

# AGENT-BASED PERSUASIVE ROUTE RECOMMENDATION FOR PUBLIC GOODS

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MASTER OF COMPUTER AND INFORMATION SCIENCES

Supervisors

Dr. Quan Bai

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By

Sotsay Sengvong

School of Engineering, Computer and Mathematical Sciences

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A handwritten signature in black ink, appearing to be 'S. H. 30/5', written above a horizontal line.

Signature of candidate

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# Abstract

Over many decades, the transport sector has played a significant role in contributing to economic growth. Unfortunately, this sector has not only provided positive effects, but also has produced a number of negative impacts on society. These impacts are known as the external costs, and include traffic pollution, congestion and accident costs. Transport users rarely take these costs into consideration when they make travel decisions. As a result, the number of external costs is growing and is likely to continue to increase in parallel with the increase of urban mobility.

This thesis proposes a novel recommendation system, known as the Agent-based Public-Friendly Route Recommendation (APF2R). The APF2R can help commuters make green, safe and less congested travel decisions, while supporting society to mitigate the external costs. A novel persuasive reward algorithm is introduced, which can be used by other researchers to balance two conflicted parties. This study demonstrates an agent-based model, which was used to evaluate the persuasiveness of recommendation systems. The result of the proposed system shows potential in addressing the problem of external costs. An analysis of the experimental results undertaken here, captures the evolution of the distance of users' ranks. These results indicate a means of persuasion in connection with behavioural change.

# Publications

Sengvong, S and Bai, Q. (2017). Persuasive public-friendly route recommendation with flexible rewards. In Proceedings of the 2nd IEEE international conference on agents, Beijing, China, accepted 1/5/2017

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# Chapter 1

## Introduction

### 1.1 Research Background and Motivations

Over many decades, the transport sector has played a significant role in contributing to economic growth. Unfortunately, this sector has not only provided positive effects, but has also produced a considerable number of negative impacts on society. These impacts are a main cause of serious problems such as global warming and urban air pollution, and are considered to be the external costs of daily transportation. Based on statistical data from Eurostat (2014a, 2014b), it is estimated that in 2014 alone the European Union accounted for 23.3 percent of greenhouse gas emissions. Around 1.4 million people were injured due to road traffic accidents. Transport users rarely take external costs into consideration when they make travel decisions. As a result, the amount of these external costs is growing and is likely to continue to increase in parallel with the increase of urban mobility.

Since the problem mainly comes from the ways that individuals choose to travel, introducing the external costs to the individuals through taxes and charges is believed to be an effective approach to reduce the negative impacts (Maibach et al., 2008). With higher transport prices, transport users would consider more when making travel

decisions. However, this approach is limited as it would need to be enforced through strict legislation, which could lead to dissatisfaction. A major issue is that increasing taxes and charges tends to elevate the cost of products and services, due to the strong correlation with freight transport and goods distribution. This, therefore, indicates a need for new methods and tools that can influence transport users' decisions without coercion and encourage them to take responsibility for the external costs.

Recommendation systems could be a possible solution to address the problem of external costs and to influence human behaviour without coercion. In the information age, recommendation systems have proved to be a powerful decision support tool in facilitating individuals to make effective decisions. With the enormous amount of content available on the internet and the limited capability for processing, decision makers generally experience some degree of difficulties in making decisions. This problem is known as information overload. However, by having recommendation systems in place, decision makers can enhance the quality of their decisions and lessen the cost of transactions, even when they have insufficient knowledge about the available options in the complex environment (Isinkaye, Folajimi & Ojokoh, 2015). Recommendation systems assist individuals by finding relevant products, contents or services, based on the needs and tastes of individuals (Ricci, Rokach & Shapira, 2011). Eventually, the recommendations provided support the users to make effective choices.

With regard to such general functions, recommendation systems are able to persuade decision makers. Empirical research by Gretzel and Fesenmaier (2006) has suggested that recommendation systems do not only provide effective recommendations, but are also capable of influencing the decision-making process of individuals. This view is supported by Yoo, Gretzel and Zanker (2012). A book by Yoo et al. (2012) defines recommendation systems as persuasive social actors that are able to influence users' perceptions as well as users' behaviours. These systems are known as persuasive recommendation systems. Unlike other types of traditional recommendation systems,

persuasive recommendation systems are able to provide a means of influencing the judgement of individuals over recommended options. Evidence suggests that individuals perceive better satisfaction in terms of recommendation quality when introducing persuasion, and they are more likely to believe and trust the system (Häubl & Murray, 2003; Tintarev & Masthoff, 2011). According to Swearingen and Sinha (2001), persuasive recommendation systems receive more user responses, which leads to performing better in understanding users' preferences and needs. Together, these studies indicate the capacity of recommendation system to deal with altering human decisions and behaviours. Despite these potential benefits, literature investigating the influence of the persuasive factors of recommendation systems is still limited.

With the increasing demand for mobility and the growing number of vehicles, there is a great demand of traffic recommendations, especially route recommendations. A great deal of previous research into route recommendations has focused on personalised supports to meet individual requirements. Many successful cases of personalised route recommendations have been proposed to meet users' personal preferences (Tumas & Ricci, 2009; Nuzzolo, Crisalli, Comi & Rosati, 2014; Xu, Hu & Li, 2016). Such studies, however, have failed to investigate the marginal effects of the recommended routes, i.e., the external costs, and have also failed to apply the idea of persuasion. This indicates the need for a new route recommendation that is able to make the external costs part of a transport user's decision by encouraging them to follow less impacted routes. This thesis therefore, is focused on designing and developing a novel route recommendation system that will be able to generate green, safe and less congested recommendations, and to persuade transport users to change their decisions as well as behaviours.

## 1.2 Research Question

The ultimate goal of this research is to develop a novel recommendation system that can address the problem of negative impacts, i.e., traffic pollution, congestion and accidents, that are generated by transportation activities. In addition to constructing the new recommendation system, and based on the fact that the problem mainly comes from the way that individuals choose to travel, this thesis also aims to create a new characteristic of recommendation systems that will be able to influence transport users to follow more socially acceptable behaviours when making travel decisions. To meet such goals, this research intends to answer two main problems and multiple sub-questions, as follows:

1. How can recommendation systems address the problem of the negative impacts, such as traffic pollution, congestion and accidents, that are generated by transportation activities?
  - (a) Do recommendation systems that consider the criteria of external costs decrease the negative impacts of the transportation sector?
  - (b) Does integrating the criteria of the external costs in recommendation systems impact user satisfaction?
2. How can route recommendation systems influence transport users to follow public-friendly travel route recommendations?
  - (a) Are route recommendation systems with a reward attached able to persuade?
  - (b) Does providing a reward to individuals in route recommendation systems impact behaviour change?
  - (c) How can the impact of persuasion in a recommendation system and a change in users' behaviours be evaluated?

Along with the aforementioned goals, there are three primary objectives of this study, which are as follows.

- Decrease the amount of the external costs from the transportation sector by using recommendation systems.
- Measure the impact of user satisfaction in relation to the recommended routes, generated by the new proposed system.
- Examine the effects of integrating persuasive elements in recommendation systems, with reference to changing the behaviour of individuals.

First, detailed insights of traffic management systems, route recommendations and various state-of-the-art recommendation techniques used to create recommendation systems will be reviewed. Potential techniques to aggregate different criteria of external costs are also investigated. Further, various characteristics of recommendation systems that can be used to persuade individuals will be inspected. Then, after developing a new recommendation system, the relationship between the negative impacts, user satisfaction and the proposed recommendation system will be examined in detail. Finally, an evaluation model will be developed to analyse the impacts of persuasion in the proposed system, with relation to behaviour changes in transport users.

### **1.3 Research Methodology**

This section provides overall information about the methodology used to address the two primary research questions and the multiple sub-questions. The methodology used in this research is a combination of an experimental method and a simulation method. This research focuses on evaluating a new recommendation system and approach, designed to solve a real problem in the transportation domain. The experiment is a specific research

method in the computer science area, which is used to observe several controlled variables, to explain the correlation between such variables and also to test hypotheses. The simulation method is used to simulate complex phenomena. To effectively perform the investigation, well-designed methodology is crucial. Therefore, we have divided the research methods into three parts, as follows.

The research initially began by performing an in-depth literature study of management and recommendation systems in the traffic and transportation context. This stage was important to gain understandings about significant aspects, current problems and what may have been done to overcome the problems, especially traffic problems. A variety of domains, such as recommendation techniques, multi-criteria recommendation approaches, multi-agent based systems and persuasive technology were investigated to obtain knowledge about constructing recommendation systems. The results of this literature study are described in Chapter 2.

The second part was the development phase. Before starting the system design, various elements needed to be defined. These included the problems, the goals and the objectives of the research shown in Chapter 1. To achieve the goals outlined in this research, it requires designing and developing a new system. The new proposed recommendation system was developed based on multi-agent architecture and a multi-criteria recommendation approach, and the detailed result is in Chapter 3. This system consists of the element of persuasion as a new characteristic which aims to create an impact on individuals' behaviours and influence the way they select recommendations by following the persuasive technology. A detailed description can be found in Chapter 4.

Finally, an experiment was conducted to evaluate the performance of the proposed system by comparing it with the conventional approach. Due to the fact that this system is an innovative system, a criteria for comparing was created. A model of human behaviour was also constructed and evaluated by the simulation method. The simulation



method aims to test the persuasiveness of the additional proposed characteristic. Data used in this study was generated and collected from traffic data providers.

## 1.4 Thesis Contribution

This research makes several contributions to the growing area of traffic management, recommendation systems and persuasive technology, especially around constructing traffic route recommendation systems with persuasive features. Three original contributions are claimed and presented in the below section.

Firstly, this research proposes a novel route recommendation system, an agent-based public-friendly route recommendation, which should prove to be particularly valuable in addressing the problem of external costs, namely traffic pollution, congestion and accidents generated by transportation activities. We believe that this is the first time that the criteria of external costs have been considered in a recommendation algorithm and that recommendation systems can make green, safe and less congested travel route recommendations to commuters. This system might bring about a big change in the transportation sector, that is, it could increase transport safety and transport efficiency. The empirical findings of the evaluation of the proposed system provide additional evidence to prove the flexibility of the multi-criteria recommendation system over the traditional recommendation system, which only consider a single criterion.

The second contribution of this study is a novel persuasive reward algorithm. The algorithm distributes reasonable values to individuals who have different preferences by considering the difference of the utility values and the distance of ranks between two conflicted parties. The proposed incentive rate has proven its effectiveness in adjusting the level of persuasion. These methods can be used by other researchers to find a balanced value between two different parties and also can help other types of persuasive technology to achieve better satisfaction rates. Additionally, this study has demonstrated,

for the first time, that a reward can be used as a new characteristic of recommendation systems and can persuade transport users to choose recommended routes without the use of coercion. The findings in this study provide a new understanding of the potential of the reward strategy as a persuasive feature.

Lastly, to the best of author's knowledge this is the first time that an agent-based model has been used to evaluate the performance of recommendation systems in terms of persuasion. By simulating human's judgement about recommended travel routes, the novel architecture of an internal agent is proposed. This has several unique functions, including the knowledge comparison and reaction functions. These functions can support other researchers in evaluating other kinds of products in multi-criteria recommendation systems, apart from travel routes. The analysis of the experimental results undertaken here, has extended our knowledge about the effects of persuasive elements in recommendation systems and behavioural change. Furthermore, we have captured the changes in the distance of individuals' ranks, which offers valuable evidence to prove the capability of persuasive recommendation systems.

## **1.5 Thesis Structure**

This thesis is composed of six themed chapters, organised as follows.

Chapter 1 presents a general overview of the negative impacts generated by the transportation sector. The background and motivation have been given. The chapter also provides the objectives of the research, a brief explanation of the research methodology, and explicit contributions, that could be beneficial to the current knowledge of the research topic.

Chapter 2 provides a literature review on the basic background of the research topic, as well as the methodology used. It begins by providing a relationship between previous research in terms of the differences and similarities in both the theoretical and

practical aspects. It also identifies gaps in the knowledge of the different viewpoints by reviewing the existing studies. The literature on state-of-the-art recommendation systems, including different characteristics and various prediction techniques, is also reviewed. A review of the multi-criteria recommendation approaches and persuasive technology is given to gain an understanding of the current situation in such areas. This knowledge is essential to facilitate the construction and development of the research methodology in Chapters 3 and 4.

In Chapter 3 there is an in-depth explanation of the novel proposed recommendation system, and the agent-based public-friendly route recommendation, in terms of the architecture and design, is provided. With respect to the multi-agent system, the roles and views of different agents, and the relations among them, are described in detail. Apart from that, the chapter gives a description of the attributes of travel routes and how such attributes are collected. It also shows how the system defines user preferences, as well as how the importance of each attribute is extracted. Finally, the chapter illustrates data normalisation, the individuals' utility function and the public's utility function.

Chapter 4 presents an additional feature of the proposed system, the flexible reward algorithm, which facilitates the agent-based public-friendly route recommendation in influencing the transport users' decision, as well as maintaining user satisfaction over the use of the system. A detailed description about the methods used to create the algorithm and the novel approach to evaluate the persuasiveness of recommendation systems is then given. It is divided into three main sections: an overview of reward in transportation discipline; a description and explanation of the proposed flexible reward algorithm, and an explanation of the internal design of user agents which is crucial to simulate an individual's judgement and behaviour.

Chapter 5 illustrates the evaluation of the proposed system, the agent-based public-friendly route recommendation and the flexible reward algorithm. This chapter shows the design of the experiments that later are used to evaluate the performance of the

proposed system in terms of public-friendly and persuasive features. It presents not only the results of the experiments, but also discusses the findings from the previous literature review, in both theoretical and practical aspects. Strengths of the proposed system are identified and presented.

Lastly, Chapter 6 provides a summary of the overall ideas of this research paper, including all theoretical and practical aspects. It restates the problems that this research tries to answer and the methodology used. The overall achievements are provided as well as a lesson learnt. Possible future work in this area of the research is given, in addition to the limitations of the research.

# **Chapter 2**

## **Literature Review**

### **2.1 Introduction**

In the previous chapter, the background and motivation of this study was given. The explicit objectives and research questions of this research were also stated. A brief explanation about how this thesis conducted research and the explicit contributions were also given.

This chapter aims to provide a literature review on the basic background of the research topic, as well as the methodology used. It shows a relationship between previous research in terms of the differences and similarities in both the theoretical and practical aspects. It also identifies gaps in the knowledge by reviewing the existing studies. Firstly, the literature on traffic management systems and route recommendations was reviewed as shown in Sections 2.2 and 2.3. Later, in Section 2.4, the review on the literature of state-of-the-art recommendation systems, including different characteristics and various prediction techniques is presented. In Section 2.5, multi-criteria recommendation approaches are reviewed. Then, the persuasive technology is reviewed in Section 2.7 to gain an understanding of the current situation in such areas.

## 2.2 Traffic management systems

Over the past decades, many urban cities all over the globe have experienced increased mobility and a growing number of vehicles. Based on such an increase, the transportation infrastructure is incapable of fully satisfying such high demands, especially in rush hours, and as a result the growing demand leads to a number of serious problems, such as transportation delays, accidents, pollution emissions and traffic congestion. According to Çolak, Lima and González (2016), residents of Beijing, Mexico City and Moscow spend more than 75 percent extra time for travelling due to traffic congestion.

To solve the transport problems, a great deal of the previous research has mainly focused on developing intelligent traffic managements systems. These systems are generally associated with the area of intelligent transport systems (ITSs). ITSs is a very broad area covering almost every single element in transportation, such as traffic lights, road sensors and ramps. Urban traffic control, dynamic route-guidance systems, variable message signs and journey-time measurement systems are some examples of ITSs. The main purpose of these systems is to increase the quality of transportation and to overcome transport problems. For instance, Xie, Smith, Chen and Barlow (2014) propose an approach to optimise the delay between vehicles and pedestrians in city environments by investigating traffic signal controls. Similarly, Di Febbraro, Giglio and Sacco (2004) studied traffic control and signalised intersections. Their study focused on improving traffic flow for special vehicles such as emergency vehicles. The results of their system with real traffic data proved its intelligence and efficiency. Dimitrakopoulos and Demestichas (2010) also introduced a traffic system that aimed to reduce traffic congestion, accident risks and emergency situations by integrating a number of technologies, i.e., cognitive networking principles, management functionality and wireless sensor networks. In their investigation, a novel functionality system is introduced,

consisting of three primary components - sensor networks, cognitive management functionality in vehicles and transportation infrastructure. These components aim to provide important knowledge and instruction about traffic data to drivers as well as the transportation infrastructure via information exchange among a group of vehicles. According to Figueiredo, Jesus, Machado, Ferreira and De Carvalho (2001), road and vehicle systems can have greater efficiency, and be safer and more environmental friendly by investigating the technologies of ITSs. They reviewed existing state-of-the-art ITSs systems and provided not only an insight into the background and major categories of ITSs, but also pointed out possible future directions in this area. Considering all of the evidence, it seems that traffic management systems are an effective solution for transport problems.

Although a variety of ITSs has been implemented for several years, Vaa, Penttinen and Spyropoulou (2007) point out that the new ITSs require an in-depth investigation into the effectiveness of their ability to influence human behaviour. The number of literature was investigated to review the effects of traffic management systems on humans' behavioural change. Dressler and Sommer (2010) studied the effects of driver behaviour on the quality of ITSs based on the four sub-models that influence a driver's behaviour, i.e., driving behaviour, preferences, reaction to messages and local knowledge. In their study, driver behaviour is defined as a key element. The simulation was developed and used to evaluate the model. They suggested that the driver model should be integrated into the process of ITSs development. Larue, Kim, Rakotonirainy, Haworth and Ferreira (2015) examined the safety of crossing railways by using driving simulation with real participants. Their main was to evaluate the effectiveness of three ITSs interventions and the results showed a change in driver behaviour. The studies reviewed here only focus on the impacts of ITSs towards the behaviour of drivers and clearly fail to consider other transport users such as pedestrians and cyclists.

## 2.3 Traffic Route Recommendations

With the increasing demand for mobility and the growing number of vehicles, there is a large demand for traffic recommendations. A great deal of previous research into traffic recommendations has been focused on recommending driving routes and navigation. According to Tumas and Ricci (2009), travelling in unfamiliar places has become easier with the rapid development of GPS technologies and the increase in commercial route service providers like TomTom, Bing Maps and Google Maps. These services generally provide route recommendations between two points based on user requests, i.e., the start point and the destination point. In general, these route services provide the shortest and fastest routes to commuters and as a result, they are able to arrive at their destination based on the estimated time.

Though many route service providers and much of the literature on route recommendations are able to generate the fastest routes, the recommended routes sometimes fail in achieving users' needs and requirements. This statement is supported by Ceikute and Jensen (2013). In their investigation, the recommended route from the routing services was compared to the actual driving behaviours of local drivers. The results of their studies suggested that there is big difference between recommended routes and popular routes. The explanation for that is commuters choose their optimal routes to travel from point A to point B based on more than just travel distance or travel cost, but might also consider other criteria, such as traffic conditions, speed limitations, walking time and road conditions. Moreover, each individual has different characteristics in terms of their needs and requirements. Such criteria and different needs are very difficult for a single routing algorithm to account for. As a result, most route service providers fail to personalise individual requirements.

More recently, attention has focused on providing routes that can meet such requirements. This type of route service is known as personalised route recommendation.



Many successful cases of personalised route recommendation have been proposed and successfully meet users' personal preferences. For instance, Tumas and Ricci (2009) generated route recommendations based on user preference such as prefer walking, prefer direct bus and actual location (GPS) via a mobile application. To receive the optimal route, their proposed algorithm calculates the overall satisfaction score from the user profile and available routes by using the matching function. Su et al. (2014) similarly proposed a system called CrowdPlanner to recommend personalised routes. The system considered not only user preference, but also the preference of other individuals from the community by asking common questions. It is worth noting that these studies required the interaction of users to obtain an understanding of user requests and preferences.

## **2.4 State-of-the-art Recommendation System**

This section reviews some important concepts and trends in state-of-the-art recommendation systems. The advantages of integrating recommendation systems in commercial applications are reviewed. A clear description of the features and functions of well-known recommendation techniques is also provided.

Recommendation systems can be defined as an assistance tool that finds relevant products, contents or services for users based on their needs and tastes (Resnick & Varian, 1997; Schafer, Konstan & Riedl, 1999; Ricci et al., 2011). The definition of recommendation systems can be varied depending on time. Manouselis and Costopoulou (2007a) identified the most interesting definitions of recommendation systems from the literature and show its evolution over time. Defining what is meant by recommendation systems allows researchers to comprehend the concept of recommendation systems.

Recommendation systems have increasingly played a crucial role in facilitating individuals to make effective decisions. Recommendation systems provide considerable advantages to both users and service providers (Pu, Chen & Hu, 2011). A major advantage of recommendation systems is to help users with insufficient knowledge make a judgement when given a considerable amount of options. Secondly, with regard to Isinkaye et al. (2015), recommendation systems enhance the quality of decisions and lessen the cost of transactions. According to a study by Ricci et al. (2011), recommendation systems are the most powerful tool to support users of electronic commerce when handling information overload problems. The provided suggestions assist users when making a choice in the complex environment by evaluating and filtering the enormous volume of information (Rashid et al., 2002). Finally, the systems are able to recommend relevant options to individuals based on their interests and needs, which is known as personalised content and services. Consequently, the decision makers save a lot of time searching and are capable of making effective decisions.

There has been an increasing amount of literature on recommendation systems with regard to such potential benefits. Since the first study investigating a recommendation system emerged during the 1990s, recommendation systems have become a popular discipline among practitioners and academics (Resnick & Varian, 1997; Shardanand & Maes, 1995). Recommendation systems have been studied by different disciplines, including information filtering, machine learning, data mining, and human computer interaction. Practitioners have fruitfully proposed novel models and algorithms, which are beneficial for theoretical knowledge, as well as methodological contributions in the context of recommendation systems. They have experimented with their proposed systems via various applications, from simple item recommendations like books and music to complex products such as health insurance and tour plans (Sohail, Siddiqui & Ali, 2013; Chang, Huang & Wu, 2016; Abbas, Bilal, Zhang & Khan, 2015). One study

by Park, Kim, Choi and Kim (2012) classified the research papers related to recommendation systems into eight application fields such as movies, shopping, documents, books and others. They reviewed 210 journal articles from 2001 to 2010. According to their systematic literature review, the vast majority of studies focused on creating movie recommendations. Recommending travel routes is part of the minority recommendation fields known as the other category. The author stated that researchers are allowed to freely use the MovieLens dataset to evaluate the recommendation algorithms and methodologies, which has led to an increase in the literature. Due to the available dataset, researching recommendation systems is even more likely to increase in the near future.

Similarly to academics, a number of organisations have studied and implemented recommendation systems in a real environment. The key players are Amazon, GroupLens and Netflix. One of the main reasons for adopting recommendation systems is to enhance both user experience and company profits. Sequentially, they are able to increase their product sales and attract more user attention by promoting alternative items that are similar to users' needs via the recommendation system (Aggarwal, 2016). For example, a user likes watching the film *The Da Vinci Code*. If other films like *The Angels and Demons*, and *The Inferno* are recommended, they are more likely to be selected and watched by the user. This is because there are a number of similarities such as genre, director and actors therefore, the sales volume is increased by providing a recommendation service. Additionally, having the ability to provide recommendations also improves user's experience towards the website performance. Based on Aggarwal (2016), users feel more satisfied with a website that is able to regularly offer relevant items to them and are more likely to return to see the sites. This means an increase in user loyalty, therefore, many companies have put great effort into investigating recommendation systems.

Adomavicius and Tuzhilin (2005) mathematically formulated the problem of recommendation as an approach that recommends information or items that are most likely to be interesting to users. Let  $I$  be the set of all items that are available and can be recommended such as music, books and movies.  $U$  is the set of all users that the system can recommend items to. The space value of  $I$  and  $U$  can be very large, possibly ranging from hundreds to thousands or millions of records. Generally,  $U$  and  $I$  are assumed to be identified by the system. The utility function calculates the value of  $i \in I$  to recommend to  $u \in U$  and is defined as  $A : I \times U \rightarrow R$ , where  $R$  is a totally ordered set, represented in real number or non-negative integers. Then for each user  $u \in U$ , we can choose an item such as  $i' \in I$  that maximises the user's utility. More formal problem can be found in Equation 2.1. In Equation 2.1,  $\forall u \in U$  denotes for all users  $u$  in the set of users  $U$ .  $arg_{i \in I}$  is a function that addresses the complex space of items.  $i_u'$  denotes the recommended item for user  $u$  and  $A(u, i)$  represents a utility function.

$$\forall u \in U, i_u' = arg_{i \in I} max A(u, i) \quad (2.1)$$

When mentioning recommendation systems, three core entities should be defined. These significant entities consist of users, the recommender system and items. A user is a person who has personal needs and tastes. He or she represents such needs and tastes by means of a personal profile and preferences. A recommender system is an actual system that provides a service to a user. The system should be able to understand the user profile and preference in some degree in order to provide effective service to the user. An item is an option that is available to be recommend to the users. The system will find the best items from a group of existing options depending on the user profile or preferences. When it has a set of suitable items, the system then presents them to the user. Items, options and recommendations may sometimes be used interchangeably.

Several lines of evidence suggest that researchers in the field of recommendation

systems have diverse views in classifying recommendation systems. Recommendation systems were traditionally classified into two main categories based on filtering techniques; collaborative recommendation and content-based recommendation (Balabanović & Shoham, 1997; Adomavicius & Tuzhilin, 2005). Popescul, Pennock and Lawrence (2001) categorised recommendation systems into three types, including economic factor-based recommender systems, content-based recommender systems and social-based recommender systems. In addition to the above types, alternative types have been proposed in literature such as demographic recommendation and utility-based recommendation. A combination of the filtering techniques has also been presented to alleviate problems and to merge the advantages of each technique (Burke, 2002). This is known as hybrid recommendation. In a study by Manouselis and Costopoulou (2007a), number of criteria are identified as the main dimensions that are used to distinguish the recommendation systems. The main categories comprise of the rationale, the approach and the operation categories, and each dimension consists of smaller sub categories. With the increasing number and the evolution of scientific literature in this field, categorising recommendation systems will only become challenging and complicated.

Different approaches for constructing recommendation systems have been developed during the last decades. Currently, the most popular and widespread approaches are the content-based method and the collaborative filtering method. Collaborative filtering models or social-based recommender systems utilise existing community ratings from people with similar tastes to the current user, and generate recommendations. Content-based recommender methods use a combination of user ratings, users' buying behaviours and descriptive attributes of items to generate recommendations by matching item features with historical ratings from the users. Although these methods are popular and are excellent techniques, they have serious drawbacks, such as cold-start problems, rating sparsity and overspecialisation. These methods do not facilitate recommendation systems well enough when the dataset related to rating is insufficient or absent. Based on

such problems, new approaches have increasingly been introduced. The aforementioned types of recommender systems give only general ideas about the characteristics of such systems, but do not provide an adequate description. Therefore, the following content will provide a further description of features and functions of well-known recommendation system techniques.

### **2.4.1 Content-Based Filtering**

Content-based filtering techniques generate predictions by focusing on analysing the attributes of the items and the user historical data. The algorithms used in this technique are not certain, but vary based on the domains of study. Isinkaye et al. (2015) state that content-based filtering is the most suitable technique to adopt when recommending documents such as publications, web pages and news. The technique is aimed at creating item recommendations by evaluating the similarities between the data of items rated in the past, which is known as a user profile and a description of items (Pazzani, 1999).

Two significant components are inevitable when constructing content-based filtering recommendations, that is, items and user profiles. An item has its properties or attributes. For instance, the attributes of books include author, type of book, language, cost and publisher. These attributes explain the characteristics of the items. Each item contains a unique identifier (ID), and each attribute of a value. The profile of the users represents the interest of the users towards the items. Pazzani and Billsus (2007) identified two common forms of user profiles, such as a model of the user's preferences and a history of the user's interactions with the recommendation system. An example of the model is a description of the types of items that can be represented in a function, while the examples of historical data of users are user rating, last viewed items, purchased items and even search queries. Such user information is derived in both explicit and implicit

ways. Users may sometimes be asked to enter their user profile. In other cases, the content-based filter systems learn the user information from provided feedback and user behaviours. The ability to obtain and learn such data is significant in indicating the success of the content-based filtering recommendations. The more the systems understand a user's interests, the more accurate the recommendations are generated.

Content-based filtering has provided a variety of advantages. It is designed to overcome the problems of collaborative filtering methods. A major advantage is that when there are no provided ratings, content-based filtering is still capable of recommending new items to users. Pazzani and Billsus (2007), say that having insufficient data about user preferences does not affect the recommendation accuracy. Furthermore, content-based filtering is able cope with a change of user preferences in a short period of time.

The literature on content-based filtering has adopted different types of models to find the similarities between items and to learn user profiles. Naïve Bayes Classifier, Vector Space Model, Neural Networks and Decision Trees have been applied to search a correlation between different items (Pazzani & Billsus, 2007). These models rely mainly upon statistical analysis and machine learning techniques. Mooney and Roy (2000) utilised a machine learning technique, the Naïve Bayes Classifier for book recommendations. The system that was designed is able to provide new recommendations without relying on ratings provided by users, and it can give explanations about what it has recommended. Alternatively, Van den Oord, Dieleman and Schrauwen (2013) proposed deep content-based music recommendations by adopting deep convolution neural networks. Although a variety of models have been introduced, according to Pazzani and Billsus (2007), selecting the appropriate algorithms is determined by the representation of content.

### **2.4.2 Collaborative Filtering Recommendation**

Collaborative filtering is a dominant recommendation technique. In order to produce reliable and efficient recommendations, it pays attention to identifying a relationship among a number of users of a recommendation system, known as the opinions of a community, and constructs a similar neighbourhood group (Shi, Larson & Hanjalic, 2014). By focusing on analysing the patterns of ratings and usage of users to predict the rating of items, it can create relevant items that have not viewed or seen by the users. Users within the same neighbourhood, who have not rated items, will receive recommendations based on their counterparts ratings. In many cases, the numerical value represents the prediction in the form of a continuous number. Collaborative filtering is not only able to identify correlations among user rating objects, but also the correlations among the objects rated (Pazzani, 1999). Differently to content-based filtering, this process of recommendation does not require any investigation of the description of items or users, only requiring only information about the likes of the users.

Previous research has illustrated a number of approaches that can be adopted to construct a collaborative filtering recommendation system. In a study by Koren and Bell (2015), two main techniques, namely the neighbourhood approach and the latent factor model, are examined to discover the correlation between two primary entities, including items and users. While the neighbourhood approach is aimed at the relationship between items or users, the latent factor model considers items and users as the identical latent factor group. Isinkaye et al. (2015) conducted a literature review of principles, methods and an evaluation of recommendation systems. The study categorised collaborative filtering into two main categories, namely memory-based and model-based filtering techniques.

A number of researchers have recognised the benefits of collaborative filtering, as



well as being aware of possible challenges. Collaborative filtering outperforms content-based filtering when the related description or content of items are insufficient and when the systems deal with nonconstructive content that is difficult to analyse, such as an opinion and an ideal (Koren & Bell, 2015). It is capable of recommending items that are relevant to the user when the users' profile is lacking, this is known as serendipitous recommendations. Despite such benefits, however, there are some potential problems in collaborative filtering. The major problem is the cold-start problem. This problem emerges whenever the systems do not have enough information related to users or items. Such information refers to a situation where new users lack opinions about items and do not have a historical record about their interactions. With inadequate data about users' tastes, the systems are unable to provide relevant predictions, which might later bring about a poor performance by the recommendation systems. Other challenges include data sparsity problems and scalability.

### **2.4.3 Knowledge-Based Recommendations**

The knowledge-based recommendation technique generates recommendations based on domain knowledge and the explicit requirements of users. This technique is suitable for recommending complex items that need a lot of customisation, such as tourism requests, real estate and expensive luxury goods (Aggarwal, 2016). Such items are rarely bought on a regular basis. Therefore, the data of ratings associated with such domains is insufficient. Unlike other types of recommendation systems, knowledge-based recommendation systems do not rely on statistical data related to specific item ratings or particular users and past buying, but require interactive feedback between users and the recommendation systems (Trewin, 2000). The interaction is significant to facilitate users to understand about complex product space while they are exploring the information in the system. Another way to explain this is that the knowledge discovery

process of particular items can be accomplished by the interaction. Upon receiving some degree of information about user requirements and general knowledge about a set of items, knowledge-based recommendation can generate recommendations to users by mapping them with item attributes. In some cases, demographic attributes might be integrated with item attributes when encoding the domain knowledge.

Knowledge-based recommendation can be categorised into two primary categories, i.e., constraint-based systems and case-based systems. In constraint-based systems, users generally define their requirements, which is sometimes known as constraints over attributes of items. After that, the systems deploy domain-specific rules to map the user requirements and the item attributes. These rules filter conditions that are represented by the domain-specific knowledge. For example, when recommending a car, a user adds constraints to the car's attributes, e.g., car price not over 3500 dollars. Users are allowed to repeatedly change the beginning constraints based on a number of recommended results until they are satisfied with the results. A study by Felfernig and Burke (2008); Felfernig, Friedrich, Jannach and Zanker (2011) show examples of these systems. Instead of deploying hard constraints like the constraint-based systems, the case-based systems use specific cases, known as anchor points. The domain knowledge is created by using similarity metrics, which are crucial in retrieving similar items between the item attributes and the anchor points. In many cases, utility functions are utilised instead of similarity metrics. Aggarwal (2016) illustrated the literature on constructing utility functions. With the similarity function, the case-based systems never experience an empty set of recommendations. The results from the first interaction regularly are used as a new case to obtain the further and closer recommendations.

In comparison to the widespread techniques, knowledge-based recommendation is more productive in numerous scenarios. Firstly, users who need more specify knowledge about items are generally willing to provide their requirements in detail, whereas the widespread techniques, content-based and collaborative filtering techniques, have failed

to provide such detailed feedback. This willingness brings about high user controls over the recommendation process, leading to a higher user satisfaction. Secondly, the complexity of some items is difficult to obtain ratings for. Other techniques suffer from the cold-start problem, but knowledge-based recommendation is suitable for such situations and still works well without item ratings.

#### **2.4.4 Utility-Based Recommendations**

Utility-based recommendation techniques focus on the ability of a utility function to determine a rank of available items (Burke, 2002). There are two crucial elements in designing this recommendation, i.e., user preferences and utility functions. User preferences frequently derive from the users via the interaction between the users and the system. This technique requires some degree of user effort to explicitly input user preferences about the important weights of each attribute (Huang, 2011). The utility function is another significant component of the utility-based recommendation. It is used to estimate the probability of users' favourites based on the attribute of items (Aggarwal, 2016). Therefore, the challenge of utility-based recommendation techniques is to identify a proper utility function and to design the way to obtain user preference with little effort from the user.

To begin the process of recommendation, the utility-based technique should have a high degree of knowledge about item attributes. In many cases, it requires some degree of user preferences or profiles that have been formed via user interactions. As a result, this method can provide a personalised service for particular users. After receiving the needed data, the utility function computes each available item for its utility value, which is generally represented by a numerical value. The utility function considers various criteria to compute the utility value. It might only consider the data about item attributes alone or only user preferences, or both sets of data at the same time. After that a rank of

items emerges. Consequently, a utility-based recommendation selects the top-n items with the highest values to recommend to the users.

Utility-based recommendations have many similarities to the knowledge-based recommendations. Aggarwal (2016) stated that utility-based recommendations are regularly deployed for ranking tasks in case-based systems in knowledge-based recommendations. Thus, they have categorised utility-based recommendations as part of the knowledge-based recommendation category. Similarly to this study, Zanker, Jessenitschnig, Jannach and Gordea (2007) state that both approaches have many similar functions because they provide recommendations based on product knowledge and user preferences. Besides that, both recommendation methods require user interaction to obtain accurate recommendations. Despite such similarities, there are some differences. Utility-based recommender systems do not have explicit mapping rules like case-based systems. However, they require clear definitions of utility values over the characteristics of specific items that are able to meet the provided user requirements. In comparison to other approaches, content-based recommendations and utility-based recommendations similarly provide recommendations based on item attributes (Burke, 2002). Different from content-based recommendation, utility-based recommendations do not experience the cold-start problem or sparsity problem (Huang, 2011).

A number of systems adopting the utility-based approach have been proposed (Schmitt, Dengler & Bauer, 2002; D.-R. Liu & Shih, 2005; Manouselis & Costopoulou, 2007b). For instance, Schmitt et al. (2002) has developed utility-based recommendation system by constructing the utility function based on a combination of the weighted scoring rule and the ordered weighted averaging operation. Their proposed utility function is able to effectively capture user preferences and dynamically provide interesting items, even when users update their user preferences. In the same vein, Bothos, Dimitris and Gregoris (2012) presented an Eco-friendly route recommendation system by adopting the ordered weighted averaging operation to build the utility function. The system

requires an explicit input from users, which will later be used to compute utility values. Another interesting paper is a study by Lakiotaki, Tsafarakis and Matsatsinis (2008). They developed a movie recommendation, UTA-Rec, by improving on utility additive method. With regard to a user oriented perspective, the result of their evaluation shows a better performance in terms of the accuracy of recommendations, in comparison to multiple rating collaborative filtering. The literature has shown some examples of utility-based recommendation systems and their abilities. It is notable that the vast majority of the literature on utility-based recommendations has adopted various approaches in multi-attribute utility theory to construct their utility functions (Huang, 2011).

#### **2.4.5 Hybrid Recommendations**

The aforementioned recommendation techniques provide good performance, based on many factors, i.e., the available sources of input and the different scenarios (Aggarwal, 2016). Collaborative filtering performs well when it receives an adequate degree of community rating, whereas content-based filtering requires more description of the items and user ratings. While knowledge-based recommendations need only the proper effort from the user to gain knowledge base and the user requirements, utility-based recommendations require a clear definition of the utility value of each item. By relying on different inputs, these techniques have different strengths and weaknesses. For instance, without sufficient ratings, collaborative filtering and content-based filtering techniques are unable to properly address the cold-start problem, but knowledge-based recommendations and utility-based recommendations do not have a problem with such scenarios.

By equipping hybrid recommendations, some problems related to recommendation techniques can be overcome. To cope with the weaknesses of common recommendation

techniques, hybrid recommendation systems are constructed by combining various recommendation techniques to create more robust, effective and accurate recommendation systems. These systems can address the problem of multiple sources of input, and also improve the performance of recommendation systems.

A number of hybrid recommendation systems have been increasingly developed and can successfully mitigate some common problems of recommendation techniques, such as the cold-start and sparsity problems. For instance, Claypool et al. (1999) developed an on-line newspaper hybrid engine by combining the strengths of content-based filtering and collaborative filtering methods. Their proposed system aims to solve the sparsity problem. In addition, Zanker and Jessenitschnig (2009) proposed hybrid recommendation systems for on-line shops. Such systems are hybridised using different techniques: collaborative filtering, utility-based methods and association rule mining.

Based on Burke (2002), hybrid recommendation systems can be categorised into seven different categories, i.e., weighted, switch, mixed, feature combination, feature augmentation, cascade and Meta-level. In a comprehensive study of hybrid web recommendation systems, Burke (2007) investigated various hybrid systems that has been built using four well-known recommendation techniques. 41 hybrid systems were constructed, based on the aforementioned hybrid strategies. Then, they were compared the performance in terms of the average rank of the correct recommendation (ARC) in order to identify the best hybrid strategy. According to their investigation, the cascade and augmented hybrids are the most effective strategies.

## **2.5 Multi-criteria recommendation approach**

Before proceeding to analyse the multi-criteria recommendation approach, it is necessary to understand the concept of multi-criteria decision making and its various methods. Later, the second section will move on to describe in greater detail the definition,

advantages and current knowledge of the multi-criteria recommendation approach.

Multi-criteria decision making (MCDM) has played a crucial role in addressing the issues around decision making. MCDM is a general class of Operations Research (OR), involving a number of decision criteria. MCDM has gradually facilitated decision makers to overcome complex problems in many disciplines, from economics to construction. (Triantaphyllou, Shu, Sanchez & Ray, 1998). Readers, for instance, would like to buy a book. They might consider authors and publishers, as well as reviewing scores and the price of the book. In a real-life situation, individuals experience difficulties when choosing from the available options, due to the fact that they take the various criteria into consideration and each criterion create conflicts. MCDM, therefore, allows the decision makers to cope with such conflicts, and provides optimal decisions by evaluating a set of alternatives with a numerical value. MCDM depends solely on its judgements for the decision makers' preferences, leading to personalised services. Another benefit of MCDM is that it is able to handle both quantitative and qualitative data.

To help in the design of MCDM, Manouselis and Costopoulou (2007a) provided six steps of the decision making process, as shown in Figure 2.1. They also provided four working principles as a guideline for MCDM designers: identification of the objective of the decision makers, selection of the criteria and the method of aggregation.

It is crucial to comprehend the general problem that MCDM attempts to solve. L. Liu, Mehandjiev and Xu (2011) defined the recommendation problem as a MCDM problem. A MCDM problem can be defined as  $m$  alternatives and  $n$  decision criteria.  $U_j^{mcdm}$  denotes the total sum score or the total utility score used for ranking and differentiation, where  $i = 1, 2, \dots, n$ ,  $a_{ij}$  is the score of  $j$ -th alternative with respect to the  $i$ -th criterion and  $w_{c_i}$  denotes the weight of  $i$ -th criterion.

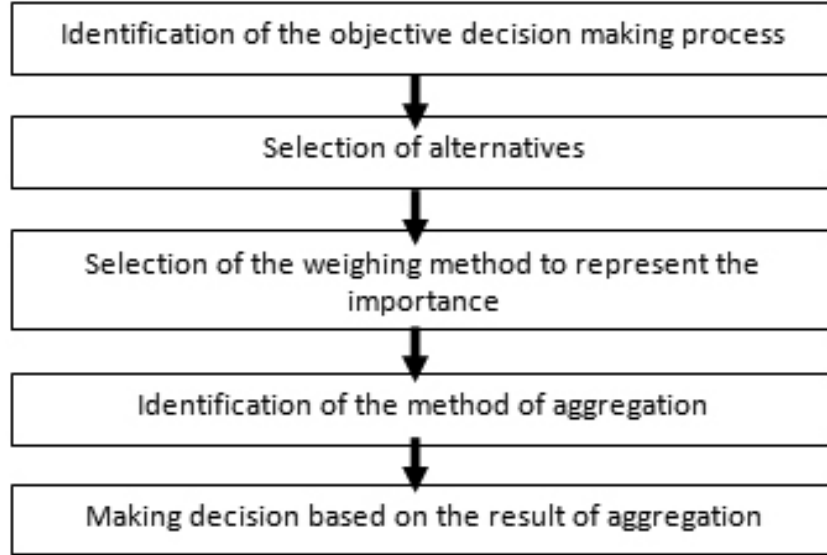


Figure 2.1: Six steps of decision making process

$$U_j^{mcdm} = \sum_{i=1}^n a_{ij} \cdot wc_i, \text{ for } j = 1, 2, 3, \dots, m. \quad (2.2)$$

For decision makers, various types of MCDM methods are available to be adopted in order to cope with the general MCDM's problems. The MCDM methods can be classified in many aspects, depending on the type of data and the number of decision makers (Triantaphyllou et al., 1998). Each method has different features and levels of complexity. The most common and widely used methods are the Weighted Sum Model (WSM), the Weighted Product Model (WPM), the analytical hierarchy process (AHP), the ELimination and Choice Expressing Reality (ELECTRE) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). A general description of some of these methods is provided in the following section.



### 2.5.1 Weighted Sum Model

The Weighted Sum Model (WSM) is an MCDM approach that addresses single dimensional problems. It belongs to the additive utility assumption, which means that the total value of each alternative is equal to the sum of the product given. According to Triantaphyllou et al. (1998), WSM is the most common and widely applied technique in MCDM and gives the most acceptable results to the decision makers. The results of this method are being used as a standard evaluation that determines the accuracy of other methods. It is believed that WSM encounters difficulties when solving multi-dimensional decision-making problems. Fishburn (1967) defines the expression of WSM, as shown below. The best alternative should meet this expression, where  $A_{WSM}^*$  is the score of the best alternative,  $n$  is the number of decision criteria,  $a_{ij}$  is the score of  $j$ -th alternative with respect to the  $i$ -th criterion and  $w_i$  denotes the weight of  $i$ -th criterion.

$$A_{WSM}^* = \max \sum_{i=1}^n a_{ij} \cdot w_i, \text{ for } j = 1, 2, 3, \dots, M. \quad (2.3)$$

### 2.5.2 Weighted Product Model

The Weighted Product Model (WPM) is known as a modification of WSM. To address the shortcomings of WSM, WPM is proposed. The main difference between the two approaches is that WPM aggregates various criteria by multiplication and can cope with the multi-dimensional decision-making problems, but WSM combines such criteria by addition. The ratio between two alternatives (i.e.  $R_k$  and  $R_l$ ) in each criteria derives from their actual values (i.e.  $r_{ki}$  and  $r_{li}$ ), which later are powered by the relative weight of the corresponding criterion (Triantaphyllou et al., 1998). This process repeats until all alternatives are compared. In equation 2.4,  $n$  is the number of criteria,  $w_i$  is the weight of importance of the  $i$  criterion. If the result of  $A(R_k/R_l)$  is greater than 1, then

alternative  $R_k$  is better than  $R_l$ .

$$A(R_k/R_l) = \prod_{i=1}^n (r_{ki}/r_{li})^{w_i}, \text{ for } k, l = 1, 2, 3, \dots, M \quad (2.4)$$

### 2.5.3 Analytical Hierarchy Process

The Analytic Hierarchy Process (AHP) is an approach to analysis a complex problem. AHP shares similarities with WSM in terms of the equation. However, this approach uses the relative value instead of the actual value. It allows decision makers to assign the relative importance of the alternatives in terms of each criterion to construct the matrix. Equation 2.5 is then applied to calculate the final value for ranking. Saaty (2008) gives a clear explanation of the functions of AHP and also provides examples of the process of AHP. In Equation 2.5,  $A_{AHP}^*$  denotes the score of the best alternative.  $n$  is the number of decision criteria,  $a_{ij}$  is the score of  $j$ -th alternative with respect to the  $i$ -th criterion and  $w_i$  denotes the weight of  $i$ -th criterion.

$$A_{AHP}^* = \max \sum_{i=1}^n a_{ij} \cdot w_i, \text{ for } j = 1, 2, 3, \dots, M. \quad (2.5)$$

This is an explanation about the traditional methods of MCDM. Many more methods are available such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and The ELimination and Choice Expressing Reality (ELECTRE). Despite such various methods, numerous studies have still attempted to extend the traditional methods to create new MCDM models, such as (Belton & Gear, 1983; Manouselis & Costopoulou, 2007a; J.-W. Wang, Cheng & Huang, 2009; Vahdani, Jabbari, Roshanaei & Zandieh, 2010). Due to the large number of methods available, this thesis can only give an explanation of the approaches related the scope of the study.

The literature on designing recommendation systems has recognised the advantages of MCDM and has increasingly applied various types of MCDM approaches. This

type of recommendation system is known as multi-criteria recommendation systems. Adomavicius and Kwon (2015) explained the theoretical assessments of multi criteria decision making methods towards designing recommendation systems. This study not only draws a rational connection between the MCDM problem and the recommendation systems problem alone, but also proposes a way to integrate them. Zeng (2011), for instance, adopted the semantic similarity function and TOPSIS methods to construct a personalised recommender system. Similarly, Maharani, Hatta and Merdiko (2014) combined AHP and TOPSIS in recommending culinary attractions. Together, these studies provide important insights into the usefulness of multi criteria decision making methods in constructing recommendation systems.

Recently, researchers have shown an increased interest in multi-criteria recommendation systems. To build multi-criteria recommendation systems, Adomavicius and Kwon (2015) focused on multi-criteria rating recommenders. L. Liu et al. (2011) created multi criteria service recommendation models by clustering user criteria preferences and extending the collaborative filtering approach. They later compared the result of their model with a single criteria collaborative filtering method. The results of their research is superior in terms of accuracy. Interestingly, a study by Nilashi, bin Ibrahim and Ithnin (2014) presented a new multi-criteria collaborative filtering system, coping with multi-criteria rating data. Evaluation of their system on a real-world dataset potentially shows an improvement in terms of accuracy. When considering this evidence, it seems that MCDM is a great ingredient in constructing recommendation systems. This combination could bring about the great achievement of recommendation systems with high user satisfaction and greater accuracy.

## 2.6 Multi-agent based recommendation systems

So far this chapter has focused on explaining and reviewing general approaches that are utilised in order to create recommendation systems. This section aims to give an explanation of multi-agent based recommendation systems and the reason why these systems are increasingly being developed. It also provides a literature review about recent trends and the gaps in knowledge of multi-agent based recommendation systems. Before reviewing recent literature on multi-agent based recommendation systems, it is necessary to have a general understanding about agent-based and multi-agent based systems.

Evidence has proven that agent based systems have played a crucial role in real applications such as supply chains, population dynamics and transportation. Agent based modelling (ABM) has been defined by Gilbert as “a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment” (2008, p. 2). ABM has been increasingly constructed because of the complexity of the world (Macal & North, 2010). Traditional modelling approaches are incapable of handling such complexities, which might have heterogeneous and dynamic features. Thus, an agent with intelligent properties capable of being autonomous, adaptable and sociable is required. Identifying the properties of the agents really depends on the nature of the system. It can have more properties with a complicated system and fewer properties with simple systems. When working with complex tasks, a single individual agent might not be able to achieve the tasks. Therefore, it requires Multi-agent Systems (MASs). MASs refer to a group of autonomous agents connecting and communicating with others in the environment in order to accomplish a common goal (Balaji & Srinivasan, 2010). MASs are mostly applied to model individual decision-making; human social and organisational behaviour with the purpose of illustrating collaboration, group behaviour and social interaction. Vlassis

(2007) illustrated the fundamental aspects used to distinguish between MASs and a single-agent system. These aspects include agent design, environment, perception, control, knowledge and communication. The study also identified difficulties in transferring single agent systems to MASs. Some examples of such difficulties are how to decompose a problem, allocate sub-tasks to agents, synthesise partial results and how to ensure coherent and stable system behaviour. In addition to the above difficulties, Balaji and Srinivasan (2010) also categorised the challenges of MASs into five sections, including environment, perception, abstraction, conflict resolution and inference. For example, if the agents could not have a proper communication that shared a global view, conflicts among them might occur and create a problem with the whole system. Although MASs provide multiple difficulties and challenges, due to their enormous advantages such as efficiency, robustness, scalability and re-usability, many application domains have still adopted MASs (Vlassis, 2007).

MASs have been applied in various transportation management systems, e.g., traffic control, congestion management and dynamic routing. Guo, Li, Song and Zhang (2003); Roozmond (2001), for instance, researched agent-based urban traffic control (UTC) systems, and developed intelligent traffic control applications that have an ability to adapt themselves depending on a change in traffic environment by integrating the agent-based approach. Bazzan and Klügl (2014) reviewed the literature associated with agent-based traffic control and management, and agent-based traffic simulation and modelling. They provide successful examples of these areas and also identified some challenges that require further research. Based on their literature review, an agent-based modelling approach has frequently been adopted in order to learn about the sophisticated decision-making processes of individuals. Additionally, individuals and micro travel behaviours have been identified as a highly influential variable in terms of overall traffic congestion. With respect to a traveller's decision-making process, Dia (2002) and S. Zhu, Levinson and Zhang (2008) conducted research on route choice and

developed agent-based route choice models that depend on individual preferences. A recent study by Zou et al. (2016) considered departure time choice and transportation mode choice. The search, knowledge learning and decision-making processes of agents are the main focus of their study. The study also implemented its proposed model in simulation to evaluate the impacts of policies and strategies. The results illustrated that the model was able to model the interactions of mode and departure time. However, they did not consider traffic condition in their study.

As far as recommendation systems are concerned, a considerable number of studies have adopted multi-agent based approaches. Cho, Kim and Kim (2002) implemented an agent-based personalised product recommendation approach, consisting of eight different agents with various functions. Such proposed systems rely on a variety of data mining techniques, such as product taxonomy, association rule mining and decision tree induction. Similarly, Birukov, Blanzieri and Giorgini (2005) developed a multi-agent recommendation system to implicitly extract knowledge about user behaviours in order to predict items of interests to other members of the same community. Such recommendation systems take advantage of the intelligent capabilities of multi-agent systems such as smart, mobility and scalability. Although there are a number of studies of multi-agent based recommendation systems, only a few have focused on route recommendation. For instance, Batet, Moreno, Sánchez, Isern and Valls (2012) presented an agent-based personalised recommendation of cultural and leisure activities. It is a hybrid recommendation engine, combining content-based and collaborative recommendation techniques. With the implicit profile update, the system can capture user's preferences automatically.

Prior studies have clearly noted the importance of integrating agent-based methods on many aspects of traffic and transportation, particularly when recommending routes, but some gaps in the knowledge still need further research, particularly in the area of individual choice. For instance, personal decision-making regarding traffic choice: route

choice, departure time choice and mode of transportation. It relies on both individual preferences and the external environment such as a current traffic conditions or a change in traffic system and policy, but the interaction and correlation between them has not been investigated well enough, especially in realistic scenarios.

## **2.7 State-of-the-art Persuasive system**

### **2.7.1 Persuasive Technology**

This following section will focus on persuasive systems, persuasive recommendation systems and how persuasiveness of recommendation systems is evaluated.

A large and growing body of literature has investigated changing human's attitudes and behaviours with computer systems. This field of study is known as persuasive technology. Persuasive technology has been associated with various areas such as social psychology, game design, communication science, computer science, human computer interaction, ubiquitous computing, behaviour changes support systems and intervention systems. In computer science, persuasive systems aim to physiologically influence humans as users of the system to change what they think and do to other specific behaviours and actions. By applying different principles, such as persuasion, authority, credibility and trust, the systems have greater abilities of persuasion. Oinas-Kukkonen and Harjumaa (2008a) defined a persuasive system as "a computerised software or information system designed to reinforce, change or shape attitudes or behaviours or both without using coercion or deception". Since the first international conference on persuasive technology in 2006, the literature in this field has increased (W. Zhu, 2007; Khaled, Barr, Noble, Fischer & Biddle, 2007; Nguyen, Masthoff & Edwards, 2007; Purpura, Schwanda, Williams, Stubler & Sengers, 2011; Kadomura, Li, Tsukada, Chu & Siio, 2014; Bartlett, Webb & Hawley, 2017).

The vast majority of persuasive systems focus on convincing individuals to follow well-behaved behaviours and actions. Promoting healthy behaviour and an ideal weight to overcome a health issue like obesity, was studied by Purpura et al. (2011). Their system adopted many persuasive design principles: personalisation, self-monitoring and social comparison in a persuasive framework, using the Persuasive Systems Design (PSD) model developed by Oinas-Kukkonen and Harjumaa (2008a). Such system consists of four sensors that are responsible for obtaining real-time data from users. This data is subsequently transferred to a mobile application, called Fit4Life, to process and track users' behaviours. In the same vein as Purpura et al. (2011), Bartlett et al. (2017) adopted various principles of the PSD model to construct three persuasive mobile applications. These systems focus on motivating patients with chronic obstructive pulmonary disease to increase physical activities, particularly walking. The evaluation of three applications with actual patients proved that dialogue support and primary task support approaches are more persuasive and satisfying. Based on the above evidence, most studies on persuasive systems aim to encourage individuals to be well-behaved and the system designed relies chiefly on the PSD model.

### **2.7.2 Persuasion of recommendation system**

The power of persuasion has been increasingly integrated in recommendation systems to provide a mean of influencing customers' judgements over recommended options. These systems are known as persuasive recommendation systems. Building persuasive recommendation systems provides numerous benefits in comparison to traditional recommendations. A major benefit is that the system's customers are better satisfied in terms of recommendation quality (Häubl & Murray, 2003). Since the performance of recommendation systems relies very much on the users' preferences and feedback such as user ratings, integrating persuasive ability receives more users' responses



(Swearingen & Sinha, 2001). A study by Gkika and Lekakos (2014) proved the effectiveness of persuasion in recommendation systems. In their study, although users had little interest in the recommended items, when explanations were introduced as persuasive strategy, users increasingly adopted the recommendations. This illustrates that when adding persuasive features, recommendation systems have an ability to convince users to choose recommended items, which can imply a change in user behaviours.

With regard to the potential benefits to both users and system designers, researchers have recently paid much attention to persuasive aspects in recommendation systems. A book by Yoo et al. (2012) provides an insightful conceptual framework of persuasive recommender systems by theoretically identifying recommender systems as persuasive social actors. It not only identifies important knowledge gaps, but also guides recommender system designers on practical implications and future directions in order to increase the power of persuasion in recommendation systems. Palanca, Heras, Botti and Julián (2014) presented a social recommendation system, *receteame.com*. By involving users' information on issues such as friendship and trust, which was collected from a social networks, the system aims to motivate users to adopt recommended recipes. Similarly, B. Wang, Ester, Bu and Cai (2014) examined how to generate social explanations in recommendation systems to persuade different types of users in social network. His study has four features, namely user relationships, user interactions, user types and user influence, which were examined to identify the most important factors that enhance the persuasiveness of the system. User relationships and interactions outperformed other factors.

A number of features in recommendation systems are recognised as persuasion. Cremonesi, Garzotto and Turrin (2012) empirically investigated recommendation systems to identify the persuasive properties in relationship to the design features of

recommendation systems. In a user-centric evaluation, explanations are a crucial element in persuasion. A system that can provide transparency to its users is considered to be a reliable system. Since it can explain how the system generates recommendations, users are more likely to believe and trust the system (Tintarev & Masthoff, 2011). The familiarity of recommended items also indicates persuasive characteristics (Yoo & Gretzel, 2011). Other examples are the amount of information about recommended items, the response time of the system and even how the system presents recommended items (Cosley, Lam, Albert, Konstan & Riedl, 2003). Having many persuasive characteristics results in a system with great persuasive ability, leading to a great outcome.

### **2.7.3 Evaluation of persuasiveness in recommendation systems**

Since investigating the persuasiveness of recommendation systems is immature, an approach used to evaluate persuasion is still limited. According to Wu, He and Yang (2012), most performance indicators - accuracy, coverage and diversity - in recommendation systems have a specific evaluation metric. For example, accuracy can be evaluated by using predictive accuracy metrics and rank accuracy metric such as normalised MAE, root mean squared errors (RMSE), mean squared errors (MSE) and Kendall's Tau correlation. Differently, persuasiveness as one significant indicator does not have a proper metric to evaluate it. Based on Cremonesi et al. (2012), developing new methodologies to evaluate the influence of recommendation systems at a sub-conscious level and measuring recommendation acceptance is needed.

As far as the correlation between the persuasiveness of recommendation systems and an individual's behaviour is concerned, only a few in the literature have conducted an investigation. Gkika and Lekakos (2014), for instance, developed a framework to evaluate the persuasion of explanations by dividing it into six strategies and six explanations. After applying the strategies, the findings showed that the participants

consumed a recommended item even if it did not match their interests. This indicates a change in behaviour. However, such a study relies on real participants' feedback in the experiment, which requires a considerable amount of time to manage, collect and process. Unlike Gkika and Lekakos (2014), Cremonesi et al. (2012) did not involve participants to evaluate the persuasiveness of the recommendation system. In their study, the characteristics of recommenders, such as novelty and accuracy, are empirically evaluated based on indirect indicators, namely the lift factor and the conversion rate. These indicators indicate the quality of persuasion and a change in user behaviour. The results successfully show an increase in the sale of recommended items. Investigating the effects of the persuasiveness of recommendation systems on an individual's behaviour needs further investigation and it open many new directions for researchers who plan to integrate persuasive features into recommendation systems, especially in the evaluation of persuasiveness in recommendation systems.

## **2.8 Knowledge Gaps**

This section examines several significant knowledge gaps that were identified by reviewing the existing literature. Firstly, most studies on solving transport problems, e.g., transportation delays, accidents, pollution emission and traffic congestion, have only focused on constructing complex intelligent transport systems. However, far too little attention has been paid to user satisfaction and the factors that influence human behaviour to follow the instructions of such systems (Vaa et al., 2007).

Secondly, the majority of the literature on route recommendation systems pays particular attention to personalised supports to meet individual requirements. Such studies, however, have failed to investigate the marginal effects of transportation, i.e., the transport problems. This indicates the need for a new route recommendation that is able to make transport problems part of the transport users' decisions and encourage

them to follow the less impacted routes.

Furthermore, previous studies on constructing persuasive recommendation systems have only explored some aspects of persuasive technology. They have not applied other persuasive strategies in the persuasive system design (PSD) model, e.g., social comparison, praise, reward and competition. Thus, it is still not known whether such strategies are capable of enhancing the ability of recommendation systems. These strategies might become new characteristics of recommendation systems and if such strategies have been adopted in some degree, persuasive recommendation systems would achieve a great persuasive ability, which could lead to a high level of user satisfaction.

Finally, while some studies have investigated the persuasiveness of recommendation systems and behavioural changes, there have been few empirical investigations into the effects of the persuasiveness of recommendation systems in relation to an individual's behaviour and the way to evaluate the persuasiveness of recommendation system. Thus, the key questions still remain, i.e., Do persuasive recommendation systems have an impact on behaviour change? How can we measure the impacts of persuasive recommendation systems in respect to a change of user' behaviours?

## **2.9 Summary**

This chapter gave a literature review of several crucial contexts in this research, for example, traffic management systems, recommendation systems and persuasive technology. It began with the various approaches used to construct recommendation systems, highlighted the benefits of adopting multi-criteria recommendation approaches and provided insight into and an understanding of the persuasive systems. Some gaps in the knowledge of such contexts have been identified by reviewing related literature.

The next chapter will present an in-depth description and explanation of the proposed methodology for an agent-based public-friendly route recommendation. It will begin by

showing each component of the system architecture, explain how the data was collected and illustrate how the proposed utility functions aggregate the decision criteria of the travel routes.

## **Chapter 3**

# **Agent-based Public-Friendly Route Recommendation**

### **3.1 Introduction**

In the previous chapter, the literature on state-of-the-art recommendation systems, multi-criteria recommendation approaches and persuasive technologies was reviewed to gain an understanding of the current knowledge. Several gaps in the knowledge were identified from both theoretical and practical studies in such contexts.

In this research, a novel recommendation approach, known as Agent-based Public-Friendly Route Recommendation (APF2R), is introduced to mitigate the negative impacts generated by transportation activities. The negative impacts, including congestion, pollution and accidents are known as external costs and refer to the impact of transport activities on society (Jokanović & Kamel, 2014). These costs represented in monetary units. APF2R adopts an agent-based architecture, and can recommend public-friendly routes by considering an individual's utilities. This chapter explains the architecture and design of the system. With respect to the multi-agent system, the roles and views of different agents, and the relations among them are described in

detail. The chapter also gives a description of the attributes of travel routes and tells how such attributes are collected. It also shows how the system defines user preferences, and the importance of each attribute is extracted. Finally, the chapter illustrates data normalisation, a individual's utility function and a public's utility function.

Conventional methods are incapable of providing an effective item in the travel route context. The collaborative filtering model and the content-based recommendation method are currently the most popular methods to create a recommendation system. Unfortunately, there are certain drawbacks associated with the use of the collaborative filtering and content-based methods. These methods require sufficient data, especially user ratings, to train the models and generate item recommendations. If the data is not available or not enough, these models will experience major problems such as cold-start problems, rating sparsity and overspecialisation (Adomavicius & Tuzhilin, 2005; Aggarwal, 2016). Such methods are excellent techniques for suggesting simple products like books and music, but are not suitable when recommending travel routes. When making a travel decision, transport users always examine more than just travel distance or travel cost. They consider other criteria such as traffic conditions, the number of transfers and walking time. Besides that, the value of each criterion in travel routes is very dynamic. The criteria always change depending on time of departure, incidents or even a change in weather. For example, road blocks and accidents create traffic jams and also increase travel time and cause delays. As a result, conventional methods are unable to effectively recommend a dynamic and complex item like travel routes.

This study, therefore, relies on the utility-based recommendation method, which adopts the multi-criteria decision making. By aiming at the ranking task, the utility-based recommendation method is able to effectively aggregate the multiple criteria of travel routes and provide a great equilibrium between public benefit and personal benefit. The following section will explain in more detail how the system is designed and how it functions.

## 3.2 Agent-based modelling

Before the proposed system is presented, it is important to understand agent-based modelling and its advantages. Extensive research has shown that agent based modelling is a powerful simulation modelling technique for modelling complex environments. Agent based modelling (ABM) has been defined by Gilbert as “a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment” (2008, p. 2). ABM is mostly applied to model individual decision-making, human social and organisational behaviour with the purpose of illustrating collaboration; group behaviour, social interaction. ABM has also been used in a variety of domains from economic to anthropology. Numerous applications developed by ABM have been utilised in real circumstances, such as in supply chains, population dynamics and transportation. Five general steps to constructing ABMs are presented by Macal and North (2005). These are agents, environment, agent methods, interaction and implementation.

ABM provides a number of advantages. One of the major advantages is that it can deal with the complex environment. ABM has been increasingly constructed because of the complexity of the world (Macal & North, 2010). Traditional modelling approaches are incapable of handling complexity that might have heterogeneous and dynamic features. Thus, an agent with intelligent properties, including being autonomous, adaptable and sociable is required. Secondly, the communication and interaction between agents allows modellers to gain insight and an understanding of cause and effect (Bazghandi, 2012). Modellers are able to capture any disclosure that happens in the model by controlling the interaction between each entity. Additionally, modellers can flexibly tune various attributes in the model, such as agent behaviour, ability and the form of interactions (Crooks & Heppenstall, 2012). As a result, they can view the model in various dimensions. Lastly, ABM is cost-effective and time efficient (Bazghandi,



2012). To simulate and analyse a complex problem, it consumes considerable time and resources. With ABM, modellers can simply use a small personal computer with a simple computer program like spreadsheets. With regard to such advantages and the research objectives, therefore, this study relies on agent-based modelling to design, simulate and analyse the proposed system.

### 3.3 System Architecture and Design of APF2R

Before describing all the functions of APF2R, it is necessary to mention the system architecture and design. APF2R focuses on recommending public-friendly travel routes to individuals. The architectural design of APF2R is illustrated in Figure 3.1. The system is modeled as a multi-agent system. The reason for adopting a multi-agent system is that the system is situated in a complex environment where any change that happens could affect other components of the system. Additionally, when generating recommendations the system considers the benefits of two parties, i.e., users and the public. The system needs to balance and distribute equal benefits to both parties.

Figure 3.1 shows the components of the system and their relationships. The system consists of two main types of agents, i.e., user agents and the recommender agent. The two parties communicate with each other via basic messages. They are delegated for different roles, but work cooperatively to accomplish an overall goal. The system aims to support the public to reduce the external costs, as well as maintain satisfaction of the transport users. In terms of perceiving the environment, APF2R receives data input from various parties, including real users and traffic data providers. It considers the public and the users when providing recommendations, and as a result the system is able to product personalised and public-friendly routes. A description of each agent and the overall architecture are described below.

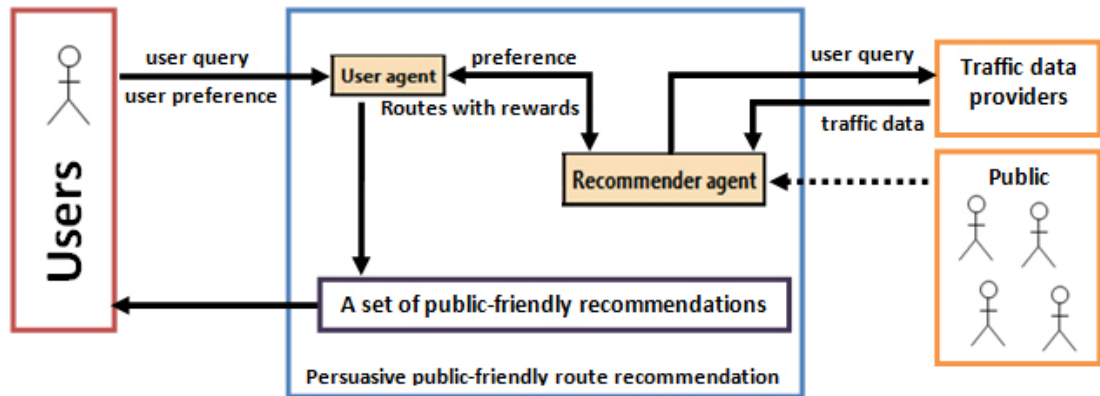


Figure 3.1: System architecture of Agent-based Public-Friendly Route Recommendation

User Agents (UAs) act as a mediator between individual users and other components of the system. UAs look after the users in terms of a user's benefit, meaning personal utility. Each user agent (UA) represents one user. They are responsible for obtaining user queries and user preferences from the users. At the same time, UAs also have other roles. They convey the received information and also present the system outputs, a set of recommendations, to the users.

The Recommender Agent (RA) is the main player of the system. Unlike the UAs, RA facilitates both players, i.e., the public and the users. The goal of RA is to provide recommendations that satisfy the benefits of both the public and users. It accounts for a number of roles. RA harvests traffic related data from the traffic data providers and generate traffic routes. It is also responsible for data pre-processing and data normalisation. The main roles of an RA is to create a rank based on its utility function, and to calculate the persuasive reward value to present to the users.

Having defined what the roles and functions of the agents are, the next part moves on to discuss the process of generating recommendations. Figure 3.2 presents the relationship and interaction between the user agents and the recommender agent. To begin the process of recommending public-friendly routes, the system requires traffic users' data from transport users. This information includes original location, destination,

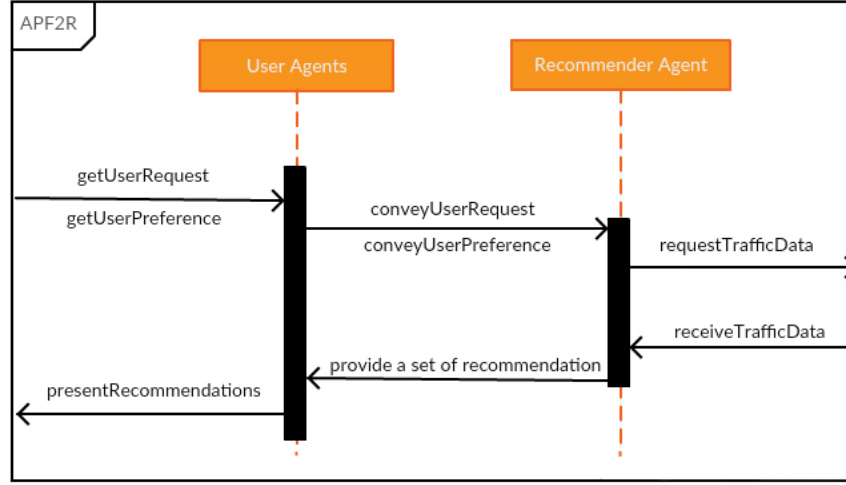


Figure 3.2: Sequence diagram of the proposed agent-based system

time of departure, and user preferences. Once the UAs obtains data input from the users, it conveys such data to the RA. After receiving information about users' requests, the RA sends a request to traffic data providers to harvest traffic related data. The traffic data providers respond to the request with the traffic related data based on users' queries. The traffic data provided is extracted to travel routes. Before passing the raw data to the utility calculation phrase, user preference and the generated routes need to be normalised by the RA. When finishing the normalisation, the RA calculates the ranking score and the reward value of each route by considering the utility values and the rank's distance of users. Finally, the RA sends the set of recommendations back to the UA for presenting to the users.

Before describing the proposed system in more detail, it is important to provide a formal definition of the various terms.

**Definition 3.3.1.** A route ( $r_j$ ) is an item that the recommendation system recommends to the transport users.  $r_j$  is a 8-tuple, i.e.,  $r_j = (tt_j, tc_j, dl_j, wt_j, cc_j, ac_j, pc_j, td_j)$ , where  $tt_j$  is the estimated travel time of  $r_j$ ,  $tc_j$  is travel cost,  $dl_j$  is delay time,  $wt_j$  is walking time,  $cc_j$  is congestion cost,  $ac_j$  is accident cost,  $pc_j$  is pollution cost and  $td_j$  is traffic condition. The term route, alternative and recommendation are used interchangeably in

this thesis.

**Definition 3.3.2.** Personal score  $U_{ij}^{ps}$  refers to the amount of satisfaction of the user  $u_i$  for a route  $r_j$ . This score is used to create a personal rank for the user  $u_i$  who has already provided their preferences to the recommendation system.

**Definition 3.3.3.** Public friendly score  $U_j^{pfc}$  is beneficial values that a particular route  $r_j$  produces for the public. This score is beneficial for all individuals in the public.

**Definition 3.3.4.** Public goods rate  $\omega_{pg}$  is a real value between 0 and 1, representing the weight of public goods. The higher the public goods rate, the more public-friendly routes are recommended by the recommendation system.

### 3.4 Travel Routes

This section gives a more detailed description of travel routes. A travel route can be defined as an item that the system recommends to transport users. There are various criteria transport users consider before making a travel route decision. This area is associated with the route choice. Some examples of such criteria are travel distance, travel cost, the number of intersections, the number of traffic lights, traffic safety, road conditions, traffic conditions, the number of bus interchanges and even comfort (Abdel-Aty, Kitamura & Jovanis, 1997; Peeta & Yu, 2004). The data of these criteria is dynamic and difficult to collect because it is associated with the traffic prediction domain, which has insufficient data available for public use. Due to the large number of route choice criteria and the availability of prediction data, this study considers eight attributes, namely travel time, travel costs, delay time, walking time, congestion costs, pollution costs, accident costs and traffic condition costs. The first four criteria are adopted from Bothos et al. (2012). Differently to other studies however, the last four criteria have been added. This is because the three criteria of congestion costs, pollution

costs and accident costs are the common elements of the external costs that can be found in studies of Jokanović and Kamel (2014) and Maibach et al. (2008). Traffic conditions is also added because it is a crucial element of most navigation systems and transport users always take it into consideration. Table 3.1 shows an explanation and description of each attribute. It assumes that the low values of these attributes are the most preferable for traffic users and the system.

With regard to the fact that traffic data is difficult to capture, each attribute of a travel route is collected from the traffic data providers. Such data is dynamic and depends on many factors such as traffic time, flow, density, speed, congestion state, incidents, social events or even road blocks. In this study, we harvest traffic data from two well-known traffic data providers, i.e., Google Maps<sup>1</sup> and the Journey Planner of Auckland Transport<sup>2</sup>. Google Maps predicts data related to traffic, based on historical data and real-time data collected from their customers. It provides data for the travel times and traffic conditions for car, bicycle and walking modes, while Auckland Transport provides the data for public transportation, including travel times and the travel costs. However, the providers do not have data about travel costs for the car mode. Therefore, the travel cost for car mode is calculated based on the national mileage rate for motor vehicles, which is 72 cents per kilometre<sup>3</sup>.

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<sup>1</sup><https://www.google.co.nz/maps>

<sup>2</sup><https://at.govt.nz/bus-train-ferry/journey-planner/>

<sup>3</sup><http://www.ird.govt.nz/business-income-tax/expenses/mileage-rates/emp-deductions-allowances-mileage.html>

Table 3.1: Attributes of travel routes

No.	Attributes name	Description	Unit/Level
1	Travel time	Travel time refers to the total time that is needed to travel from the original location to the destination.	Minute
2	Travel cost	Travel cost refers to the total cost that is needed to travel from the original location to the destination. This included fuel usage, parking fees and ticket fares on public transportation.	NZ dollar
3	Delay time	Delay time refers to a period of time by which the sum of the departure time and the travel time exceeds the expected arrival time.	Minute
4	Walking time	Walking time refers to the total walking time that traffic users should spend to travel from their original location to their destination.	Minute
5	Congestion cost	Congestion cost is an additional travel cost, such as the impact of travel-time uncertainty, time costs and operating costs.	High, Medium, Low
6	Accident cost	Accident cost is the risk of loss in traffic accidents, such as medical costs, property damage and lost productivity.	High, Medium, Low
7	Pollution cost	Pollution cost is the amount of pollution, including air, water and noise generated by the transportation mode.	High, Medium, Low
8	Traffic condition	Traffic conditions refers to the condition of the traffic at the time the traffic users are travelling.	Heavy traffic, Medium-near heavy traffic, Medium traffic, Less or no traffic

Table 3.2: The values of the external costs based on transport modes

Mode	Congestion cost	Accident cost	Pollution cost
Car	High	High	High
Bus/train	Medium	Low	Medium
Bicycle/walk	Low	Medium	Low

Table 3.3: An example of travel routes, departure from Sky City to Auckland Zoo. The departure time is 11:08 and the expected arrival time is 11:30.

No.	Route	Travel time (Min)	Travel cost (NZ)	Delay (Min)	Walking time (Min)	Congestion cost	Accident cost	Pollution cost	Traffic condition
1	SH 16 (Car)	12	4.24	0	0	High	High	High	medium-near heavy traffic
2	Franklin Rd (walk)	67	0	45	67	Low	Medium	Low	Less or no traffic
3	The Lightpath (Bicycle)	29	0	7	0	Low	Medium	Low	Less or no traffic
4	195 (Bus)	29	3.15	11	14	Medium	low	Medium	medium traffic

Measurement of the external costs is difficult. Based on Jokanović and Kamel (2014) and Maibach et al. (2008), it requires a number of theoretical assumptions and various parameters, such as the characteristics of the vehicle, the time of the day and the characteristics of the location to calculate the accurate values of the external costs. Because of such complications, this study derives congestion costs, accident costs and pollution costs from the mode of transport as qualitative data ( See Table 3.2). Table 3.3 shows an example of the data of all the criteria of travel routes, which have been collected from the traffic data providers.

To increase the reliability of the system, the data needs to pass a data pre-processing phrase. There are various equations in the feature scaling approach that are able to be applied to normalise the data, but many turn the highest value of the raw data into the highest score. This study has to turn the highest value of the raw data to the lowest score before calculating the utility score. Therefore, the study created an equation to normalise the data into a value between 1 and 5. The value of 5 is the smallest value in the criteria, but it is the most preferable. Equation 3.1 was applied to normalise the values of travel costs, travel times, delays and walking times into five scales from 1 to 5. The result is the utility score of each decision criterion. In Equation 3.1,  $i$  denotes all value of items of  $i$  criterion.  $v_{ij}$  is a value of route  $j$  of  $i$  criterion and  $vs_i$  is a value after normalisation. The value of  $v_{ij}$  is from 1 to 5. For example, if  $v_{ij}$  is 0, after applying

this equation the normalised data will be 5.

$$vs_i = \frac{(1 + 5) - (1 + (v_{ij} - \min(i)) \times (5 - 1))}{\max(i) - \min(i)} \quad (3.1)$$

Similarly to other attributes of routes, the external costs and the traffic congestion are also normalised. Tables 3.4 shows the normalisation of traffic conditions based on the traffic condition of a particular route; meanwhile Table 3.5 illustrates the normalisation of external costs based on its level. The highest value after normalisation is the most preferable.

Table 3.4: Normalisation of traffic condition

Traffic condition level	Description	Value
Red	Heavy traffic	1
Orange	Medium-near heavy traffic	2
Yellow	Medium traffic	3
Green	Less or no traffic	4

Table 3.5: Normalisation of external costs

Level	Value
High	1
Medium	2
Low	3

### 3.5 User Preferences

The following is a brief description of user preferences, and how they are gathered and extracted. To effectively provide a personalised recommendation service, the system requires user preferences. User preferences, in this study, refer to the importance of each criterion provided by an individual. Table 3.6 shows some examples of user preferences. Each individual is asked to provide his/her values for four criteria, namely travel time,



travel cost, delay time and walking time. Users can provide this data in various ways, including a web interface and a mobile application. The interval of importance is a scale from 1 to 5, where 1 is of the lowest importance and 5 is of the highest importance. Equation 3.2 was applied to this data before being used in the utility function.  $wv_i$  denotes the importance of criterion  $i$ , provided by users and  $wc_i$  indicates the result that was extracted from the importance. For example, User3 provided the weights for each criterion as (5, 3, 2, 1) and  $\sum_{i=1}^4 wv_i = 5 + 3 + 2 + 1$  is 11. Weight for travel time is  $\frac{5}{11} = 0.45$ , travel cost  $\frac{3}{11} = 0.27$ , delay time  $\frac{2}{11} = 0.18$  and walking time  $\frac{1}{11} = 0.09$  respectively. The sum of all weights or  $\sum_{i=1}^4 wc_i$  equals 1. These weights will later be used to estimate the personal utility value for each particular user.

$$wc_i = \frac{wv_i}{\sum_{i=1}^4 wv_i}, 0 \leq wc_i \leq 1 \quad (3.2)$$

Table 3.6: Example of user preference

UserID	Travel time	Travel cost	Delay time	Walking time
1	5	5	4	2
2	3	5	3	5
3	5	3	2	1
4	2	1	4	2

### 3.6 Utility Functions

So far this chapter has focused on normalising travel routes and user preferences. The following section discusses the proposed utility functions of the system.

The utility function is a significant element in this recommendation system. The thesis adopts the multi-criteria decision making approach; the weighted sum model. Adopting the weighted sum has a number of advantages in comparison to other available methods in the multi-criteria decision making approach. Firstly, the weighted sum model

is the most widely adopted (Triantaphyllou et al., 1998). The results of this method are being used as a standard evaluation to determine the accuracy of other methods, such as AHP and TOPSIS. In addition, the weighted sum model is the most practical method as it gives acceptable results to decision makers. As a result, the weighted sum model has proved reliable and sustainable when it is applied to building a utility function.

The function calculates the total utility score of each alternative by aggregating the utility score of each decision criterion. After that, ranking lists of travel routes is created based on the order of the calculated score. The best alternative with the highest score is placed at the top of the list and the worst score is placed last. The system divides the calculation of utility scores into two parts. The first aggregates the personal score ( $U_{ij}^{ps}$ ), considering four criteria, namely travel time ( $U_j^{tt}$ ), travel cost ( $U_j^{tc}$ ), delay ( $U_j^{dl}$ ) and walking time ( $U_j^{wt}$ ). The utility function of the personal score can be calculated by using Equation 3.3. The weights of these criteria are extracted from the provided user preferences (see Section 3.5).  $w_{c_i}^{tt}$  denotes the weight of travel time of  $u_i$ .  $w_{c_i}^{tc}$ ,  $w_{c_i}^{dl}$  and  $w_{c_i}^{wt}$  denotes the weight of travel cost, delay and walking time, respectively. The sum of the weights equals to 1, i.e.,  $w_{c_i}^{tt} + w_{c_i}^{tc} + w_{c_i}^{dl} + w_{c_i}^{wt} = 1$

$$U_{ij}^{ps} = w_{c_i}^{tt} \cdot U_j^{tt} + w_{c_i}^{tc} \cdot U_j^{tc} + w_{c_i}^{dl} \cdot U_j^{dl} + w_{c_i}^{wt} \cdot U_j^{wt}, \quad w_{c_i}^{tt} + w_{c_i}^{tc} + w_{c_i}^{dl} + w_{c_i}^{wt} = 1 \quad (3.3)$$

The second utility function calculates the public friendly score,  $U_j^{pfc}$  (see Equation 3.4). In general,  $U_j^{pfc}$  is determined by four cost factors; congestion costs ( $U_j^{cc}$ ), accident costs ( $U_j^{ac}$ ), pollution costs ( $U_j^{pc}$ ) and traffic conditions ( $U_j^{td}$ ). Different weights, i.e., congestion costs ( $w_{c_{cc}}$ ), accident costs ( $w_{c_{ac}}$ ), pollution costs ( $w_{c_{pc}}$ ) and traffic conditions ( $w_{c_{td}}$ ), can be assigned to the four cost factors. To simplify the problem, here, we give the same weight value to the four factors, i.e.,  $w_{c_{cc}} = w_{c_{ac}} = w_{c_{pc}} = w_{c_{td}} = 0.25$ .

The sum of the weights equals 1, i.e.,  $w_{cc} + w_{ac} + w_{pc} + w_{td} = 1$

$$U_j^{pfc} = w_{cc} \cdot U_j^{cc} + w_{ac} \cdot U_j^{ac} + w_{pc} \cdot U_j^{pc} + w_{td} \cdot U_j^{td}, \quad w_{cc} + w_{ac} + w_{pc} + w_{td} = 1 \quad (3.4)$$

The personal score and the public friendly score are eventually integrated by using Equation 3.5. The result of this equation will be used for ranking travel routes. In Equation 3.5, the public goods rate denoted by  $\omega_{pg}$  is the weight of public goods. The higher the public goods rate, the more public-friendly travel routes are recommended by the system. By having  $\omega_{pg}$ , the proposed system is more flexible and able to increase and decrease the degree of recommending public-friendly routes.  $U_{ij}^{total}$  is the total utility score of a travel route  $r_j$  for user  $i$ .

$$U_{ij}^{total} = \omega_{pg} \cdot U_j^{pfc} + (1 - \omega_{pg}) \cdot U_{ij}^{ps}, \quad 0 \leq \omega_{pg} \leq 1 \quad (3.5)$$

### 3.7 Summary

In summary, this chapter has met the research goal and successfully filled the knowledge gap. To the best of our knowledge, there is no record of any literature on recommendation systems that addresses the marginal effects of the transportation sector, i.e., the external costs. In this chapter, a novel recommendation system known as the agent-based public-friendly route recommendation (APF2R), which can address the problem of external costs, has been presented. This recommendation system considers the criteria of external costs in its algorithm and can generate green, safe and less congested travel routes to commuters.

In addition, this chapter has given an in-depth description of and explanation of system architecture. It has shown not only how the system is designed, what methods are used, and why these methods are adopted, but also each component of the system's

architecture. It has also explained how the data was collected and has illustrated how the proposed utility functions aggregate the decision criteria of the travel routes.

The next chapter introduces a reward algorithm as a persuasive element of the proposed recommendation system and a new characteristic of the persuasive recommendation system. In addition, an overview of rewards in the transportation discipline is described.

## **Chapter 4**

# **Persuasive Recommendations with Flexible Rewards**

### **4.1 Introduction**

The previous chapter introduced the overall architecture of an agent-based public-friendly route recommendation in detail. The introduction covered all key components, which include the role of the agents, the travel routes and the utility functions, and it also showed an example of how the system functions in terms of data normalisation, multi-criteria aggregation and recommendations for public-friendly routes.

This chapter presents an additional feature of the proposed system, i.e., the flexible reward algorithm. This facilitates an agent-based public-friendly route recommendation in influencing transport users' decisions, as well as maintaining user satisfaction with the system. This chapter aims to describe the methods used to create the algorithm and also presents a new way to evaluate the persuasiveness of recommendation systems. It is divided into three main sections. The first section gives an overview of rewards in transportation discipline and the second section provides a description and explanation of the proposed flexible reward algorithm. The last section provides further explanation

about the internal design of the user agents that will be used to simulate an individual's judgement and behaviour.

The power of persuasion has been increasingly integrated into recommendation systems, which are known as persuasive recommendation systems. A possible explanation is that building recommendation systems with a persuasive ability gives numerous advantages in comparison to traditional recommendations. A persuasive recommendation provides a means of influencing customers' judgement over recommended options (Bilgic & Mooney, 2005). The customers perceive better satisfaction in terms of recommendation quality when persuasion is introduced (Häubl & Murray, 2003). The persuasive recommendation systems receive more users' responses which leads to better performance in understanding users' preferences and needs (Swearingen & Sinha, 2001). As a consequence, researchers pay much attention to the persuasive aspects of recommendation systems.

Various characteristics of recommendation systems have been identified as being persuasive. In user-centric evaluations, a system that provides transparency to its users is considered to be a reliable system. As this explains how the system generates recommendations, users are more likely to believe and trust the system (Tintarev & Masthoff, 2011). The familiarity of recommended items also indicates persuasive characteristics (Yoo & Gretzel, 2011). Other examples include the amount of information about recommended items, the response time of the system, and even how the system presents recommended items (Cosley et al., 2003). Through having many persuasive characteristics, the system is able to achieve a greater level of persuasion.

In contrast to previous researchers, this study introduces a new characteristic of persuasion into the recommendation system, which is a flexible reward. This new feature can help the proposed system, improve users' satisfaction towards public-friendly routes and also psychologically influence users' behaviours. The section below provides more detail about the flexible reward algorithm.

## 4.2 Definition of reward

Before introducing the reward algorithm, it is worth beginning by defining a reward. A reward is defined differently in various disciplines. In linguistics, a reward can be defined as things that are given in exchange for good behaviour or good work<sup>1</sup>. The terminology considers the relationship between two parties. If the behaviours of one party are acceptable to another party, one will be rewarded. Similarly to linguistics, a reward in business management has more than one function. Giving rewards might enhance the loyalty of employees and customers. It is not only defined as a tool to motivate the workforce to feel satisfied with their organisation alone, but is also a competitive strategy to attract customers, who are targeted of organisations (Kressler, 2003). Efficient workforces are significant in terms of the overall performance and profitability of an organisation, so they are always rewarded. Rewarding new and previous customers is significant for the future of the organisations to maintain customer selection and increase sales. For instance, offering cumulative points to customers is more likely to promote prompt purchases. In the case of business investment, a reward is a vital component of the standard technique that is able to indicate loss and gain (Basu & Nair, 2015). By applying this standard technique as a decision support tool, organisations can measure and identify the risks and rewards of business activities. Alternatively, in the behaviour change theory a reward is a motivational factor that can induce attempts to make appropriate actions or stop misbehaviour (Michie, van Stralen & West, 2011). Overall, the definition of a reward is defined as being based on its function and context.

Reward are a persuasive element. The notion of a reward related to behaviours change has been studied by a numbers of literature in various disciplines. The first serious discussions and analyses of rewards emerged during the early 19th century in

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<sup>1</sup><http://dictionary.cambridge.org/dictionary/english/reward>

social exchange theory when George Homans, a well-known sociologist, published his work. Social exchange theory is always associated with a real-life situation and refers to the exchange of an activity for a reward and a cost between two parties (Homans, 1974). Homans presented three propositions: success, stimulation, and deprivation satiation, and stated that individuals tend to repeatedly take action when they recognise that they will be rewarded for the action. Based on Homan's propositions, this could indicate that the action with a reward attached to it is more preferable. Similarly, behaviour change has been studied in human psychology. Further knowledge came from a study by Fogg (2009). He identified three factors; motivation, ability and triggers, and claimed that individuals could be convinced to choose a target action when they have an adequate number of these factors. The reward and behaviour change are in relation, as shown when they were highlighted by Oinas-Kukkonen and Harjumaa (2009), who studied persuasion theory. By relying on Fogg (2009) 's model, Oinas-Kukkonen and Harjumaa (2009) identified the framework to design and implement persuasion systems. The reward strategy lies in the dialogue support of his framework. Oinas-Kukkonen and Harjumaa (2009) suggested that users who follow the system's instructions should be rewarded and as a result of the virtual reward, the system might receive more persuasive powers (Oinas-Kukkonen & Harjumaa, 2008b). Overall, these studies highlight the evidence that a reward can be used as a motivation to trigger individuals to change their behaviours, and by applying the reward strategy, it indicates that the system has persuasive ability.

This study recognises rewards as a positive encouragement that is given to individuals who are well-behaved to the public. In this case, individuals who select public-friendly routes are rewarded by the system. The reward is not only a mechanism to increase user satisfaction alone, but it is also used to convince individuals to follow well-behaved recommendations, which will bring about a change in behaviour. In the transportation context, rewards can be given in various forms such as points, fuel



discounts, public transport fare concessions and even cash rewards. For example, an individual travelling in their own car can earn a point when they switch to public-friendly modes such as buses and trains. A user can redeem these points as a discount for other services such as fuel, parking and bus fare. With regard to giving rewards, users can contribute achieve benefits for themselves as well as for the public, as they can gain rewards and support the public in reducing external costs. To recommend a public friendly route, e.g.,  $r_j$ , a reward can be given to persuade the user to adopt the recommendation. Hence, we give the formal definition for rewards below.

**Definition 4.2.1.** Reward  $rw_j$  is for balancing the conflicts between the two utility scores of the personal utility score and the total utility ( $U_{ij}^{ps}$  and  $U_{ij}^{total}$ ) for a public-friendly route  $r_j$ . Rewards are attached in route  $r_j$  and act as a positive encouragement that can increase users' satisfaction, influence users' decisions and persuade them to adopt a good behaviours.

### 4.3 Flexible Reward Algorithm

This section gives a clear introduction and description of the proposed reward algorithm. It also has a description of a number of attempts to create the algorithm.

Building an effective reward algorithm creates new challenges. In the proposed recommendation system, the reward algorithm is a balancing factor between the conflicting interests of individual users and the public. The two parties have different utility functions and consider different criteria. Both parties seek to maximise their utilities, and later this leads to a different order of items, unmatched ranks. In this case, the public focuses on public friendly routes without considering the individuals' lifestyle, which cannot be satisfied by the individuals. Therefore, we use rewards to maintain users' satisfaction and persuade them to choose public friendly travel routes. By applying this approach, society benefits from individuals in the form of a public-friendly score, as

well as individuals increase their utility with the rewards provided.

Designing a reward algorithm creates a few challenges. Rewards come with costs, and it is impossible to provide infinite rewards to all individuals. This raises questions about how much the system should provide rewards to individuals with different preferences, and when the system should or should not give rewards.

To overcome these challenges, we experimented with numerous approaches. In the first attempt, we created a prototype function by combining the linear search and the insertion sort algorithm. Initially, since two parties produce different rankings, the linear search looked for the order of an item in both ranks. If the order is unequal, the insertion sort will move the item one position. Each shift of insertion sort will add one value to the recommendation items as a reward. This process continues until every pair of both ranks are equal. It was successful in terms of matching ranks, but failed to explain the meaning of reward value, since it only considered the order of the rank.

The second attempt at creating the reward algorithm considered that the reward is desired mainly from the dissimilar distance between the two ranks, namely the individual rank and the public rank by adopting the displacement function of the Spearman approach (Diaconis & Graham, 1977). Various methods can be used to measure and calculate the distance between ranks. Yao (1995) proposed an evaluation framework, based on Kemeny and Snell's distance function, to estimate the total value of the agreement between two rankings on the ordinal scale. However, its main purpose is to evaluate the efficiency of the system's performance. Similarly, the distance between ranks has been widely studied in the statistics arena. Kendall's Tau, Pearson and Spearman's Footrule is currently the most popular approach to measuring the rank correlation. This attempt allows the researcher to gain an understanding of the distance between ranks. However, it only captures the difference between two ranks but still cannot explain the meaning of the reward value.

After many attempts, we finally achieved the reward algorithm shown in Equation

4.2. This algorithm takes the distance between two ranks and the utility values of items into consideration when determining reward values. It also defines the maximum value that the system can provide to users to sustain the value of the reward. This reward algorithm is flexible because it is able to adjust the reward value by introducing the incentive rate.

$$U_j^{imb} = \begin{cases} |U_{ij}^{total} - U_{ij}^{ps}|, & \text{if } rkP_j > rkG_j \\ 0, & \text{otherwise} \end{cases} \quad (4.1)$$

$$rw_j = \gamma \cdot (U_j^{imb}), 0 \leq \gamma \leq 1 \quad \text{and} \quad rw_j \leq U_j^{pfc} \quad (4.2)$$

A reward value can be calculated by using Equations 4.1 and 4.2. Equation 4.1 aims to calculate the imbalanced values of the alternative  $j$ .  $U_j^{imb}$  denotes such imbalanced value among two different utility scores, i.e.,  $U_{ij}^{total}$  and  $U_{ij}^{ps}$ .  $U_{ij}^{total}$  refers to the total utility score, whereas  $U_{ij}^{ps}$  is the personal score (see Section 3.6). In Equation 4.1,  $rkP_j$  denotes the order of the alternative  $j$  in the ranking of the individual, and  $rkG_j$  is the order of  $j$  in the ranking of the public ( $U_j^{total}$ ). The value of  $U_j^{imb}$  depends on two conditions. If  $rkP_j$  is higher than  $rkG_j$ ,  $U_j^{imb}$  will be equal to the subtraction of  $U_{ij}^{total}$  and  $U_{ij}^{ps}$ . Otherwise,  $U_j^{imb}$  equal to 0. These two conditions validate the fairness of distributing rewards among individuals in the society. The system only provides a reward when individuals have a different rank order.

After having the imbalanced value, the reward can be distributed. However, to make the agent-based public-friendly route recommendation or the proposed system more flexible, an incentive rate is introduced. The rewards differ in value depending on the incentive rate ( $\gamma$ ). The incentive rate denoted by  $\gamma$  determines the rate of giving a reward. It also determines the level of persuasion of the proposed system as well as the level of overriding previous behaviours of individuals. This rate has a value between  $0 \leq \gamma \leq 1$ . The value of 0 will return no reward to individuals, while a factor

approaching 1 increases the persuasion of the proposed system by returning higher rewards, but not exceeding the benefit of the system regarding the public-friendly score  $U_j^{pfc}$ .

## 4.4 Evaluation of Persuasion and Behaviour Change

This section provides a new approach to evaluate the persuasiveness of a recommendation system towards a change in behaviours. According to Cremonesi et al. (2012), investigating in developing new methodologies to evaluate the influence of recommendation systems at a sub-conscious level is limited.

This study demonstrates, for the first time, that the agent-based model has been used to evaluate the impact of persuasiveness of recommendation systems on an individual's behaviour. The overview of the architecture of the proposed multi-agent based system was presented in Section 3.3 in Chapter 3. This section gives more detail about the internal design of agents and their functions.

In general, the effectiveness of recommendations in terms of persuasiveness can be evaluated by involving users. Unfortunately, such an approach has some difficulties. Relying on real participants requires a considerable amount of time to manage, collect and process the participants and their responses. Differently to other studies, evaluating the persuasion of the proposed system will be conducted through simulations, using an agent-based model. Since the proposed system is designed based on a multi-agent architecture, a simple user agent is supplemented by extra functions, i.e., knowledge comparison and reaction functions. The internal design of a UA is presented in Figure 4.1. A UA is designed to simulate a humans' judgement and behaviour. A UA has the function of making a judgement about the recommended items, which is known as the knowledge comparison function. If the recommended items from the RA conflict with the internal knowledge of a UA, UA will respond by changing its state. This response is

based on functions known as reaction functions. UA has two states, i.e., the passive state and the active state. The passive state refers to dissatisfaction towards the recommended items, while the active state refers to satisfaction. A UA has internal knowledge, which refers to experience and knowledge of the environment. In our case, this means an internal rank. Equation 4.4 was used to generate an internal rank. In this equation,  $U_{ij}^{ps}$  represents the satisfaction of individuals. In addition, reward ( $rw_j$ ) is also considered as a factor affecting an individual's satisfaction. An explanation of other parameters of UA can be found in Chapter 3.

To make a judgement about recommended items, UAs use a knowledge comparison function. This function measures the distance between the internal ranks and a recommended list by using Spearman's rank correlation coefficient (Equation 4.3) (Spearman, 1904). The function returns a value between 0 to 1 and the greater distance between two ranks, the lower results of the coefficient will be. In Equation 4.3,  $n$  denotes the number of observations. For example, if there are 12 routes for observation,  $n$  will be 12.  $d$  denotes the difference between the two ranks of each observation and  $S_{degree}$  denotes the satisfaction degree of UAs. As mentioned previously, the value of  $S_{degree}$  is between 0 to 1. UAs change state whenever  $S_{degree}$  is less than the system threshold; otherwise, the state remains the same. The system threshold, known as the threshold of state changing is denoted by  $ST_{change}$ , and is defined by a simulator controller.

$$S_{degree} = 1 - \frac{6 \sum d^2}{n(n^2 - 1)} \quad (4.3)$$

$$U_{ij}^{ps} = (wc_i^{tt}U_j^{tt} + wc_i^{tc}U_j^{tc} + wc_i^{dl}U_j^{dl} + wc_i^{wt}U_j^{wt}) + rw_j \quad (4.4)$$

Regarding another agent in the proposed system, RA uses Equation 3.5 to calculate travel routes and recommends a set of routes to the UAs based on their preference. It is active whenever it receives travel routes requests from the UAs. A goal of this agent

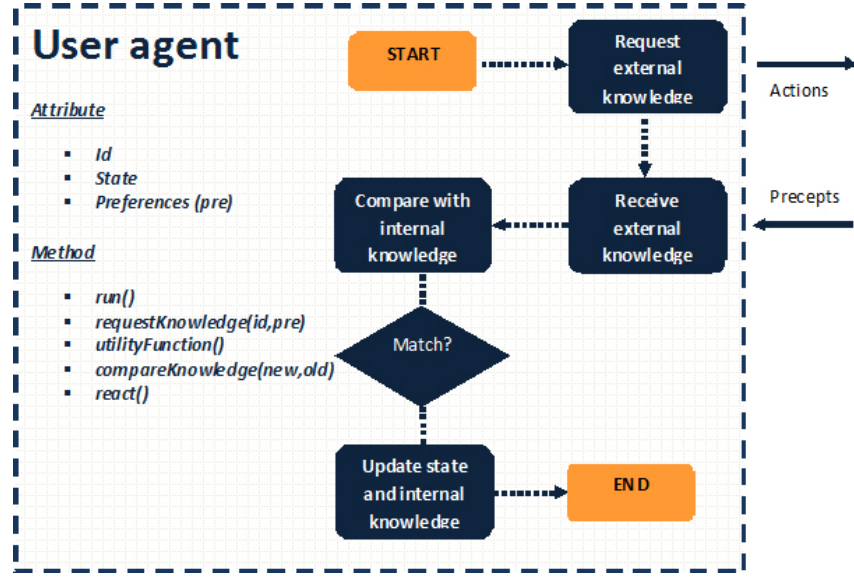


Figure 4.1: Internal design of user agents

is to maximise the UAs' satisfaction as well as the total public-friendly score ( $U_j^{pfc}$ ). This is accomplished by using the incentive rate in the reward algorithm (Equation 4.2). However, this rate needs to be assigned before running the simulation as well as the threshold of state changing.

## 4.5 Summary

This chapter has successfully fulfilled the research objective and several knowledge gaps. Firstly, it introduced a new characteristic of recommendation systems that is capable of maintaining user satisfaction and influencing transport users to follow well-behaved behaviours by applying the reward strategy in the persuasive system design (PSD) model. The reward algorithm used here considers both the distance between two ranks and the utility scores of the parties, so it can be beneficial for other researchers who are looking for a way to balance two conflicting parties. It could also help other types of persuasive technology to achieve a higher level of satisfaction.

This chapter fulfilled knowledge gaps in measuring the effects between persuasive elements of recommendation systems, with reference to changing the behaviour of individuals, by presenting the novel architecture of the internal agent. It consists of several unique functions; the knowledge comparison and reaction functions. These functions can support other researchers in evaluating other kinds of products in multi-criteria recommendation systems apart from travel routes.

In addition, this chapter identified various definitions of a reward from a number of disciplines. The formal definition of a reward and some examples of reward related to the transportation context have been provided. It has thoroughly explained the reward algorithm and how the algorithm works.

The next part of this thesis focuses on an evaluation of the proposed system in terms of the amount of the public-friendly score, the personal score and persuasiveness in different scenarios. The experimental design results will be described and analysed. It also discusses and compares the findings of the proposed system with the previous literature in detail as well as identifying a few strengths of the system.

# **Chapter 5**

## **System Evaluation**

### **5.1 Introduction**

The previous chapter introduced the flexible reward algorithm for route recommendations in a thorough manner. The definition and functions of a reward in various disciplines was provided. It also presented a new way to evaluate the persuasiveness of recommendation systems. Additionally, the basic background of theoretical methodology used to construct the reward algorithm was explained in detail.

This chapter illustrates the experimental results for evaluating the performance of the proposed system, the agent-based public-friendly route recommendation and the flexible reward algorithm. Meanwhile, the chapter includes a discussion about the research findings by comparing them with some of the existing literature on both the theoretical and practical aspects. Strengths of the proposed system are also identified and presented.



## 5.2 Design of the Experiment

This section provides in-depth information about the experimental design and the tools were used. It is divided into two main sub-sections. To evaluate the performance of the proposed system, two experiments were designed. The first experiment focused on a comparison of the total public-friendly scores and the personal scores, whereas the latter experiment evaluated the persuasion power of the proposed system. The evaluation compares the outcome in two traffic scenarios, i.e., normal time and peak time. Before moving into more detail about the experimental design, it is necessary to explain the data collection and the environment when running the experiments.

The data used for the experiments needed to contain the information about travel routes and user preferences. In the research, the user data was generated randomly with 10 and 100 simulated users (See Appendix A). The data of travel routes was manually extracted from *Google Maps* and the *Journey Planner* of *Auckland Transport*. The data was collected in two different time stamps one from the normal hours (10:20am) and one from the peak hours (8:20am). The origin (O) of the users was the three campuses of Auckland University of Technology (AUT), and the destination (D) was the Sky Tower. There are three Origin-Destination requests (ODs): AUT city campus to the Sky Tower (OD1), AUT north campus to the Sky Tower (OD2) and AUT south campus to the Sky Tower (OD3) (See Appendix B). In this study, the environment that ran running all the experiments was the Windows 10 Enterprise 64bit operating system with Intel(R) core i-5-4570 3.20 GHz CPU and 16 GB RAM. The following sections will give more detail about the experimental designs.

### 5.2.1 Comparison With the Conventional Approach

In Experiment 1, the proposed public friendly recommendation approach (PF) was compared to the fastest route recommendation approach (FR). The FR recommends

routes based on the time of travelling. This experiment measured total public-friendly scores and personal scores in two traffic scenarios, i.e., normal time and peak time. A total public-friendly score is the sum of the public-friendly scores (refer to Equation 3.4) of the top-n recommended routes. The total personal score is the sum of the personal scores (refer to Equation 3.3) of the top-n recommended routes.

The total public-friendly score and the total personal score are indirect factors in measuring the performance of PF and FR. These scores are calculated by the utility functions of individuals and the public. As mentioned previously, the personal score considers user preference, whereas the public-friendly score considers both user preferences and external costs. Therefore, the outputs from such utilities indicate the satisfaction level of the two parties.

A Java application was developed to compare the output of the two recommendation systems, i.e., PF and FR. The data of user preferences and travel routes are the CSV files. Both systems received the input data by reading directly from these files. FR generates top-n recommendations for each user and also calculates the total personal score and the total public-friendly score at the same time. FR does not have any particular setting, but PF, the proposed system, needs to define one significant parameter before running the experiment, i.e., the public goods rate (refer to Equation 3.5). The public goods rate denoted by  $\omega_{pg}$  is the weight of public goods and has a value between 0 to 1. The higher the public goods rate, the more public-friendly travel routes are recommended by the proposed system. By having  $\omega_{pg}$ , the proposed system is more flexible and able to increase and decrease the degree of recommending public-friendly routes. However, it is hypothesised that the personal score might drop, if  $\omega_{pg}$  is increased.

Like other route planners and navigation systems like Mapquest<sup>1</sup> and TomTom<sup>2</sup>, FR treats the time of travel as the highest priority as shown in Equation 5.1. This is

<sup>1</sup><https://www.mapquest.com/routeplanner>

<sup>2</sup><https://www.tomtom.com/drive/car/>

where  $U_j^{fr}$  denotes the value used to rank the alternative  $j$  and  $U_j^{tt}$  is the value of travel time as a single criteria. It recommends routes with the shortest travelling time to individuals without considering the marginal impacts to the public, such as congestion costs, accident costs and pollution costs. The routes from the FR might be favoured by some individuals who only care about their own benefit, but it might not be suitable for individuals who consider the public as the first priority.

$$U_j^{fr} = U_j^{tt} \quad (5.1)$$

There are a few reasons to answer as to why FR has been selected as for a comparison approach. A major reason is that there is no record about recommendation systems that focus on the impacts of the route chosen, especially the external costs. Another reason is that there is no available data about route ratings to create new content-based filtering and collaborative filtering recommendations. It requires a degree of user ratings over travel routes in order to create recommendation systems from such well-known approaches. As a result, FR was selected to be a counterpart system to compare PF with.

### 5.2.2 Evaluating Persuasion of the Proposed System

In Experiment 2, the impact of the proposed system on users' behaviours was investigated by using an agent-based model. The purpose of this experiment was to evaluate the persuasiveness of the proposed reward algorithm as the persuasive feature. It is believed that modelling human behaviours is highly complicated. This study, therefore, focuses on a ranking task. The ranking task was adopted from the studies by Moon (1998); Andrews and Manandhar (2009). They state that the persuasion of a system can be measured in terms of the ranking tasks, and the evolution of distance of users' ranks implies a change in human behaviour and the persuasive power of the system.

To simulate human behaviours, an agent-based model was built using MASON (See Appendix C). MASON<sup>3</sup> is an open-source discrete-event multi-agent simulation tool written in Java. The architecture of MASON consists of three main layers; the model layer, the utility layer and the visualisation layer (Luke, Cioffi-Revilla, Panait, Sullivan & Balan, 2005). The model layer is a collection of classes that are responsible for scheduling discrete events and schedule utilities. The utility layer facilitates various functions like movies and snapshot-generating, and a random number generator. The last layer, the visualisation layer, is separated from the others and as a result, it allows modellers to freely integrate or separate a model and its visualisation. This layer can be used to visualise GUI and to manipulate the model. MASON has proved its efficiency by being widely implemented to simulate multi-agent based models in many disciplines such as machine learning, swarm robotics and social complexity. In this context, MASON facilitates the human behaviour model. A clear architectural explanation of the agent-based model can be found in Section 4.4.

Prior to running the simulation, there were three crucial parameters that needed to be defined, i.e., the public goods rate, the incentive rate and the threshold of state changing. Similarly to the previous experiment, the public goods rate denoted by  $\omega_{pg}$  needs to be defined. The second parameter is the incentive rate denoted by  $\gamma$ . It determines the rate of giving a reward and the level of persuasion of the proposed system, as well as the level of the overriding previous behaviours of individuals. The last parameter is the threshold of state changing. This parameter is denoted by  $ST_{change}$ . A more detailed explanation about these parameters can be found in Chapter 4. These parameters have a value between 0 to 1. ,i.e.,  $0 \leq \omega_{pg} \leq 1$ ,  $0 \leq \gamma \leq 1$  and  $0 \leq ST_{change} \leq 1$ . It is hypothesised that a number of user agents with active state will slowly decrease, if  $\omega_{pg}$  is increased. However, when increasing  $\gamma$ , the number of user agents with an active state will increase.

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<sup>3</sup><http://cs.gmu.edu/~eclab/projects/mason/>

## 5.3 Experimental Results

The previous section explained the design of the experiments. This section will report the results obtained from Experiment 1 and Experiment 2.

### 5.3.1 Results from Experiment 1

To compare the performance of the proposed system in terms of being public-friendly, a dataset with 10 simulated users was run. Both PF and FR recommended three travel routes to each user at the top-n setting. The sum of the public-friendly scores and the sum of the personal scores of the recommended routes were calculated. In every ODs,  $\omega_{pg}$  of PF was set at 0, 0.5 and 1 ( $\omega_{pg}$  0,  $\omega_{pg}$  0.5 and  $\omega_{pg}$  1).

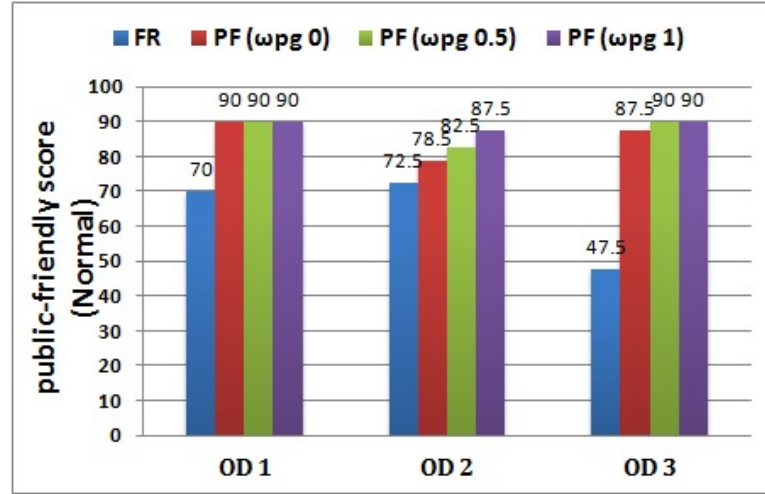


Figure 5.1: Comparison of public-friendly scores in normal time

Figure 5.1 illustrates the result of the total public-friendly score of FR and PF in the normal time scenario. What is striking about the figures is that in all ODs the public-friendly score of the PF is higher than for FR. The explanation might be FR did not consider criteria, such as travel cost and delay, but only considered the travelling time, which may not be accepted by some transport users who prefer other criteria over the travelling time. For example, in OD3, the public-friendly score of FR is 47.5, while the

PF starts with a value of 87.5. The value of PF is almost double the value of FR. Further analysis showed that the results of PF varied in value when  $\omega_{pg}$  increased. Confirming the hypothesis, the total public-friendly score of PF increased when  $\omega_{pg}$  is approaching to 1. However, no increase in public-friendly score of OD1 and OD3 was detected after increasing  $\omega_{pg}$  to 0.5. This is because the experiment defined the value of the external costs based on transportation mode, and the bicycle and walking modes have similar values. Although the values were identical at 90, further analysis of the recommended routes showed that the set of recommended routes was different.

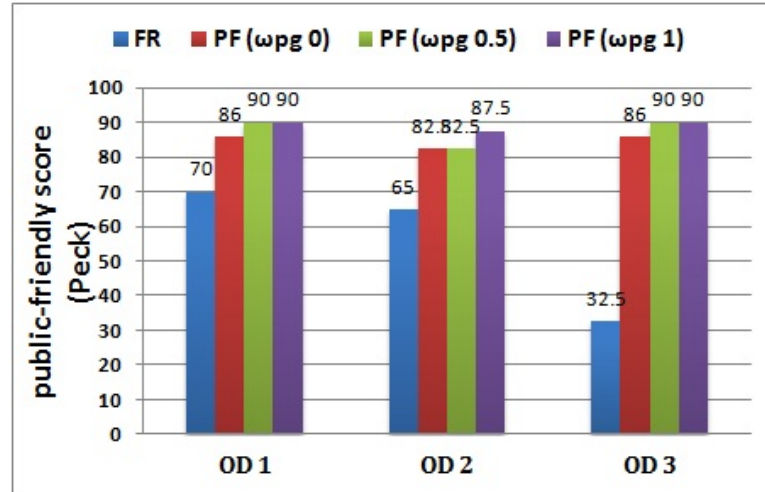


Figure 5.2: Comparison of public-friendly scores in peak time

Figure 5.2 presents the results of the total public-friendly score of FR and PF in the peak time scenario. Similar results were produced at the peak scenario. The total public-friendly score of PF increase when  $\omega_{pg}$  is approaching to 1 and the total public-friendly score of PF in all ODs is higher than the FR. In OD3, for instance, the total public-friendly score of PF is almost the triple of the FR (32.5 and 86). When considering both scenarios, the results of PF have slight differences, but the public-friendly score of FR decreased in the peak time. A possible explanation for this might be that car mode created less public-friendly score due to the traffic condition at peak time and FR always recommends car routes. Overall, the experiment was successful as it showed that the

performance of PF outperforms FR in terms of the total public-friendly score. These results suggest that the public goods rate or  $\omega_{pg}$  allows the proposed system to have more flexibility in promoting diversity as public-friendly routes in the recommendations.

Turning now to the experimental evidence on the personal score, Figures 5.3 and 5.4 show the total personal score of FR and PF in normal and peak time scenarios. Similarly to the previous results, at the beginning, where  $\omega_{pg}$  equals 0, the total personal scores in all the ODs of the proposed system are higher than FR in both scenarios, but when the value of  $\omega_{pg}$  was increased, the total personal scores were slightly decreased, especially when the  $\omega_{pg}$  equals to 1. This experimental results paralleled the hypothesis. What is surprising is that no decrease was found at OD1. An explanation for this might be that the travelling distance of OD1 is quite short and both systems recommended the walk mode, which is the fastest route as well as the most public-friendly route. Taken together, these results suggest that the proposed system should be flexible in setting the public goods rate. Too high and the public goods rate decreases the personal score, leading to less user satisfaction.

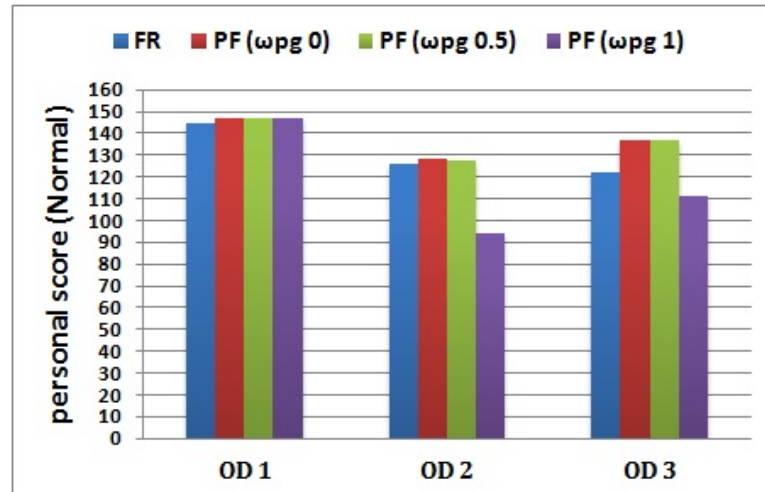


Figure 5.3: Comparison of personal scores in normal time

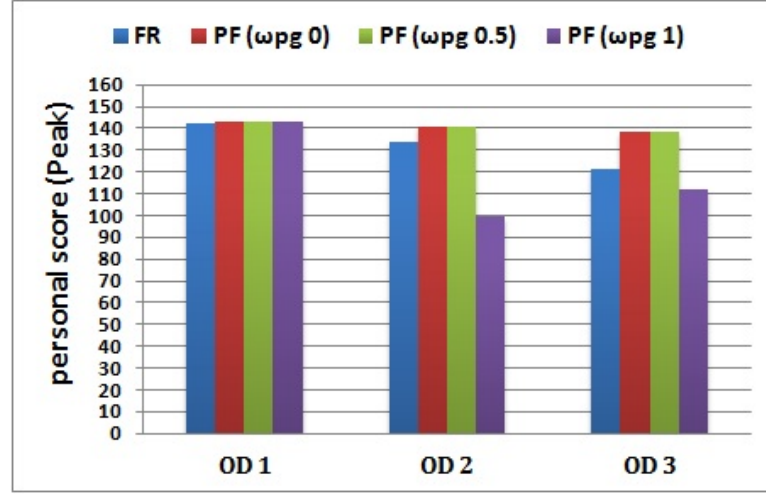


Figure 5.4: Comparison of personal scores in peak time

### 5.3.2 Results from Experiment 2

In Experiment 2, the impact of the proposed system in terms of user's behaviour is investigated. A dataset of 100 simulated users was used in Experiment 2. The state changing threshold of the UAs was set at 0.7. The incentive rate or  $\gamma$  was set between 0 and 1. The  $\omega_{pg}$  was placed at 0.7. The simulation expected there to be an increase in active agents when the value of the incentive rate was raised.

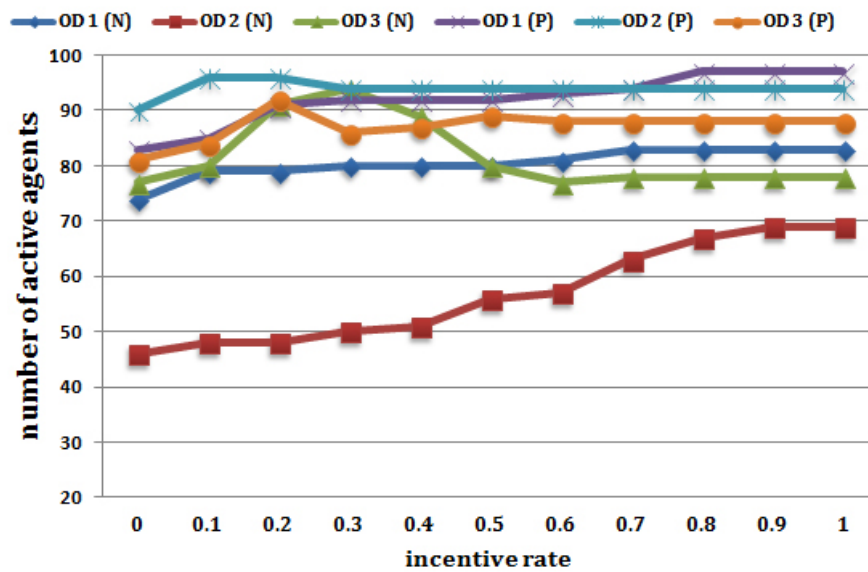


Figure 5.5: Evaluation of persuasion of the system in the three ODs



Figure 5.5 presents the experimental results of three ODs with two scenarios: normal (N) and peak time (P). What stands out in this figure is that the number of active agents increased in each OD when the incentive rate approached 1. This means more users were satisfied with the recommended routes when the system provided more rewards. When comparing the two scenarios, the peak time of all ODs has a higher number of active agents at the beginning. This shows that user agents are aware of a change and adapt themselves to maximise their utilities. This, therefore, suggests that UAs do not need much incentive at peak time. One unanticipated finding was the fluctuation. During the values of 0 to 0.5 of the incentive rate of OD3, a number of active agents rose and fell in both scenarios. This fluctuation could be explained by the fact that the distance of the user agents' internal rank and the recommended rank are quite close and reach a point where adding rewards to some items impacts other items in the rank. This suggests that the incentive rate should vary, depending on the time of the day and the ODs. Taken together, these findings suggest that the proposed system is able to persuade user agents to evolve the distance of their internal ranks. With regard to Andrews and Manandhar (2009), the measured persuasion of the system influences the internal beliefs as well as the behaviours of users. The results in this section indicate the success of the validation between the proposed system and the hypothesis. The next section, therefore, moves on to discuss the findings in a thorough manner.

## 5.4 Discussion

So far this chapter has demonstrated the results of the experiments. The following section discusses the findings and implications of this investigation. It identifies the strengths of the proposed system, the agent-based public-friendly recommendation system, and the flexible reward algorithm.

This study aimed to construct a recommendation system that can address the negative impacts, the external costs, in the transportation sector. To the best of our knowledge, there is no previous study that has investigated using a route recommendation system to cope with external costs. The results of this study indicate that the proposed recommendation system, known as the public-friendly recommendation system, is able to recommend a public-friendly route. When compared to the conventional recommendation system, the proposed system shows a superior performance in terms of its public-friendly score. This is because it takes the criteria related to the external costs into account when making a recommendation and aggregate such criteria effectively, i.e., the congestion costs, accident costs, pollution costs and traffic condition costs. Unsurprisingly, the public goods rate ( $\omega_{pg}$ ) allows the proposed system to be more flexible in suggesting different degrees of public-friendly routes and can be easily modified to respond to altered scenarios. This result may be explained by the fact that the proposed recommendation takes advantage of the weight sum model, which relies on the relative weight. With regard to the personal score, the experiment results paralleled the hypothesis. When introducing more public-friendly routes, the personal score or the utility of individuals dropped slightly. This may be explained by the fact that the criteria of the external costs conflicts with the personal criteria. Taken together, these findings suggest that the proposed system is successful in generating public-friendly routes. It is flexible due to the weight of the public goods rate, but setting the wrong weight will drop user satisfaction. Therefore, setting the right weight for different user preferences and in the right circumstances needs further investigation.

As mentioned in the literature review, when adding persuasive features, recommendation systems have the ability to convince users to choose recommended items, which leads to a change in their behaviours. In the current study, investigating the impact of persuasive features on an individual's behaviour showed that more virtual users are satisfied with the recommended routes when the system provided more persuasion and

are willing to change their behaviours. These results are likely to be related to the fact that users often use recommendation systems when they lack knowledge and an ability to make a judgement in the complex environment. When they are in need, they are easily persuaded by recommendation systems, particular when rewards are used. These results seem to be consistent with other research. According to Häubl and Murray (2003) and Swearingen and Sinha (2001), persuasive recommendation systems have better satisfaction in terms of recommendation quality and obtain more responses from users. Additionally, a study by Gkika and Lekakos (2014) shows that although users may have little interest in recommended items, when they are introduced to a persuasive strategy they increasingly adopt the recommendations.

The present study has many possible implications. With the ability to promote public-friendly routes, the use of the proposed system will lead to positive impacts in the transportation sector. For example, if the system was used by many commuters, societies could reduce not only a significant transportation pollution, but also achieve greater transport efficiency and better transport safety, which is beneficial for both individuals and the public. Although recommendation systems present recommendations that conflict with individual's interest, they are content. In our case, we discovered individuals are at first reluctant to consider the external costs when making travel decisions, but when they receive a trade-off in return, they become more willing to embrace the external costs. In other cases, the findings of this thesis could be used to help promote other society friendly behaviours, such as the disposal of household waste and energy conservation in the workplace.

A key strength of the present study was the flexibility of the algorithm, which was used to provide recommendations to individuals. Various settings of the proposed system are able to be modified to respond to various types of users and situations. The proposed system can adjust not only to the level of recommending a public-friendly route, but also to tune the level of persuasion. For example, the public goods rate

allows the proposed system to adjust the level when recommending public-friendly routes. Another strength is that the proposed system can increase the user satisfaction of recommended routes without coercion or intervention. Besides that, the proposed reward algorithm treats various individuals equally without bias by considering both the utility values and the distance of ranks. As a result, each individual receives moderate rewards in a sensible way.

## 5.5 Summary

This chapter has illustrated the evaluation of the proposed system, the agent-based public-friendly route recommendation and the flexible reward algorithm. It has shown the experimental design of two experiments including the comparison between the proposed system and the fastest route recommendation system, and the evaluation of the persuasiveness of the reward algorithm. The results of the experiments have been comprehensively presented and discussed. In addition, this chapter has shown several strengths of the proposed system.

The next chapter provides a summary of the ideas of this research, including all theoretical and practical aspects. It restates the problems that this research has tried to answer and the methodology used. Some achievements are noted, as well as a lesson learnt. Future work for the research is presented, in addition to the limitations of the research.

# **Chapter 6**

## **Conclusion**

### **6.1 Research Findings**

The majority of transport users are likely to overlook a considerable number of the negative impacts that they generate. In many cases, such impacts have a strong correlation with the way that transport users choose to travel. For example, if transport users choose to travel by personal cars, they would arrive their destination early in comparison to walking. However, the personal car generates more negative costs to society when compared to the walking mode. Such impacts are one of the main causes of many traffic problems, including traffic pollution, congestion and accidents, and has become a serious obstacle that prevents many countries from becoming sustainable societies. With the increase in urban mobility, these impacts are likely to grow in the near future.

To overcome this problem, this thesis has presented a novel route recommendation system to facilitate transport users and to support society to mitigate the external costs. The system presented aims to provide public-friendly recommendations, along with providing a mean of persuading transport users' decisions. Instead of recommending the fastest routes that regularly generate a high degree of the external costs, the proposed

system alternatively provides green, safe and less congested recommendations, which are beneficial to both individuals and the public. In addition, this research introduced a novel reward algorithm as a persuasive element that could be used by other researchers to balance two conflicted parties with the utility values and ranks. Further, this study has demonstrated that an agent-based model is capable of being used in evaluating the persuasiveness of recommendation systems.

This research has answered the two main research questions and the multiple sub-questions. The following paragraphs summarise the answers.

Firstly, the present study has presented a new recommendation system that can address the problem of negative impacts, i.e., traffic pollution, congestion and accidents, that are generated by the transportation activities. The experiment successfully showed that the proposed route recommendation system, known as the public-friendly recommendation system, is able to flexibly recommend a public-friendly route for individuals. The results confirmed that when introducing more public-friendly routes, the value of external costs represented by the public-friendly score decreased, as did user satisfaction. The findings suggest that if the public goods rate is too high the value decreases the personal score, leading to less user satisfaction. When compared to the conventional recommendation system, the proposed system has shown a superior performance in terms of the public-friendly score. With the ability to promote public-friendly routes, our society could reduce not only a large amount of transportation pollution, but also have greater transport efficiency and better transport safety.

The second aim of this study was to investigate the effects of persuasive elements in recommendation systems in relation to behaviour change by proposing new characteristics for recommendation systems. The investigation of the flexible rewards in the simulation environment has shown that the proposed persuasive reward is able to persuade user agents to improve the distance of their internal ranks. These results indicate the influence of rewards and the changes of an individual's behaviour. This

study has demonstrated that a reward can be used as a new characteristic in recommendation systems as it can persuade transport users to choose recommended routes without coercion. The analysis of the experimental results undertaken here has extended our knowledge about the effects of persuasive elements in recommendation systems and behavioural change. The change in the distance of an individual's rank that we captured offers valuable evidence to prove the capability of persuasive recommendation systems.

## 6.2 Limitations

So far this chapter has focused on presenting the achievements of the research. The section below discusses several limitations of the study. There are potential shortcomings that could affect the results of the study. These are as follows.

A major limitation of the proposed system is that the proposed recommendation algorithm takes only user preferences into account when generating recommendations. It does not consider other user data, such as demographic data and the capability of the users. This proposed system could result in a low degree of satisfaction when it is evaluated by different groups of users. Elderly people, for instance, have different demographic data (e.g., age and physical ability) in comparison to young people. They might perceive recommended routes differently and perhaps feel unsatisfied with the recommendations, which require a lot of physical movement like bicycle and walking routes. They are likely to prefer public transportation routes rather than bicycle or walk modes.

Secondly, this study was limited by the small sample of travel routes collected manually and synthetic user preferences. Synthetic user preferences could affect the calculation of the relative weights in relation to the decision criteria. In the real environment, users could provide the values of the relative weights differently. In addition, though the samples of the travel routes were collected from well-known traffic

providers, the values of criteria in the travel routes vary, based on a variety of factors such as incidents and events. Therefore, the limitations caused by these factors could lead to generalisations.

Thirdly, the method used in this study has its limitations. We used the weighted sum model as a main approach to aggregate travel decision criteria. Although it is the most frequently used and most practical method for aggregating a number of conflicting criteria, this method encounters difficulties when solving multi-dimensional decision-making problems. Further research on using other methods of the multi-criteria decision approach needs to be undertaken to evaluate the real effectiveness of the weighted sum model.

The study was also limited to the fixed default setting of two parameters in the study, namely the public goods rate and the incentive rate. It was not a practical method to apply in real circumstances where the system provides services simultaneously to a number of different types of real users.

Lastly, one of the shortcomings in this study that could have impacted the measurements of the level of persuasion and the users' behaviours was the function that generates an internal rank of user agents. It is assumed that this function represents user satisfaction and that individuals prefer rewards. This assumption can only apply for some individuals, but might not be applicable in other cases.

### **6.3 Future work**

In this thesis, the proposed system was presented as a way mitigate external costs and to persuade transport users to follow appropriate behaviours. To effectively implement the proposed system in the real scenario, the aforementioned limitations need to be addressed and more work needs to be done. Several possible future research areas are provided, as follows.



First of all, more research is required to investigate in gathering user data, such as the criteria weight and demographic information in an implicit way. This data is crucial in understanding the user needs, but in many cases it requires user time and effort. Therefore, with implicit ways to automatically extract user data, such as browsing behaviour, historical records and social network data, transport users might feel better satisfied with recommendation systems. Over time, this could bring about greater persuasive abilities.

Another possible area of future research would be to determine the correlation between three factors - the ability of users, the willingness of users and the power of persuasion on a route recommendation system. It is believed that humans do not need much triggering when these factors are met in some degree. Thus, being able to comprehend this kind of relationship might bring success in changing human behaviour and would provide more flexibility and robustness in persuasive recommendation systems.

Another question that needs further investigation is about whether the persuasive algorithm proposed in this thesis is also suitable for other domains apart from travel routes. It would be necessary to apply the proposed persuasive algorithm to other dominant products such as books and movies where the dataset is available. Further findings on this matter would help us to establish a greater degree of influence on persuasive recommendation systems.

Future research needs to examine the links between user interaction and persuasive ability more closely. To investigate this matter, a well-designed interface of a persuasive route recommendation system should be developed. It should be able to integrate with other commercial systems, like navigation system and mobile applications. Properly designed, with a user friendly interface and interaction capabilities, this system could bring about important findings and contribute valuable knowledge to the field of persuasive recommendation systems.

Finally, it would be interesting to examine other social psychological incentives such as social facilitation and social comparison, and combine them with the proposed persuasive algorithm in persuasive recommendation systems, especially in the context of the social network. According to social comparison theory, humans have an ability to evaluate and adjust to fit into society by comparing themselves with others. If individuals can share how much of the public-friendly score they have contributed with their friends, this might improve their self-esteem as well as creating a means of gently triggering others in the community. When this appears to be the case, choosing public-friendly routes would become a social norm and the external costs would not be a problem for the future.

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# Appendix A

## User preference data

Table A.1: user preference for 10 simulated users

ID	UserID	Travel time	Travel cost	Delay time	Walking time
1	1	3	4	2	3
2	2	3	3	4	1
3	3	5	3	5	5
4	4	3	5	5	3
5	5	3	4	3	2
6	6	2	2	5	4
7	7	5	4	4	4
8	8	4	5	3	3
9	9	5	3	3	5
10	10	1	2	4	5

Table A.2: user preference for 100 simulated users

ID	UserID	Travel time	Travel cost	Delay time	Walking time
1	1	5	5	2	5
2	2	2	3	2	4
3	3	4	1	4	4
4	4	4	1	1	5
5	5	3	5	4	2
6	6	4	4	2	5
7	7	4	1	2	1
8	8	5	2	3	4
9	9	1	4	1	2
10	10	1	2	1	3
11	11	2	4	3	1
12	12	3	1	2	5
13	13	4	4	3	3
14	14	1	2	2	2
15	15	2	5	3	3
16	16	2	3	3	3
17	17	3	1	2	1
18	18	2	3	1	2
19	19	4	5	2	4
20	20	5	5	2	4
21	21	4	3	2	3
22	22	2	5	3	1
23	23	1	4	5	3
24	24	1	5	1	5
25	25	3	5	3	3
26	26	5	4	2	1
27	27	4	4	2	4
28	28	2	3	2	2
29	29	5	3	4	5
30	30	3	2	1	1
31	31	1	4	3	3
32	32	2	4	1	2
33	33	2	5	2	3
34	34	2	2	1	5
35	35	2	3	2	3
36	36	4	2	1	1
37	37	4	2	4	4
38	38	4	4	5	4
39	39	1	5	2	4
40	40	4	5	2	5

ID	UserID	Travel time	Travel cost	Delay time	Walking time
41	41	3	1	1	5
42	42	1	3	5	2
43	43	3	2	4	4
44	44	3	5	1	2
45	45	5	3	3	3
46	46	5	1	4	1
47	47	1	2	3	2
48	48	4	4	1	5
49	49	3	4	1	1
50	50	1	2	3	4
51	51	3	1	3	4
52	52	3	4	2	2
53	53	1	3	5	4
54	54	5	1	4	2
55	55	2	3	4	3
56	56	4	5	1	5
57	57	1	5	4	3
58	58	2	2	2	4
59	59	2	1	2	2
60	60	1	3	5	2
61	61	3	2	1	3
62	62	1	5	4	5
63	63	3	3	2	1
64	64	5	5	5	3
65	65	3	2	4	5
66	66	3	1	2	4
67	67	4	3	3	2
68	68	2	1	2	2
69	69	4	4	2	2
70	70	3	3	1	1
71	71	2	3	2	1
72	72	5	5	3	1
73	73	4	4	5	1
74	74	1	4	1	2
75	75	2	4	4	4
76	76	2	3	1	3
77	77	1	3	2	5
78	78	1	5	1	5
79	79	1	3	3	1
80	80	5	5	5	2

<b>ID</b>	<b>UserID</b>	<b>Travel time</b>	<b>Travel cost</b>	<b>Delay time</b>	<b>Walking time</b>
81	81	3	3	4	4
82	82	1	2	5	3
83	83	5	3	2	4
84	84	2	3	4	3
85	85	2	4	3	2
86	86	3	4	3	5
87	87	2	2	3	4
88	88	5	2	2	5
89	89	2	3	1	2
90	90	1	2	1	5
91	91	1	3	1	2
92	92	3	4	1	3
93	93	1	5	2	4
94	94	4	5	1	4
95	95	3	2	3	2
96	96	3	4	1	4
97	97	1	1	5	4
98	98	3	1	5	3
99	99	3	5	4	5
100	100	2	5	1	5

# Appendix B

## Travel route data

Table B.1: Travel routes OD1 at Normal hours

No.	Route	Travel time (Min)	Travel cost (NZ)	Delay (Min)	Walking time (Min)	Congestion cost	Accident cost	Pollution cost	Traffic condition
1	Car via Wellesley St E Kitchener St and Victoria St E	4	0.613	0	0	1	1	1	1
2	Bus via 222	9	1.85	0	6	2	3	2	4
3	Bus via 246	9	1.85	0	6	2	3	2	4
4	Bus via 858	13	1.85	5	8	2	3	2	4
5	Bicycle via Victoria St E	5	0	0	0	3	2	3	4
6	Bicylce via Wellesley St E Kitchener St and Victoria St E	5	0	0	0	3	2	3	4
7	Bicycle via Wellesley St E Queen St and Victoria St W	5	0	0	0	3	2	3	4
8	Walk via Wellesley St E Queen St and Victoria St W	11	0	0	11	3	2	3	4
9	walk via Wellesley St E and Albert St	11	0	0	11	3	2	3	4

Table B.2: Travel routes OD1 at Peak hours

1	Car via Wellesley St E Kitchener St and Victoria St E	4	0.613	0	0	1	1	1	1
2	Bus via 249	11	1.85	0	6	2	3	2	4
3	Bus via 243	11	1.85	0	6	2	3	2	4
4	Bus via 248	11	1.85	0	6	2	3	2	4
5	Bicycle via Victoria St E	5	0	0	0	3	2	3	4
6	Bicycle via Wellesley St E Kitchener St and Victoria St E	5	0	0	0	3	2	3	4
7	Bicycle via Wellesley St E Queen St and Victoria St W	5	0	0	0	3	2	3	4
8	Walk via Wellesley St E Queen St and Victoria St W	11	0	0	11	3	2	3	4
9	walk via Wellesley St E and Albert St	11	0	0	11	3	2	3	4

## B.1 AUT north campus to Sky Tower (OD2)

Table B.3: Travel routes OD2 at Normal hours

1	Car via State Highway 1	10	6.912	0	0	1	1	1	4
2	Bus via 839	37	3.15	7	27	2	3	2	4
3	Bus via 922 and NEX	30	3.15	8	12	2	3	2	4
4	Bus via NEX	32	3.15	16	23	2	3	2	4
5	Bicycle via via Auckland-Birkenhead	32	4.6	14	32	3	2	3	4
6	Walk via Auckland-Birkenhead	78	4.6	62	78	3	2	3	4

Table B.4: Travel routes OD2 at Peak hours

1	Car via State Highway 1	12	6.912	0	0	1	1	1	1
2	Bus via 920	25	3.15	0	11	2	3	2	4
3	Bus via 920 and NEX	23	3.15	8	4	2	3	2	4
4	Bus via 952	15	3.15	11	5	2	3	2	4
5	Bicycle via via Auckland-Birkenhead	32	4.6	14	32	3	2	3	4
6	Walk via Auckland-Birkenhead	78	4.6	62	78	3	2	3	4



## B.2 AUT south campus to Sky Tower (OD3)

Table B.5: Travel routes OD3 at Normal hours

1	Car via State Highway 1	18	15.192	0	0	1	1	1	4
2	Car via State Highway 20	28	19.22	0	0	1	1	1	4
3	Car via State Highway 1 and Urban Route 9	28	17.352	0	0	1	1	1	2
4	Bus via 33 East Manukau	67	4.85	50	16	2	3	2	4
5	Bus via 33 South Papakura	78	4.85	66	16	2	3	2	4
6	Bus via 33 East Manukau	72	4.85	70	16	2	3	2	4
7	Bicycle via Great South RdUrban Route 5 and Great South Rd	76	0	36	0	3	2	3	4
8	Bicycle via Urban Route 4	98	0	58	0	3	2	3	4
9	Bicycle via Great South Rd	81	0	41	0	3	2	3	4
10	Walk via Great South RdUrban Route 5 and Great South Rd	255	0	215	255	3	2	3	4
11	Walk via Great South Rd	283	0	243	283	3	2	3	4

Table B.6: Travel routes OD3 at Peak hours

1	Car via State Highway 1	26	15.192	5	0	1	1	1	1
2	Car via State Highway 20	30	19.22	15	0	1	1	1	2
3	Car via State Highway 1 and Urban Route 9	35	17.352	25	0	1	1	1	1
4	Bus via 352 East Manukau	72	6.1	40	23	2	3	2	4
5	Bus via 33 South Papakura	74	4.85	42	16	2	3	2	4
6	Bus via 33 East Manukau	67	4.85	50	16	2	3	2	4
7	Bicycle via Great South RdUrban Route 5 and Great South Rd	76	0	36	0	3	2	3	4
8	Bicycle via Urban Route 4	98	0	58	0	3	2	3	4
9	Bicycle via Great South Rd	81	0	41	0	3	2	3	4
10	Walk via Great South RdUrban Route 5 and Great South Rd	255	0	215	255	3	2	3	4
11	Walk via Great South Rd	283	0	243	283	3	2	3	4

# Appendix C

## Code

This code below is some examples of the simulation. The full application code of the proposed system for simulation and evaluation can be found on Github (<https://github.com/SotsaySeng>).

```
package SocialRecSimulation;  
import java.util.List;  
import org.apache.commons.math3.stat.correlation.  
    SpearmansCorrelation;  
import sim.engine.SimState;  
import sim.field.grid.SparseGrid2D;  
  
public class AgentSimulation extends SimState {  
    public SparseGrid2D agentsSpace;  
    public int gridWidth = 100;  
    public int gridHeight = 100;  
  
    private final double statusThreshold = 0.7;  
    private int countStatusTrue = 0;  
    private int countStatusFalse = 0;  
    private double socialWeight = 0.7;  
    private double wCongestion = 0.25;  
    private double wAccident = 0.25;  
    private double wPollution = 0.25;  
    private double wTrafficCon = 0.25;  
    private double incentiveRate = 0.8;  
  
    public AgentSimulation(long seed) {  
        super(seed);  
    }  
}
```

```

public void start(){
    super.start();

    agentsSpace = new SparseGrid2D(gridWidth ,
                                    gridHeight);
    RSAgent rAgent = new RSAgent(socialWeight ,
                                   wCongestion , wAccident , wPollution ,
                                   wTrafficCon );
    List<UserDetail> users = InputReader.
        readUserDetailFromCSV ();
    /*
     * Now create the agents and put
     * them in the space.
     */
    for(int i=0;i<users.size();i++){
        int x = random.nextInt(gridWidth);
        // a random number < gridWidth
        int y = random.nextInt(gridHeight);
        int id = Integer.parseInt
            (users.get(i).getUserId());
        // a random number < gridWidth
        int vTime = Integer.parseInt
            (users.get(i).getTimeWeight());
        //a random number < gridHeight
        int vCost = Integer.parseInt
            (users.get(i).getCostWeight());
        //in the range -1 to 1
        int vDelay = Integer.parseInt
            (users.get(i).getDelayWeight());
        int vWalk = Integer.parseInt
            (users.get(i).getWalkWeight());
        boolean agentStatus= true;
        //in the range -1 to 1
        Agent agent = new Agent(x,y,id ,vTime ,
                                vCost ,vDelay ,vWalk ,agentStatus );
        agentsSpace.setObjectLocation(agent , x,y);

        //start agent request
        System.out.println("User_" + id);

        List recommendedItems = rAgent.mineRecList
            (id , vTime , vCost , vDelay , vWalk);
    }
}

```

```

        List rewards = rAgent.reward(id, vTime,
                                      vCost, vDelay, vWalk, incentiveRate);
        System.out.println("Recommended_route_" + id);
        System.out.println(recommendedItems);
        //agent calculate its utility
        System.out.println("Personal_route_" + id);
        List agentList = agent.agentSelection
                        (recommendedItems, rewards);
        System.out.println(agentList);
        //compare
        Double spearCo = calculateRankCo
                        (agentList, recommendedItems);
        //check spear coefficient result
        System.out.println(spearCo);
        //change status
        System.out.println(agentStatus);
        //change status
        if (spearCo < statusThreshold){
            agentStatus = false;
            countStatusFalse++;
        }
        else {
            agentStatus = true;
            countStatusTrue++;
        }
        System.out.println(agentStatus);
    }

    System.out.println("Total_active_user_"+countStatusTrue);
    System.out.println("Total_passive_user_"+countStatusFalse);
}

public Double calculateRankCo
    (List<Double> X, List<Double> Y) {
    SpearmansCorrelation SC = new SpearmansCorrelation();
    double[] xArray = toDoubleArray(X);
    double[] yArray = toDoubleArray(Y);
    double corr = SC.correlation(xArray, yArray);

    return corr;
}

public static double[] toDoubleArray

```

```
        (List<Double> list) {
    double[] arr = new double[list.size()];
    for (int i=0; i < list.size(); i++) {
        arr[i] = list.get(i);
    }
    return arr;
}

    public static void main(String[] args) {
        doLoop(AgentSimulation.class, args);

        System.exit(0);
    }
}
```