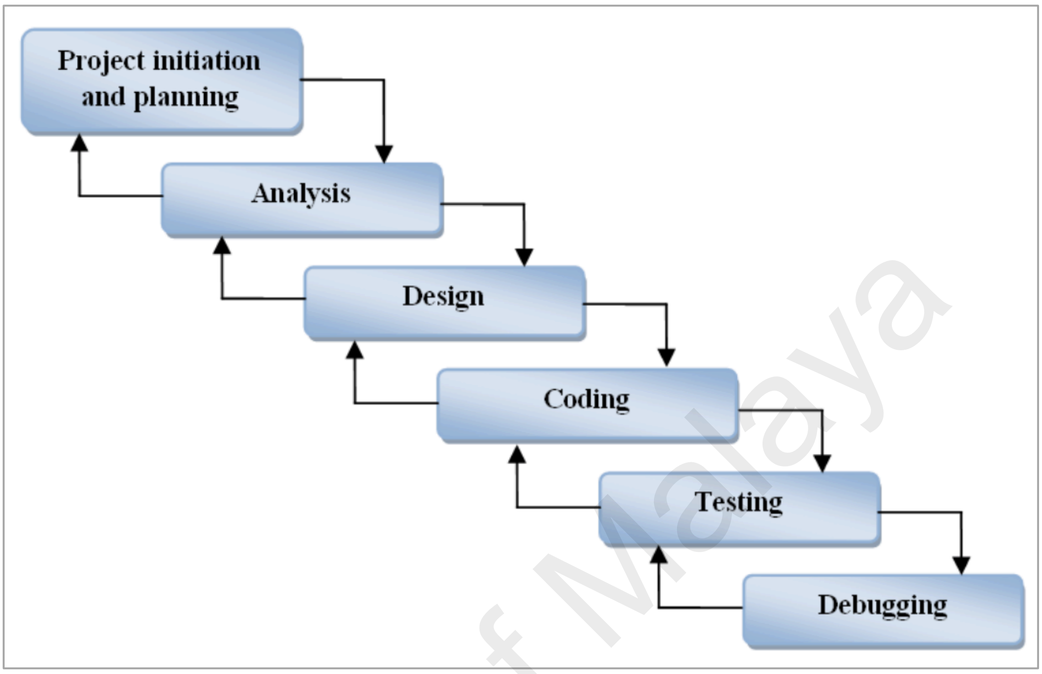


Figure 3.18: Waterfall Model (Mahalakshmi & Sundararajan, 2013)

There are three basic principles that needs to be considered (Berkling et al., 2009):

1. The project is divided into phases, in a sequential manner and two phases may overlap.
2. The designer should emphasize on the budget and project duration.
3. The designer should perform the information and user management at the end of each phase, to maintain a perfect control over the project and written documentation.

During the first two phases, the SDLC make sure to have a solid plan as well as system requirements for developing the proposed information system (Arora & Arora, 2016; Mahalakshmi & Sundararajan, 2013). Then in the Design phase, all the gathered requirement specifications are studied for defining the overall system architecture. By considering the information from the design phase, we start to code and develop the system in different sub-programs called units. After all the units are developed, they are combined after testing each one of the units individually. There will be a final testing when all the parts are integrated for assuring no failures or faults. If there are any identified bugs or errors, they will be fixed during the debugging phase (Arora & Arora, 2016). After completing each phase, system review is performed for a better outcome. The following sections discuss each phase in more details.

3.2.3.1 Planning Phase

The planning phase would make sure that when this phase is completed, there will be a perfect and solid plan for building the RS desired (K. S. Church et al., 2016). In the phase, three primary activities need to be ensured for optimality. In this phase, it is important to consider that the proposed system needs to have three activities, needs to be well-defined, recognised and chosen according to our objectives and strategic aims (Balaji & Murugaiyan, 2012). Secondly, the aim of this study is to developing a Hybrid personalised RS that integrates multiple user and product contextual features to generate recommended books. Lastly, the project plan needs to be defined (K. S. Church et al., 2016). During this phase, the scheme is initiated by studying the project terms, such as how does an RS algorithm work and how to develop it. Then the problem statement is formulated and it needs to be monitored to overcome the issues through achieving the research objectives.

3.2.3.2 Analysis Phase

During this phase, the system's requirements is determined without considering the accomplishment of these requirements. The requirement document would be the outcome and result of this phase (K. S. Church et al., 2016). Primarily at this stage, enough information and data according to the RS or user requirements needs to be obtained (Rosenblatt, 2013). In literature review, we have studied systems and frameworks that generate recommendation to their user and that gave us the basic understand about user's requirements. In order to define the RS as a successful system, it needs to fulfil the end user's requirements and requests. The system requirement is divided into two parts, hardware and software requirement.

The hardware requirement for the server layer, where the system control and the web portal are hosted, is listed in Table 3.3. The components of the server layer are hosted on a remote cloud server, which is able to handle at most 100 concurrent users. These requirements change if the total number of users varies in the RS. The system need to be scalable to handle more users and the hardware can be enhanced anytime without changing the current system's performance and affecting the user interaction (Eijkhout, 2014). The server administrator should monitor the server activities and analyse the daily performance report.

Table 3.3: Server's Hardware Requirement

Hardware	Requirement
Memory	2 GB
CPU	Core™ i5-2500
SSD Disk	30 GB

A software system needs to present the requirements that explains the descriptions of each services and also the limitation that it needs to operate under (Wiegers & Beatty, 2013). Both web portal and server layer were deployed using the application server, called Tomcat application server. The application server helps to host the program on the real physical computer that can be accessed via the web portal from the http port and creates the user interface and logical tiers of the RS's platform (Sahoo & Feigen, 2014). As Figure 3.19 shows, a listener was installed in between the server and the web portal to be responsible for handling of all user's requests. It takes the request then pass it to server, after the request is processed, it returns the data back to web portal. The web portal is the visualized form of data in the database.

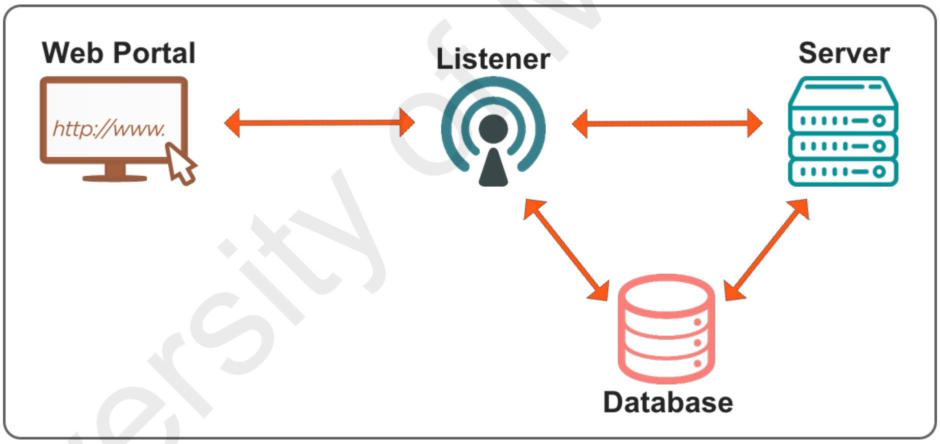


Figure 3.19: Server Internal Architecture

3.2.3.3 Design Phase

The design phase has a main and important objective to outline a design which matches the application requirements. The SDLC in design phase, shifts from the "what" phase of analysis to the "how" phase (Rosenblatt, 2013). In the previous phase, PHyBR's architecture and design was presented in details. It provides the overall understanding about system structure and what it really needs to be as the outcome after system development is completed. In this phase, we need to produce the computing vision of the application concept that produced in analysis phase. The outcome of this phase should be well-specified, so it contains all the detail functions ready for the development phase. Therefore, it must even list the needed technologies for the RS to be implemented and executed.

3.2.3.4 Coding Phase

Now that we have all the application details from the design phase, we can start converting the designs into a working application (Arora & Arora, 2016). We used Visual Studio Code to have the basic programming environment to build the PHyBR's prototype. We used PHP as the server side programming language to develop the core of the server back-bone. Generally, PHP is a popular worldwide multi-purpose programming language, which is usually used for building web applications. HTML and JQuery is used to develop the client side where is the interface for the end user to communicate with the platform.

3.2.3.5 Testing Phase

This is the phase, which we start testing the developed application. As the Fifth step of SDLC steps, it is very necessary to make sure everything works properly (Arora & Arora, 2016; Balaji & Murugaiyan, 2012). During this phase we need to verify whether the PHyBR's prototype is accomplishing all the defined requirement as mentioned in analysis phase. The system is tested against many cases and conditions to make sure it performs as we would expect in real time. The first task is to check whether the computer hardware is compatible with our system. In this step, the system is divided into multiple parts and modules, then they will be tested individually to make sure the system is working well (K. S. Church et al., 2016).

3.2.3.6 Debugging Phase

Any bugs or errors found during the testing phase are corrected in the debugging phase. The bug is not just coding or syntax error, it can be any deficiency in any of the modules, such as not being user friendly. After debugging, the system becomes more reliable and user friendly (Arora & Arora, 2016). During this phase we are going to fix and debug any issue or problem that we had encountered in the previous phase (Testing Phase).

3.2.4 Phase 4: Experimental Evaluation

Evaluation is the last phase where it critically inspect the system's performance and accuracy. It involves monitoring the interaction between user and the system, and collect all the required information that can be used for analysis. The main objective of this phase is to judge the program from different aspect and to enhance its accuracy and effectiveness (Kazai et al., 2016; Rikitianskii et al., 2014). In this section we will elaborate the outline of the experiment and evaluation, which includes the experimental setup, dataset and metrics that will be used. Then, there will be a presentation and discussion of the results of the evaluation in next chapter (Chapter 4).

The aim of the experimental evaluation is to verify the accuracy of PHyBR and to assess the accuracy of recommendations provided using users' personality traits and their demographic details together with their geographical location, review sentiments and purchase reason. We evaluated the effectiveness of PHyBR by using two kinds of experiments. In one experiment, we evaluated the overall PHyBR's algorithm, and perform the comparison between PHyBR and other existing algorithms (i.e. PLMTA, TISP, LBSM and MediSem) in terms of quality and accuracy of providing personalised recommended items to user (refer to Table 3.4). We have chosen these algorithms, because they developed hybrid personalized RSs that utilized user and product contextual features to generate the recommendation result. Also, they have used the same evaluation metric to examine the effectiveness of their RSs and achieved very good results.

Table 3.4: Personalised Recommendation Algorithms

Recommendation Algorithms
PHyBR: Personalized Hybrid Book Recommender
PLMTA: Personalized Location-based Mobile Tourism Application
TISP: Social Presence on Personalized Recommender System
LBSM: Location-based Recommendation Using Sparse Geo-Social Networking Data
MediSem: Personalized Medical Reading Recommendation – Deep Semantic Approach

In another experiment, we examined the individual filtering methods used in PHyBR and how effective each filtering method increases the accuracy when it is integrated together with other filtering methods. The experiment was conducted with fifty users. We have evaluated PHyBR in four different scenarios: PHyBR_D, PHyBR_DP, PHyBR_DPG and PHyBR (refer to Table 3.5). The user's demographic data was combined with the user's personality traits in scenario B, and, in the scenario C, we combined them with the user's geographic location. PHyBR was represented in scenario D where all three filtering methods were used together with having sentiment analysis on reviews and natural language processing on purchase reason personalize the recommendation.

Table 3.5: Experimental Scenarios

Evaluation Methods	
PHyBR_D	Demographic
PHyBR_DP	Demographic + Personality Trait
PHyBR_DPG	Demographic + Personality Trait + Geographic Location
PHyBR	Demographic + Personality Trait + Geographic Location + Analysing Review + Purchase Reason

3.2.4.1 Experimental Setup

This experiment took place in computer labs of two universities, a public university in Kuala Lumpur and a private university in Malacca. Twenty-five users majoring in Computer Science participated from each university. All users were in the age range of 19 to 24 years, twenty female users and thirty male users. PHyBR was uploaded to the cloud server to be accessible via the computer's Web Browser software. We provided a printed user guide (Appendix B) for all users and gave a demonstration of how to use PHyBR and create all the scenarios step by step. We elaborated and guided them to follow our instruction. Then we let them use and browse the system for 10 minutes to really become familiar with it. After that we started the experiment by monitoring their behaviour and tried not to interfere their interactions. First, the users signed up and took the personality test. This was followed by searching for fixed keywords in 5 genres (refer to Table 3.6), rating and adding books to their wish list. The experiment lasted for 15-20 minutes and all the data were saved in the MySQL database.

Table 3.6: Experimental Search Keywords

Genres:	Mystery	Romance	Travel	Computer	Science Fiction
Keywords:	Police	Love	Journey	Programming	Demon
	Murder	Romance	Planet	Computer	Dragon
	Killer	Angel	Travel	Coding	Vampire

3.2.4.2 Experimental Dataset

To evaluate our algorithm, we downloaded a book dataset from www.amazon.com. The dataset contains information about 200,000 books in 27 genres, namely “Arts & Photography”, “Biographies & Memoirs”, “Business & Investing”, “Children's Books”, ”Comics & Graphic Novels”, “Computers & Technology”, “Cookbooks, Food & Wine”, “Christian Books & Bibles”, “Crafts, Hobbies & Home”, “Education & Reference”, “Health, Fitness & Dieting”, “History”, “Humour & Entertainment”, “Literature & Fiction”, “Medical Books”, “Mystery”, “Thriller & Suspense”, “Parenting & Relationships”, “Politics & Social Sciences”, “Professional & Technical”, “Religion & Spirituality”, “Romance”, “Self-Help”, “Science Fiction & Fantasy”, “Science & Math”, “Sports & Outdoors”, “Teen & Young Adult” and “Travel”. For each book, we collected its ISBN, title, author’s name, genre and synopsis text. The performance stability of our algorithm can be evaluated on these datasets.

3.2.4.3 Evaluation Metrics

The effectiveness of PHyBR was measured using two popular evaluation metrics: Standardized Root Mean Square Residual (SRMR) and Root Mean Square Error of Approximation (RMSEA). SRMR is the absolute measure of fit, and it is estimated by the square root of the estimated discrepancy due to approximation per degree of freedom (Marais & Andrich, 2007), as shown in Eq. 3.5.

$$\text{SRMR} = \sqrt{\sum_{i=1}^{p}\sum_{j=1}^{i}\left[\frac{s_{ij}-\hat{\sigma}_{ij}}{s_{ii}s_{jj}}\right]^2 / p(p+1)/2} \qquad \textbf{Eq. 3.5}$$

Differences between data (s_{ij}) and model ($\hat{\sigma}_{ij}$) predictions comprise the residuals where p is the total number of observed variables, then the average is computed, and the square root taken. SRMR is a badness-of-fit index (larger values signal worse fit and lower values indicate better performance) which ranges from 0.0 to 1.0. If the SRMR is zero, that means the model predictions match the data perfectly, with a value of 0.08 or less being indicative of an acceptable model (Marais & Andrich, 2007). SRMR is enhanced (lowered) when the measurement model is clean (high factor loadings). The index is a good indicator of whether the system captures the data, because it is relatively less sensitive to other issues such as violations of distributional assumptions (Iacobucci, 2010).

The second metric is RMSEA (Buccafurri & Semeraro, 2010), as shown in Eq. 3.6:

$$\text{RMSEA} = \sqrt{\max\left([((\chi^2/\text{df}) - 1)/(\text{N} - 1)], 0\right)} \qquad \textbf{Eq. 3.6}$$

Where χ^2 is the chi-square value, df is its degrees of freedom and N is the sample size. The RMSEA has a best estimation of zero when the data fits the model. When data is over fitted to the model, $\chi^2/df<1$, is ignored. For a given χ^2, RMSEA decreases as sample size, N, increases. The RMSEA ranges from 0 to 1, with lower values showing a greater model fit. A value of 0.06 or lower is expressive of acceptable model fit. RMSEA considers two errors: the error of approximation that demonstrates the absence of fit of the system when the parameter is ideally picked, and the error of estimation that shows the absence of fit of the system to population data (Marais & Andrich, 2007). RMSEA and SRMR have been used in many other works (Cheng et al., 2011; Huemer & Lops, 2013; Cui, 2012; Hennig et al., 2012; Knijnenburg & Kobsa, 2013).

3.3 User Case Study

In the following section, we illustrate scenarios of five users (User 1, User 2, User 3 and User 4, User 5) using PHyBR. These scenarios are being illustrated to understand the proposed RS's algorithm better, and they are not taken from the users in the experimental phase. The system determines the user personality and performs the user profiling after the user keys in his information and takes the personality test.

For example, in Figure 3.20, assume User 1 has Extraversion personality with demographic information as Male (20-40 age group) from Kuala Lumpur. User 1 searches the keyword "Travel" and rates the book "Age of Kali Travel" 5 stars (Figure 3.20: Step 1.2). In Step 1.3, when the user goes back to the recommendation page, he views his latest rated book on top of the list. The rest of the recommended books are affected by his latest search keyword and his personality, as well as books that have the search keyword in their title and that also match the user's personality trait.

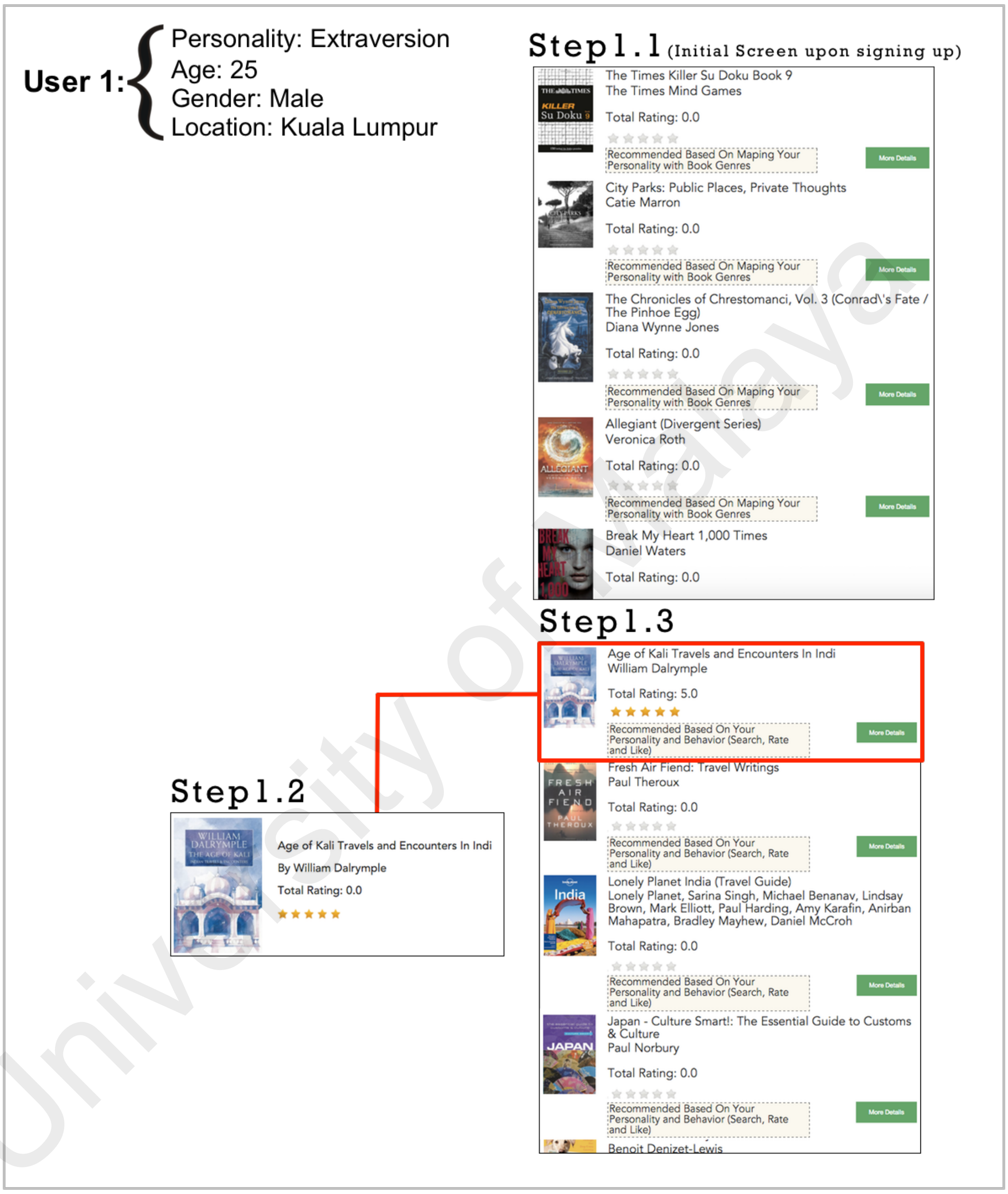


Figure 3.20: Recommended books for User 1

Assume User 2 has the same personality and group age as User 1 and is also from the same city. When he visits the recommendation page for the first time (Figure 3.21: Step

2.1), his list of recommended books is affected by User 1's behavior. PHyBR determined User 2's preferences as the same as User 1's because they have the same personality traits, age group, and city. The book "Age of Kali Travel" that User 1 rated as 5 stars appears on top of the list for User 2. Assume User 2 searches the keyword "War" and rates the book "The Strange Death of World War II" as 5 stars. Now the recommendation list changes according to his latest keyword search and the rated book appears on top of the list (Figure 3.21: Step 2.3). However, the recommendation list contains books that are rated by similar users. For example, the second recommended book is a book which User 1 had rated before.

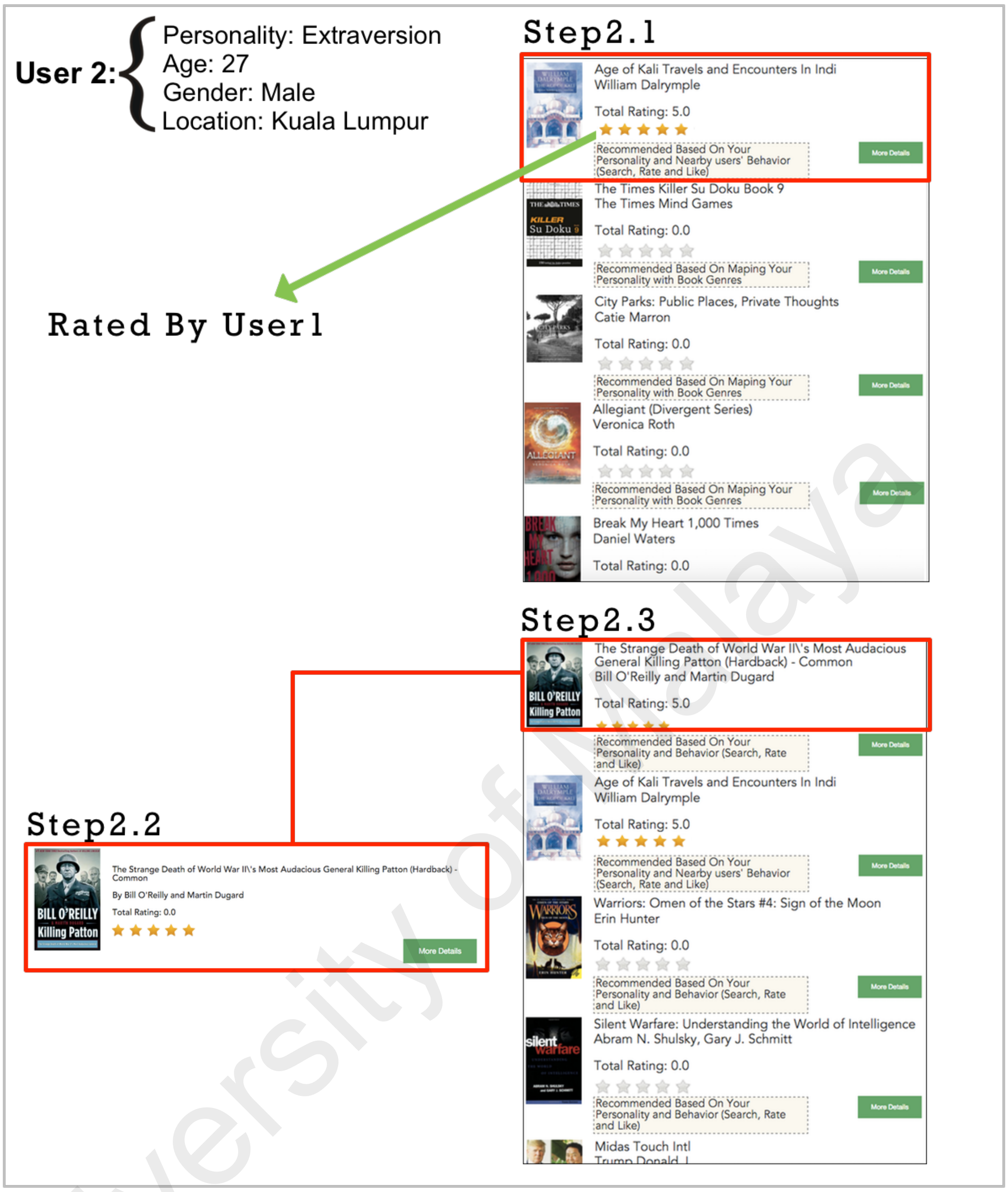


Figure 3.21: Recommended books for User 2

In the example (Figure 3.22), User 3 has a different personality trait (Openness) and age group but is from the same city (location). PHyBR is unable to find any similar nearby users to match with User 3, so books are recommended based on User 3's personality traits and book genres (CB filtering).

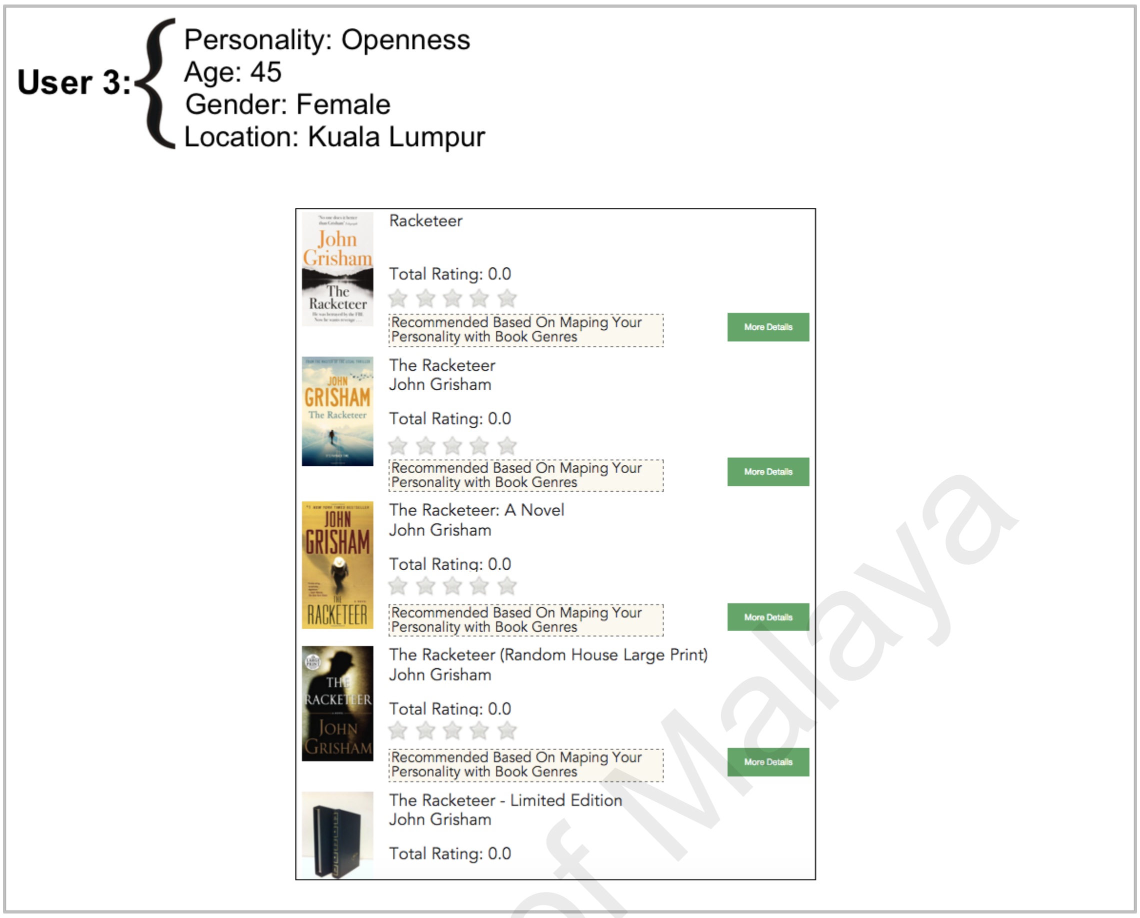


Figure 3.22: Recommended books for User 3

When a user travels from one city to another, he will receive different recommendations based on a similar group of users from that location. Assume User 4 has the same personality and age group as User 1 and User 2. He views the recommendation when he is in Malacca (Figure 3.23: Step 4.1) and after he travels to Kuala Lumpur he would receive different recommended books based on similar user behaviour that affects his recommendation (Figure 3.23: Step 4.2).

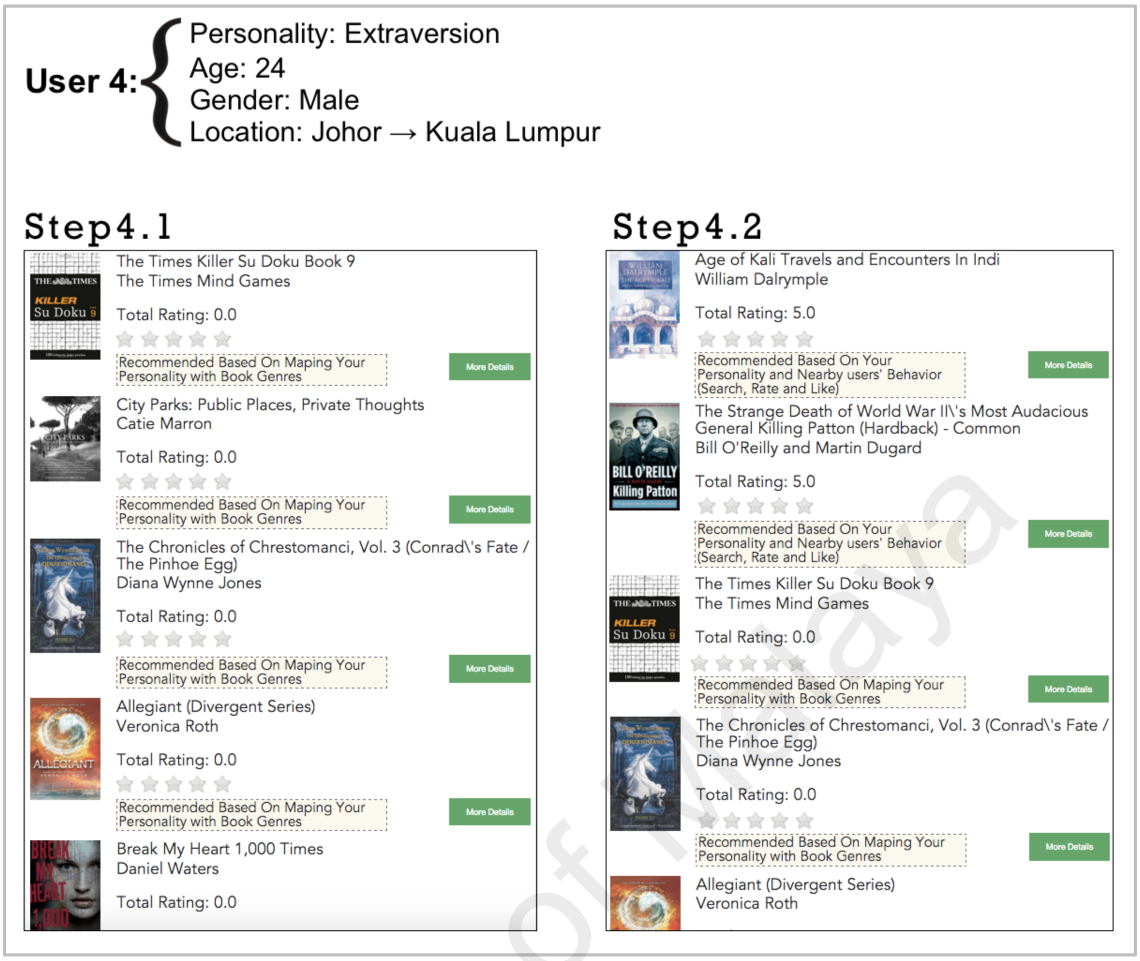


Figure 3.23: Recommended books for User 4

In the last example, User 5 enters a positive purchase reason as illustrated in Figure 3.24. As he entered the reason, the recommended result will be updated with the positive reason added to the relevance weight of "The Strange Death of World War II" book (shown in Figure 3.25).

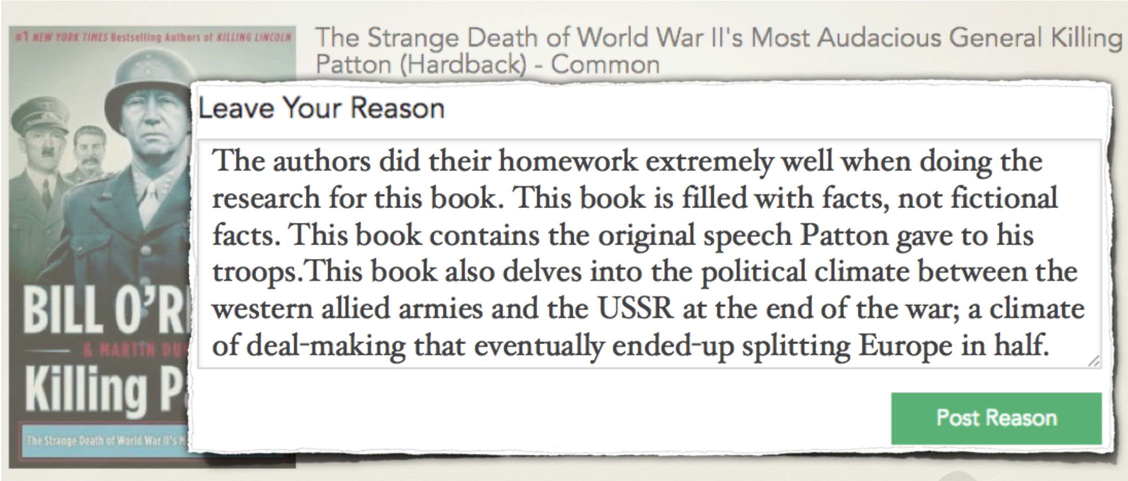


Figure 3.24: User 5's purchase reason

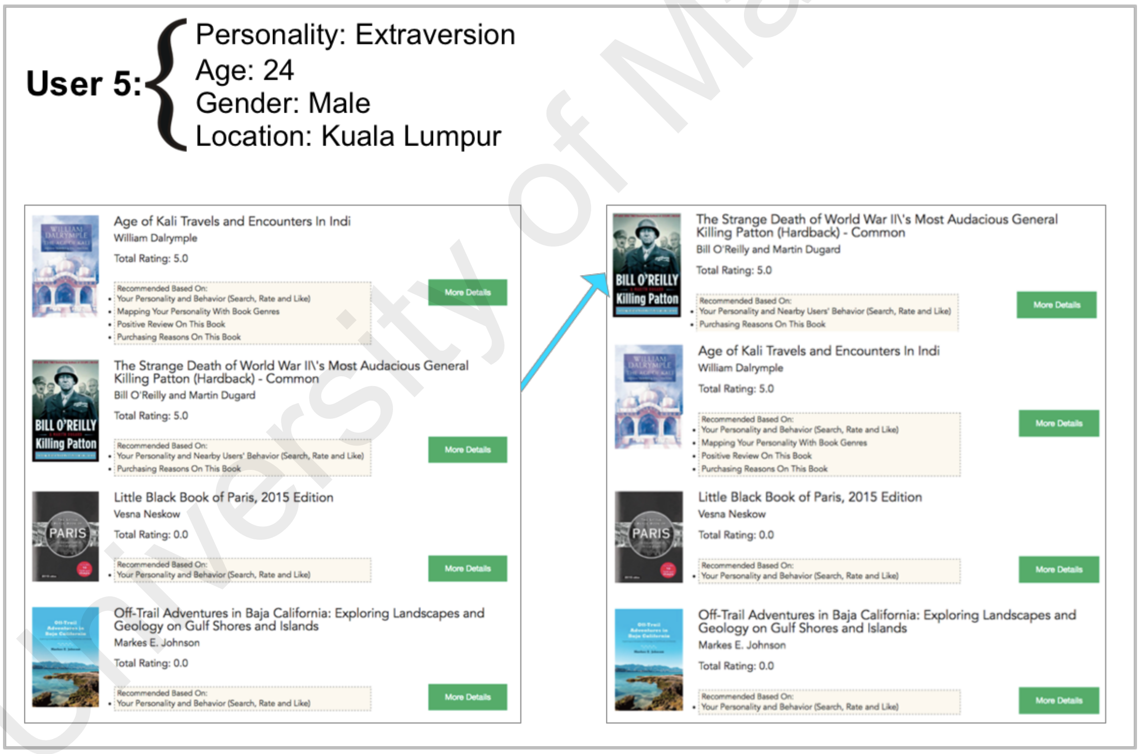


Figure 3.25: User 5's updated recommended list

3.4 Summary

The chapter described the components of the research methodology in detail which are LR, the issues that existing systems face and the solution to overcome these issues. We have discussed all the phases of the proposed methodology as well as, the proposed solution's steps. It also summarised the development process, which involved with different phases of SDLC and provided sufficient information to understand the proposed RS's functionality in details.

Overall system design of PHyBR was discussed as well. System design and implementation are important for system development. It is important to understand the system requirements clearly and to determine data input, data store and output information in context of an organization. Database development and programming modules also have to be implemented. After complete certain processes, the integration process is carried out, the review of all processes in order to turn the appliance and any problems and life affirming meet the needs of users.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Overview

RSs research is having a great and strong effect on the recent business and profession applications. It is essential to understand that evaluating the effectiveness of the RS is the main problem related to the practical side of building the RS. This chapter's main objective is to examine the effectiveness of the proposed hybrid RS and measure that it fulfils its required results.

Before the evaluation process starts, it is important to revise the goals and objectives of the RS for which it is being built. All the RSs have a common goal and that is to generate accurate and meaningful suggestions and recommendations for their users. It is obvious that the appreciation of RS's users is the perfect way of measuring the success of the RS, in other words, its ability to fulfil and satisfy each one of the user's distinct needs. In our research, we have achieved to build an optimised hybrid RS that produced personalised recommendation based on the individual user's personality and preferences. This research tried to bring the novelty and diversity to the process of recommendation and not just to the items or contents of the recommendation list and this would create a new opportunity for future research.

The quality of a recommended list is a broad concept that is not defined generally yet. However different evaluation methods and metrics, mostly from the Information Retrieval field, are introduced and applied on different RSs. Evaluation of RSs comprising wide spectrum of metrics, from rating prediction in explicit rating systems to the accuracy based F-measure and ranking based methods. All these metrics look at the quality of the proposed system based on the user's preferences and mimic the user's taste.

In this chapter, the experimental evaluation result is discussed in two parts. First the individual filtering method used in PHyBR is evaluated and how effective each filtering method increases the accuracy when it is integrated together with other filtering approaches. In the second part, the evaluation of the overall PHyBR algorithm is discussed, and compared with other existing algorithms in terms of quality and accuracy of providing personalised recommended items to user.

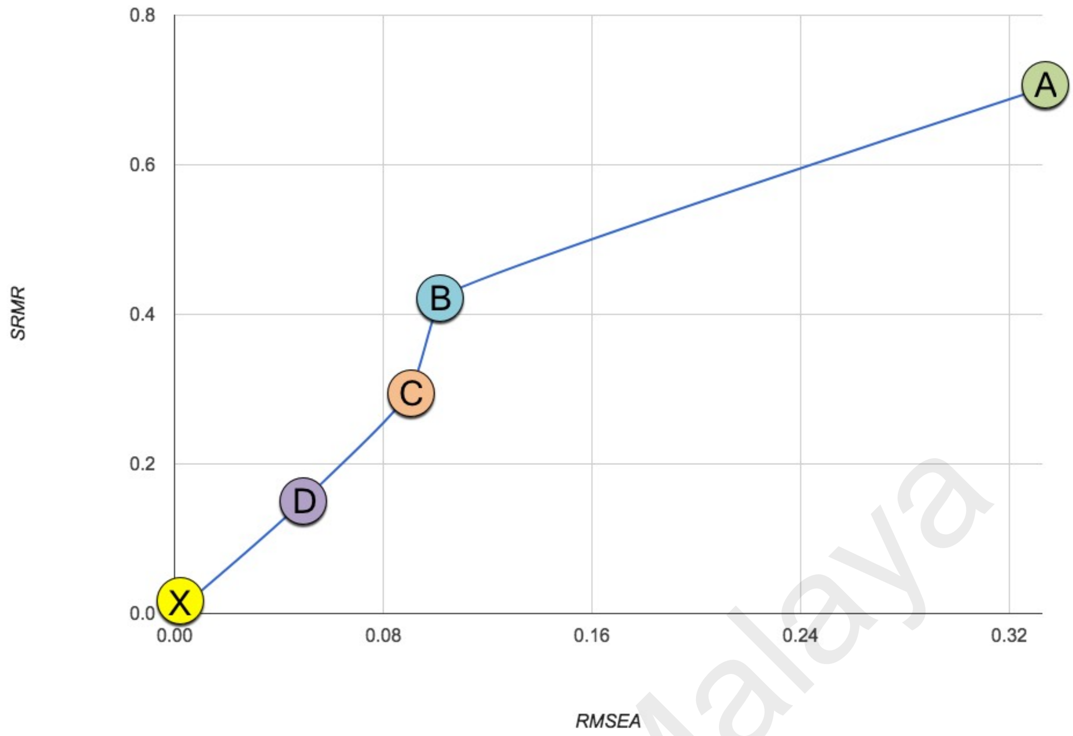
4.2 Filtering Evaluation Results And Discussion

As the experimental evaluation section showed, the experimental goal is to verify the effectiveness of PHyBR and to assess the accuracy of recommendations provided using users' personality traits and their demographic details together with their geographical location, review sentiments and purchase reason. As Table 4.1 shows, the effectiveness of PHyBR's integrated filtering methods were evaluated in four different scenarios by two evaluation metrics (i.e. RMSEA and SRMR). The evaluation was based on the top 15 recommended books. The experiment was implemented from August 21st 2016 until December 21th 2016, collected 1,320 ratings from fifty users in four scenarios.

Table 4.1: Statistics for relevancy in recommendation

Evaluation Methods		RMSEA	SRMR
PHyBR_D	Demographic	0.3325	0.7020
PHyBR_DP	Demographic + Personality Trait	0.1022	0.4221
PHyBR_DPG	Demographic + Personality Trait + Geographic Location	0.0909	0.3011
PHyBR	Demographic + Personality Trait + Geographic Location + Analysing Review + Purchase Reason	0.0501	0.1531

According to the progress of four algorithms (PHyBR_D, PHyBR_DP, PHyBR_DPG and PHyBR), the improvement of recommendation accuracy with the decreasing error values for RMSEA and SRMR is observed. Figure 4.1 illustrates the evaluation metrics' values, as points A, B, C and D refer accordingly to algorithms PHyBR_D, PHyBR_DP, PHyBR_DPG and PHyBR, and considering point X as the origin coordinates (0,0), which shows the absolute accuracy. The graph shows the overall improvement when additional filtering method is added. The RMSEA value decreased from point A to point B by 69%. At point C, the RMSEA evaluation is 0.0909, which is 11% lower compared to point B, that is, the recommendation without considering the user's geographic location. Finally, when all the filtering methods (PHyBR) are combined, the RMSEA's result dropped to 0.0501 which is 44% improvement on the recommendation accuracy.



PHyBR_D (A): Demographic
PHyBR_DP (B): Demographic + Personality Trait
PHyBR_DPG (C): Demographic + Personality Trait + Geographic Location Reason
PHyBR (D): Demographic + Personality Trait + Geographic Location + Analysing Review + Purchase Reason

Figure 4.1: Recommendation Performance Evaluation

As the RMSEA value moves closer to 0, it shows higher accuracy, similar with SRMR evaluation. It can be observed that the personalized recommendation accuracy is improved when user's demographic data were considered with personality traits, location, review sentiments and finally purchase reason. RMSEA is considered as "good fit" when its value is equal or less than 0.05 (Tsai & Chuang, 2011), which indicates that PHyBR has good fit model.

Prior studies have showed the effectiveness of contextual-features when tested in silo (Bao, 2012; Braunhofer et al., 2014; Cantador et al., 2013; Chen et al., 2015; Lu et al., 2015; Qi et al., 2015; Tewari & Barman, 2016; Zhang et al., 2017, Bhosale et al., 2017; Gavalas et al., 2014; Hu & Pu, 2010; Pera et al., 2011). For instance, Xin et al. (2014) achieved higher book recommendation accuracy when they took users' personality traits into consideration. Pera et al. (2011), Gua et al. (2016) and Gil et al. (2016) who improved book recommendations based on users' personality traits echoed similar findings. Nirwan et al. (2016) on the other hand found book recommendations to improve when users' demographic data were taken into consideration. User's demographic data is used as the additional factor to personalize the recommendation and it improves efficiency when it is used together with personality trait filtering (Kanetkar et al., 2014; Nirwan et al., 2016).

The third aspect that pushes the accuracy of recommendation further in PHyBR is the user's geographic location. The geographic location is used mostly in tourism applications to recommend POIs (Bao, 2012; Braunhofer et al., 2014; Chen & Tsai, 2017; Gavalas et al., 2014). Based on our result, we found that users living in the same context (city, state or country) tend to share more interests that are similar. This is in line with Yang et al. (2008) who categorized users based on geographic location to find their similar interests or preferences. Overall, this implies that it is important to consider user's geographic location during user profile creation and always retrieve his latest geographic location before recommending an item.

4.3 Algorithm Evaluation Results And Discussion

As in the previous section was elaborated, each added filtering method could have improved the accuracy of PHyBR. PHyBR was also compared with other previous personalized recommendation studies in order to assess its' recommendation accuracy.

Table 4.2 lists four algorithms that developed hybrid personalized RSs that utilized user and product contextual features to generate the recommendation result and they used RMSEA evaluation metric to examine the effectiveness of their algorithm's effectiveness.

Table 4.2: Statistics for relevancy in personalised recommendation algorithms

Recommendation Algorithm	RMSEA
PHyBR	0.050
PLMTA	0.063
TISP	0.070
LBSM	0.055
MediSem	0.060

- **PHyBR:** Personalized Hybrid Book Recommender
- **PLMTA:** Personalized Location-based Mobile Tourism Application
- **TISP:** Social Presence on Personalized Recommender System
- **LBSM:** Location-based Recommendation Using Sparse Geo-Social Networking Data
- **MediSem:** Personalized Medical Reading Recommendation – Deep Semantic Approach

Figure 4.2 illustrates the RMSEA values to have a better visual understanding. Here we will go through each of the algorithm to study and discuss about their accuracy result. Chen and Tsai (2017) developed a personalized location-based mobile tourism application for travel planning. Chen and Tsai utilized location-based filtering to make more efficient customized tourism recommendations. This research showed an improvement in recommendation accurecy with having the RMSEA value of 0.063, which yet PHyBR's result is lower than by 26%.

Choi et al. (2009) proved that by adding social factor to the RS, they could gain the user's trust which leads to have a better performance. They developed a RS called "TISP" to investigate relationships between social elements and evaluation of RS in terms of trust. They have achived the RMSEA value of 0.07, which meets the good model fit but yet Choi et al. (2009) claim that it may work out even better when it is mergered with other contextual factors such as geographical location and they mention it as the future work for that research.

Furthermore, Bao et al. (2012) proposed a location-based social network RS (LBSN) that helps the user to find an interesting restaurant for dinning. The online recommendation part selects candidate local experts in a geospatial range that matches the user's preferences using a preference-aware candidate selection algorithm and then infers a score of the candidate locations based on the opinions of the selected local experts. LBSN works by integrating social-based filtering with geographical location filtering to achieve better accuracy recommendation. LBSN with RMSEA value of 0.055, showed that incorporating multiple related filtering methods can improve the RS's accuracy. Location-based filtering is one of the key factors in tourism and social applications (Lee et al., 2017; Memon et al., 2015; Ravi & Vairavasundaram, 2016; Santos et al., 2016; Takahashi et al., 2017). However, It is proven by other studies that geographical location can be used in other domains to improve recommendation accuracy (Arunkumar & Raviraj, 2017; del Carmen et al., 2015; Räsänen et al., 2018; Wang et al., 2015; Yu et al., 2017). This filtering method had a great impact on PHyBR performance and it was used to group the users in correlation of other CF filtering methods (i.e. personality and demographic filterings).

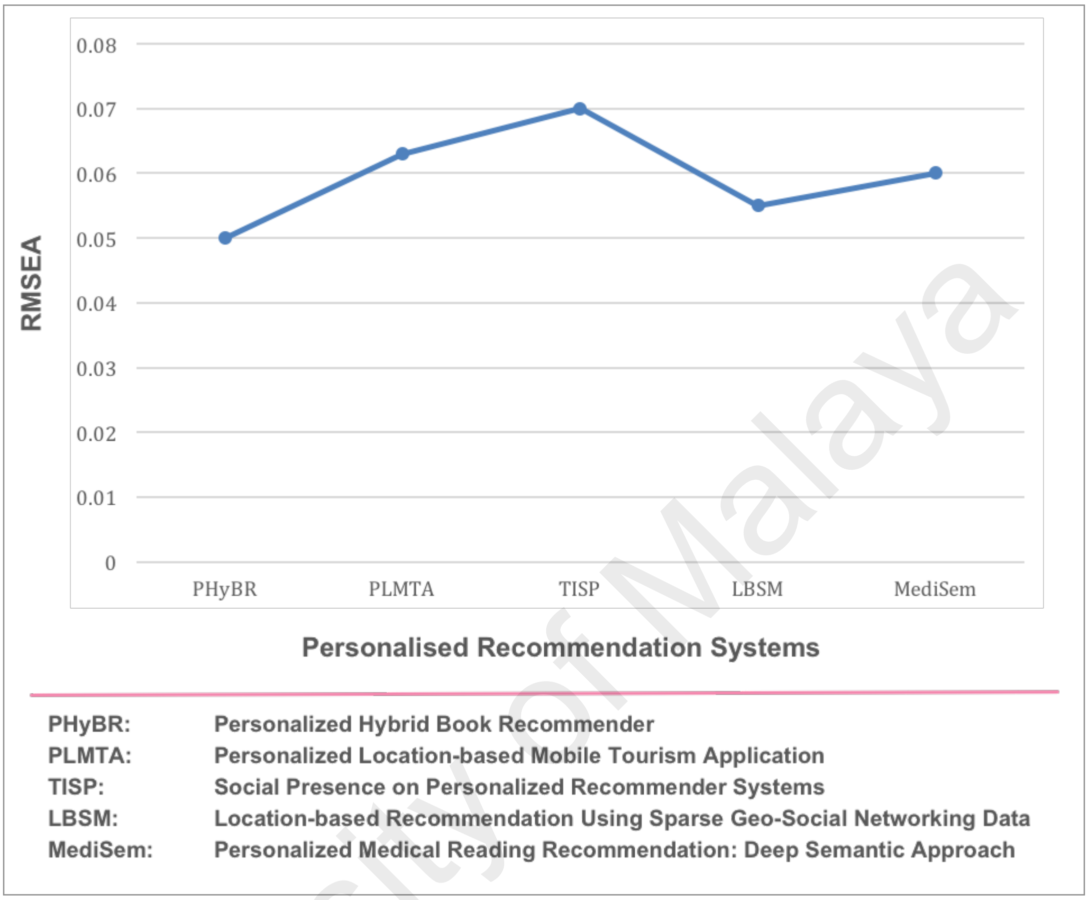


Figure 4.2: Recommendation Systems Evaluation Result Chart

In the recent years, semantic analisys and natural language processing gain researches attention by perfoming well on recommendation accuracy. For example, Erekhinskaya et al. showed a great progress in their work (MediSem) by having the RMSEA value of 0.060 which yields a better model fit compare with other medical RSs. They performed the recommendation based on the extracted knowledge that was gathered semantically from the patient's profile. It analysed the textual records and medical articles, then performed Deep semantic extraction. Semantic text analysis approaches need to be used to extract meaningful and valuable insights about the product's textual content for better understanding the user's context and interests (Gefen et al., 2017; Koudas & Bansal, 2016; Kuznetsov et al., 2016; Martini, 2018). Studies showed that by integrating the traditional CB approach with semantic techniques, it would be a context-aware RS, which makes the recommendation more aligned with the intended context of user (Bansal et al., 2015; Codina et al., 2016; Koenig et al., 2015; Kuchmann-Beauger et al., 2015). Therefore, it can be observed that when PHyBR applies sentiment analysis on the user reviews to identify most relative books to recommend, it results a great improvement.

The development of more complete model of user's interests and behaviours opens up an opportunity for the development of more sophisticated technique for personalisation that more accurately capture the user's context in the real world. Aside from the mentioned algorithms' results, PHyBR showed clearly that when several effective filtering techniques were integrated, recommendations can be greatly improved, and thus resulting in a much improved user satisfaction as well.

Additionally, PHyBR can be further extended to support other user behaviours or traits, such as emotion. For instance, Ferwerda and Schedl (2014) conducted research on obtaining more personalized information such as a user's emotional state through social media to provide a better recommendation, with results showing a great improvement when the system obtains the user's emotional state before recommending the items or service. Therefore, it would be interesting to investigate if PHyBR has improved performance when such traits are incorporated into it (Ferwerda & Schedl , 2014).

4.4 Summary

In previous chapter, the main goal of our proposed RS was clarified and explained well that is to enhance the accuracy of the personalised RS. However, in this chapter, our proposed system is evaluated in two ways. First, each of the filtering method was evaluated to examine the effectiveness of the individual approach. Second, PHyBR was compared with other existing personalised RSs that used similar filtering approaches. we have presented the evaluation result in Section 4.2 and it present the effectiveness of PHyBR's performance on recommendation accuracy. In Section 4.3, we have discussed about the outcome result and how well it perform against other existing RSs which have used the similar metrics to evaluate their works.

CHAPTER 5: CONCLUSION, LIMITATION AND FUTURE WORK

5.1 Overview

RSs have been successfully used to solve overwhelming problems of finding relevant items and services. RS has broad range of domains such as news, articles, books, movies, music and etc. According to the user's input, different kind of products or items can be recommended, which is tightly relative with user interest. Integrating user and product contextual features is an effective method to enhance and improve the accuracy of the personalised recommendations. Therefore, this study integrated several users' characteristics, namely their personality traits, demographic details and current location, together with review sentiments and purchase reasons to improve their book recommendations. In the following sections we will explain the limitations in details and will talk about the future work of this study.

5.2 Analysis of Objectives

The goals of this study were achieved at a high level and standard. In section 1.6 (Research Aim and Objectives), we have listed three objectives that here they will be explored and analysed in details.

iv. To identify user and product contextual features that can be used to personalise recommendation.

According to the comprehensive research conducted in Chapter 2 (Literature Review), the main approaches to personalise RS were presented and compared in strengths and weaknesses. The proposed RS gathers data about user's interaction with items, both explicitly and implicitly. Our review of approaches showed that there is a need of hybrid book recommender, which uses CF filtering methods with CB filtering methods. The system should learn about users' preferences, produce serendipitous recommendations, handle cold start situations and scale well for a large set of users and items. We concluded that no single approach support all of these features. Therefore, according to the literature, it is beneficial to use a combination of approaches, so that the advantages of one approach could reduce the disadvantages of another. Both CF and CB approaches learn about the users as they interact with the system. The CF can produce serendipitous recommendations, while the CB filtering can handle cold start problems in a good way. Among the CB approaches, the Geographical Location, Personality and Demographic Filtering were chosen to be integrated with CB approaches, i.e. Purchase Reason, Item-based and Review Filtering.

v. To develop an enhanced hybrid RS based on the identified user and product contextual features.

This objective was achieved by developing a hybrid personalised RS (i.e. PHyBR), which the system design and development were discussed comprehensively in Chapter 3. In the overall PHyBR's architecture, there are three main processes that are registration, user profiling and recommendation. In order to build a real-time recommender, we needed to consider performance and scalability as the main factors when the system is under development. The user completes the registration process by entering the required personal data and completing the personality test. The user profiling process is always running at background to monitor the user's interaction with items, unlike the registration process that happens only once at the beginning. During this process, PHyBR records user's activities such as browsing, searching, rating, writing review and purchase intention. In the final process, PHyBR performs the book recommendation and displays the list of top fifteen recommended books that user might be interested in. The filtering methods were arranged in a proper sequence to help to speed up the recommendation process. PHyBR begins with geographic filtering method, because it minimizes the number of users which need to be checked to be considered as the similar users.

vi. To assess the effectiveness of the proposed technique in recommending relevant items.

Finally, the last objective needed the PHyBR to be evaluated for accuracy of recommendations. The evaluation of the implemented algorithm was the most difficult part of in this study. In order to evaluate and examine the proposed system (PHyBR) perfectly, we have spent a considerable amount of time on the research's experimentation. Our experiment was completed in two different ways, first, we evaluated each of filtering approach (PHyBR, PHyBR_D, PHyBR_DP, PHyBR_DPG) and second, we compared PHyBR with other existing systems that are explained well in Chapter 4. The evaluation results show that using user's personality traits, demographic details and current location, together with review sentiments and purchase reason, results in better and more accurate recommendation. We have also discussed and compared PHyBR with other existing studies which have the similar goal and objectives, and yet our evaluation results show a better performance and accuracy. In addition, PHyBR was also compared with other exiting RS algorithms such as PLMTA, TISP, LBSM and MediSem.

This section elaborated on how well we have achieved our study's objectives and showed that they have been completed at a very good level of satisfactory. The result shows that our proposed RS approach can be used to solve the issue of information overload in existing commercial platforms.

5.3 Contributions

In particular, this research has some offerings and contributions to recommendation process since the results significantly enhanced the system precision. In fact, we introduced a new hybrid approach for RS in which personalised books are recommended to users based on user and item contextual features. Thus, the prominent contributions are listed as follows:

- This study conducted a comprehensive research on the most popular recent RSs and would be good start point for future studies. Chapter 2 has a very comprehensive explanation on RS’s terms, types, functions and background history.
- It is a novel approach to integrate user and item contextual features, personality traits, demographic details and current location, together with review sentiments and purchase reasons to recommend personalised books to the user. As the evaluation result shows in Chapter 3, the effectiveness of this study is beyond the existing algorithm in personalised recommendation field.
- In this research the sentiment analysis and natural language processing were applied on reviews and purchase reasons to improve the recommendation. It is for the first time where the users is asked to explicitly enter his/her purchasing intention to be used with user’s product review, in addition with user’s contextual

features (i.e. personality trait, demographic and location) to generate the recommendation result.

- Findings and discoveries of this research contributes to appropriate literature by demonstrating that such RSs grows continuance intention of online customers by increasing standard and quality of overall satisfaction, decision and by minimizing search effort while purchasing a product over internet. Results of this research can be considered by e-commerce websites' owners by assisting them to understand how much incorporating intelligent system with e-commerce portal could be advantageous and beneficial.

5.4 Limitation of the Study

This study, however, has its limitations. First, the experiment conducted involved users who are technologically savvy (i.e. Computer Science background), therefore they would have also found it easy to use PHyBR to locate the books that are relevant to them. It would be useful to evaluate PHyBR involving users with no or low technology skill to determine the effectiveness of PHyBR in recommending books that are more relevant to the users. Future studies therefore, could replicate the current study and expand it to include users from various background and digital skill.

Secondly, it was rather challenging to test PHyBR in different countries (i.e. Thailand and Singapore) with more complex user preferences and interests. It is very important for user preferences in different contexts to find similar users. This would encourage us to have a plan on creating scenarios where users from different countries and contexts use the PHyBR, so it can generate more accurate data and evaluations.

Finally, it was relatively more efficient to evaluate and analyse PHyBR with having a larger sample size. The more data is collected in an experiment, the more accurate the result would be. However, choosing the right participants who have skills, knowledge, and experiences in the field, caused to overlook the sample size. It is very important to overcome this limitation in the future for achieving higher validity.

5.5 Future Works

Although all the objectives and goals of the proposed RS were achieved, but still there are some domains that can be enhanced to have a better performance with more functionalities. The following enhancements are the most important:

- **Other domains:** Please note that PHyBR's recommendation engine can be easily scaled to support other similar products such as movies and music. Future studies therefore can enhance PHyBR so that it can continuously suggest any kind of items, provided that collaborative data describing items of interest and explicit connections among users can be extracted from a social networking environment.
- **Enhancing experiment:** Our experiment was done on the proposed system in a limited amount of time with a small size of data set. It is difficult to find similar databases to perform efficiency tests and to compare with similar existing RSs that consider users' personality traits and their demographic details together with their geographical location, review sentiments and purchase reason. It would be better to test PHyBR on an existing e-commerce platform having millions of users testing the RS accuracy. It will enhance the recommendation quality and performance to meet a better accuracy, if the experiment was performed over a longer period of time with having a larger size of data set.

5.6 Summary

In this research, a new hybrid contextual RS framework was proposed for developing a personalized RS that integrates user's personal data with other contextual data to have a better accuracy. Based on the research conducted on the existing RSs, we had a reasonable and clear mind about the problems that PHyBR was going to overcome and that helped us to clarify our goals and objectives. Throughout this study the proposed RS methodology and architecture were outlined. The system design explained the process of book recommendation step by step, from the moment the user logs in to the system until he is able to view the top recommended books. The evaluation metrics were used to examine the PHyBR recommendation accuracy and the results were presented and discussed well in details in previous chapter. Results indicate that these contextual-features can be used effectively to improve recommendation accuracy. We are very determined at continuing this work to achieve greater result in real world applications.

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