Measuring the impacts of mobile commerce on activity-travel behaviour

Yunlei Hu

A thesis submitted for the degree of Doctor of Philosophy and Diploma of the Membership of Imperial College London

Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London, United Kingdom

June 2009
Acknowledgements

I would like to express my sincere gratitude to my supervisor, Professor John Polak for his valuable guidance, support and encouragement throughout my study. He deserves strong recognition for the freedom he gave me, for the share of his knowledge and for the patience in listening to my fuzzy conjectures.

Also, my genuine appreciation goes to the members of Centre for Transport Studies, in particular, Apivat Jotisankasa, Scott E. Le Vine, for their fruitful discussion with me regarding the design of survey and model estimation, which enriched my study and inspired me a lot.

I am deeply grateful to the UK department for Transport for partially supporting my work, and the students and staff in Civil and Environmental Engineering Department for their patience and assistance in attending my personal interview for the data collection.

Last, but not least, a very special thank to my parents for the generous emotional support that keep me going through the ups and downs in the past four years. Without their encouragement and love, this work would not have been possible.
Abstract

Recent developments in information and communication technology have meant that mobile commerce will have an increasingly important influence on the travel behaviour; in particular on how, when and where people choose to use their time to conduct activities. In the cases of activities involving the use of mobile services, such as m-shopping or m-banking, the conventional strong connection between the utility which one derives from an activity and its timing and duration are weakened or even broken such that existing utility-maximization models are not suitable in these contexts. This thesis presents a novel approach to characterising the utility of activities which can be applied in a broader set of circumstances, especially those such as m-services in which technology relaxes the patio-temporal constraints of activity participation.

Building on concepts from both the microeconomic literature and the activity scheduling literature, the thesis proposes a unified utility framework based on an activity production approach, which is characterised by an activity production function. In this approach, an activity is regarded as the archetypal ‘small firm’ theorised by Becker (1965). An individual transforms the inputs (purchased market goods, time, and technology) into the outputs (consumption ‘commodities) through some activity production process. Both the production process and the outcome of consumption are potential sources of (dis)utility. We show how this framework generalises existing activity utility model and demonstrate how it can be extended to accommodate activities performed in both electronic and mobile contexts.

A stated choice exercise was undertaken to obtain the data necessary to estimate utility models based on this new framework. In this exercise, a hypothetical shopping choice scenario was presented to respondents and a D-efficient design was adopted to investigate people’s decision making with respect to shopping.
Using the cleaned data generated by this data collection program, the basic model with the best overall level of fit was identified. Theoretical and empirical implications were discussed. Strong evidences of taste heterogeneity among respondents were also found.
Table of Contents

Acknowledgements........................................................................................................... 2
Abstract................................................................................................................................. 3
List of Figures........................................................................................................................ 8
List of Tables........................................................................................................................ 9

1 Introduction....................................................................................................................... 11
   1.1 Background.................................................................................................................. 11
   1.2 Aim of this thesis........................................................................................................ 13
   1.3 Outline of this thesis................................................................................................... 14

2 Mobile Commerce services ............................................................................................... 16
   2.1 Introduction ............................................................................................................... 16
   2.2 M-commerce services ............................................................................................... 17
       2.2.1 Definitions ........................................................................................................... 17
       2.2.2 Technological bases and market potential ......................................................... 18
       2.2.3 Commeral services ........................................................................................... 20
   2.3 Behavioural impacts .................................................................................................. 22
   2.4 Modelling implications .............................................................................................. 25
   2.5 Summary .................................................................................................................... 26

3 Review of utility models of activities ............................................................................. 28
   3.1 Introduction ............................................................................................................... 28
   3.2 Microeconomic models ............................................................................................. 29
       3.2.1 Household production models and general time allocation models ............... 29
       3.2.2 Goods/Leisure/Activity choice models ............................................................. 39
       3.2.3 Summary ............................................................................................................ 48
   3.3 Activity-based travel demand models ....................................................................... 50
       3.3.1 Trip-based models and activity-based models .................................................. 50
       3.3.2 Duration-dependent models ............................................................................ 51
       3.3.3 Timing-dependent models .............................................................................. 57
       3.3.4 Duration- and Timing-dependent models ......................................................... 59
       3.3.5 Summary ............................................................................................................ 65
   3.4 Conclusions and discussions ..................................................................................... 66

4 The activity production approach ................................................................................... 69
   4.1 Overview of activity production approach ................................................................ 69
   4.2 Theoretical modelling framework ............................................................................ 69
   4.3 Utility function .......................................................................................................... 74
       4.3.1 Process utility function ..................................................................................... 74
       4.3.2 Outcome utility function .................................................................................. 85
List of Figures

Figure 4.1 Conceptual activity production model for single activity..............................73
Figure 5.1 Hypothetical flower shopping scenario ..........................................................95
Figure 5.2 Conventional shopping scenario .................................................................96
Figure 5.3 Mobile shopping scenario ..............................................................................96
Figure 5.4 Flow chart of computer-based interview .......................................................98
Figure 5.5 A screenshot of typical choice scenario from the SC survey .........................105
Figure 5.6 Error rate of each parameter for choosing different $S$ ............................115
Figure 6.1 Relationship between $V_m^p$ and $T_{journey}$ ............................................173
Figure 6.2 Relationship between $V_m^p$ and $T_{online}$ ...............................................175
Figure 6.3 Relationship between $V_m^p$ and $C_{online}$ ...............................................176
Figure 6.4 The indifference curves of mobile shopping .................................................178
Figure 6.5 Disutility of travel itself ...............................................................................181
Figure 6.6 Overall utility of travel compared with disutility of travel ........................182
Figure 6.7 Relationship between $V_c^p$ and $T_C$ .......................................................184
Figure 6.8 Relationship between $V_c^p$ and $TT + T_{conventional}$ ............................185
Figure 6.9 The indifference curves of conventional shopping ......................................187
Figure 6.10 Comparison of process utilities with respect to input time .......................190
Figure 6.11 Comparison of process utilities with relates to input money expenditure ...191
Figure 6.12 Indifference curves of both shopping activities ........................................192
Figure A.1 Proposed framework of conventional activity modification .....................234
Figure A.2 Decision tree with use of pull information ...............................................236
Figure A.3 Decision tree with use of push information .............................................238
List of Tables

Table 3.1 Summary of existing microeconomic models ........................................... 49
Table 3.2 Summary of existing activity-based utility models .................................. 66
Table 5.1 Comparisons of survey methodologies .................................................... 92
Table 5.2 Estimation results for linear MNL model using pilot data ....................... 100
Table 5.3 Attributes identification and levels ......................................................... 104
Table 5.4 Estimation results for choosing different numbers of choice situations using linear MNL model ................................................................. 113
Table 5.5 Results of error rate of choosing different number of choice observations .. 113
Table 5.6 Summary of statistical design of SC exercise .......................................... 116
Table 5.7 Main personal characteristics of SC sample ............................................ 117
Table 5.8 General internet usage of SC sample ....................................................... 118
Table 5.9 Measurements of Big Five Inventory of SC samples ............................... 119
Table 5.10 Estimation results for filtered sample and non-filtered sample ............... 120
Table 5.11 Initial estimation results for model of non-trading behaviour ................. 122
Table 5.12 Best estimation results for model of non-trading behaviour ................. 122
Table 5.13 Estimation results for filtered and non-filtered sample......................... 124
Table 5.14 Results of tests of internal consistency of SC data ............................... 126
Table 5.15 Estimation results for basic MNL model and the extended ML model incorporating sequencing effects ......................................................... 129
Table 6.1 A generalisation of MNL model structure ............................................ 137
Table 6.2 Combinations of process utility functions and relevant model numbers ..... 153
Table 6.3 Estimation results for the generic and alternative specific models .......... 155
Table 6.4 The estimation results for restricted and unrestricted forms ................. 156
Table 6.5 Estimation results for Model 2 ................................................................ 158
Table 6.6 Estimation results for Model 3 ................................................................. 159
Table 6.7 Estimation results for Model 4 ................................................................. 160
Table 6.8 Estimation results for modified Model 4 ............................................... 161
Table 6.9 Estimation results for Model 5 ................................................................. 162
Table 6.10 Estimation results for Model 6 ............................................................... 163
Table 6.11 Estimation results for Model 7 ............................................................... 164
Table 6.12 Estimation results for Model 8 ............................................................... 165
Table 6.13 Estimation results for Model 9 ............................................................... 166
Table 6.14 Comparisons of the overall level of fit of various models ................. 167
Table 6.15 C-test results ......................................................................................... 169
Table 6.16 P-test results ......................................................................................... 170
Table 6.17 Estimation results for response heterogeneity of $\beta_{Gn}$ .................... 199
Table 6.18 Estimation results for response heterogeneity for $\lambda_{c1}$ .................... 201
Table 6.19 Estimation results for response heterogeneity of $\lambda_{m2}$ .................... 202
Table 6.20 Estimation results for response heterogeneity for $\lambda_{m1}$ .................... 203
Table 6.21 Estimation results for response heterogeneity of $\beta_{c2}$ ....................... 204
Table 6.22 Estimation results for extended model with response heterogeneity of $\beta_{Gn}$ and the corresponding specification with sequencing effect ....................... 208
1 Introduction

Internet-based electronic commerce enables access to goods and services through some form of fixed network connection, hence potential buyers are unable to access information and services or complete transactions whilst away from a PC. The stationary nature of e-commerce connections limits potential usage. Recently, the growth of wireless E-commerce, also termed mobile commerce, has had an increasingly important influence on the travel behaviour and in particular on how, when and where people can use time to conduct activities. Hence, measuring the behavioural impacts of mobile commerce services has become a major concern of transport researchers. In this thesis, we present a novel approach to formulate a unified utility model of activities which can be applied in the context of mobile commerce services, such as m-shopping and m-banking. We also show how this approach can generalise existing activity utility model in a conventional context.

The first chapter of this thesis describes the orientation of this research. It begins with a brief background of the topic. The aims of this thesis are then provided in Section 1.2. The document structure is given in the final subsection.

1.1 Background

In the past decade, the use of wireless and mobile networks and devices has grown rapidly. Since 2007, the total number of mobile subscribers has exceeded 3 billion globally (PortioResearch, 2007). The advanced mobile technologies (such as 2.5G, 3G and 4G broadband networks) facilitate the application of mobile commerce services anywhere anytime, which provides individuals with increasing activity opportunities for communication. In 2004 in the UK, the added value of mobile services grew by 29% than 2003 to £1.4 billion, reaching 4.3% of total mobile revenues (Ofcom, 2004). According to
a recent market survey, mobile data service revenues for the year 2008 rose to more than $32 billion corresponding to 39% increase over 2007. With this increase in mobile commerce, the possibility of significant behavioural impacts in transport demand becomes relevant. The rapid diffusion of mobile devices has brought about a new branch of research about the relationship between mobile technology and activity-travel behaviour (Couclelis, 2000; Golob and Regan, 2001; Townsend, 2003; Srinivasan and Raghavender, 2006). These empirical studies have found the behavioural impact of mobile communication technology to be significant and far-reaching, primarily in two categories:

1. More frequent coordination and facilitation of physical travel behaviour, involving the use of various context-aware information services provided by mobile commerce; and

2. Increasing opportunities to participate in various virtual activities (such as mobile shopping and mobile ticketing), likely constituting a substitution of physical activity participation.

This thesis principally concentrates on examining the second category of impacts.

A key element in most activity-based transport demand models is the interplay between the utility obtained from participating in activities undertaken at different times and locations, and the disutility associated with travelling to these activities. Thus the issue of how to measure the utility of a virtual activity is of central importance. The conventional approach adopted in the activity based modelling literature is to conceive of the utility of an activity as a function of its duration and timing, sometimes modified by contextual and personal characteristics. This reflects both the importance of scheduling considerations in most activity-based frameworks and the fact that for activities undertaken in a physical, face-to-face context, duration and timing are indeed likely to be

---

1 Taken from the following website on 2nd April 2009

http://www.wirelessandmobilenews.com/mt/mt-search.cgi?IncludeBlogs=1&tag=research&limit=20
major components of the overall benefit that individuals derive from participation.

In the case of virtual activities performed via mobile services, such as m-shopping or m-banking, the use of mobile technology relaxes the conventional spatio-temporal constraints of activity participation, as individuals can pursue such an activity anywhere and anytime the need/desire arises. Therefore, the conventional strong connection between the utility of an activity and its timing and duration are weakened or even broken. To date, few attempts have been made to formulate a new framework to model the utility of an activity under these contexts. Hence characterising the utility of activity participation involves new research challenges if one seeks to extend the existing body of literature to a broader context which incorporates mobile activities.

1.2 Aim of this thesis

The overall aim of this thesis is to examine the impact of mobile commerce services on individual’s virtual activity participation behaviour. The motivation for this research has been briefly described in Section 1.1 and will be further explored in subsequent chapters. To best achieve this aim, we set ourselves the following research objectives:

- Specify a novel approach to formulate a theoretical framework which accommodates the behavioural pattern of virtual activity participation associated with m-commerce;
- Motivate a more operational specification dealing with utility of an activity involving the use of substituting mobile technology; and
- Presents model estimation results and discusses the implications for behavioural pattern associated with mobile commerce
1.3 Outline of this thesis

The thesis is organised into seven chapters so as to achieve these objectives. Each chapter consists of several subsections, starting with an introduction and finishing with a summary. This thesis is structured as follows.

Chapter 1 Introduction
This chapter introduces the overall context of this study, describes the research objectives and presents the outline of this thesis.

Chapter 2 Mobile commerce services
This chapter starts with a brief overview of mobile commerce services, including the history, development, technological basis, application services, etc. It goes on to characterise behavioural patterns involving the use of m-commerce and propose the relevant modelling implications in the demand for transport, which provide a foundation for further model development.

Chapter 3 Review on existing utility models of activities
The third chapter reviews the approaches adopted in both the existing transport literature and microeconomic literature to define the utility of activities. Connections between the various studies and their relevant strengths and weaknesses in being applied to the m-commerce context are highlighted.

Chapter 4 A new paradigm-activity production approach
This chapter presents our new approach – termed the activity production approach – which combines elements of the existing transport literature with ideas from household production theory. Based on this approach, a new modelling framework was developed to model the utility of activities in the presence/absence of different technologies. We show how this approach generalises existing activity utility model and demonstrate how we propose extending it to the context of activities performed in electronic and mobile
contexts.

Chapter 5 Data collection-Stated choice survey

The fifth chapter outlines a stated choice exercise undertaken to estimate this utility model based on the proposed modelling framework. We discuss details regarding the design and procedures of the survey. Diagnostic tests and preliminary analysis of the stated choice (SC) data are also provided in this chapter.

Chapter 6 Estimation results

This chapter applies discrete choice modelling techniques to the stated choice data collected through the program described in Chapter 5. It starts with the identification of basic utility specifications proposed in Chapter 4. It continues with an extension of the basic utility model to accommodate taste heterogeneity across individuals and stated preference (SP) sequencing effect using mixed logit model structures. Estimation results are provided. The implications in the basic utility function and various extended formulations are also presented.

Chapter 7 Conclusion

This thesis ends with a chapter outlining the conclusions of this study, and suggesting areas for further research.
2 Mobile Commerce services

2.1 Introduction

The last decade was marked by the rapid development of mobile technologies. In Europe, UK has the largest mobile market with all major providers have launched 3G services. By the end of 2006, UK mobile services market was worth £16.5 billion. Mobile subscribers made up of 109% of total population and this figure increased to 125% by mid 2008 (Centre for Telecoms Research Ltd, 2007). The market is matured in some developed countries, such as Japan, many countries belonging to the European Union and North America and so on, but it is still expanding rapidly in developing countries, such as China, India and Latin America.

For mobile operators, there is huge customer potential for the growth of wireless E-commerce commonly known as mobile commerce or m-commerce. M-commerce allows information to be disseminated and transactions completed whenever the need or desires arises, even if the mobile users are on the move (such as on the train, in a bus station or at a restaurant etc.). As oppose to electronic commerce (i.e. enabling the access to goods and services through some form of fixed connection), the anytime anyplace nature of m-commerce through wireless computing devices (such as PDA, pocket PCs and so on) can overcome the limitation of stationary e-commerce (Ling and Haddon, 2001). In recent years, as the convergence of Internet and wireless communication, a new application and services called location-based services are emerging with significant implications for the future of m-commerce. Popular examples include real time traffic alert, identifying near options (such as restaurant search in the vicinity), tourist guide, yellow pages and weather information.

On the other hand, to travel behaviour researchers, the impacts between
information and communication technology (ICT) and travel behaviour have traditionally been one of our major concerns. Recent studies have suggested that the use of m-commerce services has dramatically changed individual activity-travel behaviour. In particular, it has provided individuals with a lot of new activity opportunities and enabled the decisions of activity scheduling and rescheduling to be more flexible. These impacts are important and bring about new challenges to our transport researchers.

This chapter aims to provide a brief introduction of m-commerce so as to prepare the ground for this research in chapter 4. This chapter starts with an overview of m-commerce, including its development, the technological bases, commercial services, and market potential. The relevant behavioural impact and implications in travel behavioural modelling are then provided in Section 2.2 and Section 2.3. A brief summary is given in the end.

2.2 M-commerce services

2.2.1 Definitions

M-commerce is the term used to describe information and services that are accessible with mobile computing devices (such as PDA, smart phone and so on) through a mobile network. Various definitions of m-commerce have been given in the recent literature (Clark, 2001; Barnes, 2002; Sadeh, 2002). Narrow definitions point to only transaction-dependent services involving the exchange of monetary value through wireless network. Broader definitions also include a wide range of information and entertainment services, such as mobile advertising, mobile music, mobile gaming and so on. When the provision of the information and service is based on the individual’s current location, it constitutes a special case of m-commerce, namely, a location-based service. Location-based services take user’s location into account in order to disseminate the
information or deliver a service (van der Meer, 2001). Using various positioning techniques, operators can offer localized information and commercial services which are of interest to the users. Hence, localization and personalization can be considered as additional value creation of LBS (Anckar and D'Incau, 2002).

2.2.2 Technological bases and market potential

The development of m-commerce, as well as LBS, is attributed to the recent technological advancements in wireless communication technology (Sadeh, 2002; Tsalgotidou et al., 2003; Steinfield, 2004). Since the 1990s, the emergence of broadband wireless infrastructures (e.g. 2.5G, 3G, and 4G) has provided mobile users with higher transmission capacity and more advanced service capability. All these network infrastructures can support m-commerce. For the evolution of 2G to 3G networks, a range of wireless systems, including GPRS, EDGE, and Bluetooth, were developed. These networks are also termed as 2.5G networks in that they use existing 2G infrastructures (such as GSM and CDMA) to deliver some enhanced feature of 3G networks, (e.g. packet-switched technology). For example, GPRS provides up to 114 kbps of data transmission for the services such as Short Message Service (SMS), Multimedia Messaging Service (MMS), Wireless Application Protocol (WAP) access, email and so on. Bluetooth, as a technology for very short range (10 meters) ad hoc network to support personal area networks (PAN), also has evident impact on m-commerce as well as LBS. Using this technology it will be possible to conduct m-commerce transactions without a heavy network infrastructure. Thus, handheld devices could talk directly with the service points (e.g. cash registers). Bluetooth advances are that the infrastructure is simple, relatively cheap, and operated in unlicensed frequency bands.

With the third generation of mobile telecom systems (3G) being available, a
higher transmission speed up to 2Mbp are provided. 3G networks offer a truly global roaming, and the global coverage of the services. They also provide superior voice quality and advanced multimedia services such as video streams, animations, pictures, etc. The International Telecommunication Union (ITU) has specified a framework standard for the global 3G system, called International Mobile Telecommunications 2000 (IMT-2000). Different mobile systems have been developed to fulfil the IMT-2000 standard, including UMTS, CDMA-2000, and TD-SCDMA etc. Meanwhile, the mobile terminals are correspondingly developing, getting new features and enhanced hardware, at fast pace. Most of the new handsets (such as smart phone, PDA, Blackberry and so on ) have already supported for 3G, GPRS, Bluetooth and MMS, inbuilt camera, as well as sophisticated applications.

Nowadays, 4G is being developed as the next generation of wireless communication networks and scheduled for fully commercialisation by 2010 by many countries. 4G can theoretically provide up to 1Gbps of data transmission and enable more enhanced multimedia applications than 3G, such as video chat, mobile TV, HDTV content, Digital Video Broadcasting (DVB).

On the other hand, regulatory change after 911 has also created a conductive environment for the development of localised m-commerce, such as LBS. Most industrialized countries have initiated rules requiring cellular operators to deliver information about the location of a subscriber to public safety answering points in the event of an emergency, for example, through E911 in the U.S., and E112 in the EU (D'Roza and Bilchey, 2003; Millar, 2003). These are not meant to be e-commerce services, but have had the effect of pushing mobile network operators to build the location detection infrastructure which can then be exploited for other commercial purposes. The emerging position techniques include cell-location position technique (cell-ID),

---

II Taken from the following website on 10th April 2009: http://articles.jimtrade.com/1/52.htm
advanced network-based position technique (E-OTD and OTDOA) and satellite-based position technique (GPS).

So far, mobile commerce has been a huge success in some markets such as Japan (Ohmori, 2006), while not as flourishing in other markets such as the USA, UK and Australia (Yang et al., 2004; Kurnia and Lee, 2007). Most recently, mobile commerce market has shifted from the entertainment dominated services (such as purchasing ring tones and games) to the services such as purchasing ticket and shopping. According to a recent study from Jupiter Research, worldwide revenues from mobile commerce would reach $40billion excluding entertainment purchase by the end of 2009\[1].

2.2.3 Commercial services

A wide range of services have been provided by m-commerce and LBS. Various categorizations have been examined in recent studies. van de Kar and Bouwman (2001) classify the services into three categories: emergency service, mobile network operator services and value added services (VAS) focusing on the primary e-commerce opportunity including information, entertainment, transaction, mobile office and business support. D’Roza and Bilchey (2003) give a simple classification scheme distinguishing between push services and pull services in terms of whether there is user interaction or not. Pull services deliver information corresponding to the user’s request, such as mobile shopping and mobile banking. Push services are delivered without request or with indirect request form the user, such as a mobile advertisement of promotion when entering an area close to the shopping centre, or a message of traffic warning. An indirectly requested service could be service subscription event information regarding the actual object. Levijoki (2000) describes the classification scheme in terms of the application areas, distinguishing between safety, tracking, proximity service, billing and

\[1\] Taken from the following website on 11\[th\] April 2009: http://www.onmobile.com/news-160.html
In this research, in order to prepare the ground for the model development in later chapters, we broadly classify these services according to the role of m-commerce applied to the mobile users, distinguishing between functional services and information services. Functional services enable mobile users to perform virtual activities, mainly consisting of the following two types.

- **Transaction and billing:** Narrow definition of m-commerce includes only the use of mobile device to exchange monetary value, including mobile shopping for goods, mobile ticketing for theatre and public transportation, and mobile banking simply involving the payment transfer between different bank accounts. This service capability often requires the exchange of payment information between wireless devices and local Point of Sale (i.e. a retail shop, a counter in a retail shop etc.) devices. Therefore the security issue is the major concern of mobile users.

- **Entertainment:** This includes mobile game, mobile gambling, music and mobile communication (such as friend/colleague finder, chatting, dating in a short distance) and so on.

Information services provide mobile users’ with localised information, which facilitate the individual’s conventional activity participation. These information services include the following types.

- **Context-aware information service:** Mobile user can be provided with a wide range of context-aware information services by filtering the current location. Service includes local weather forecasting, nearest location of interested service, yellow pages, traffic information, public transport schedules, and tourist guide and so on. More sophisticated services rely on the development of more advanced geographical information system (GIS). For example, a mobile user who is not
familiar with the city can find his preferred restaurant by pressing a few buttons on his mobile device, search a review of places, and retrieve the map.

- **Asset tracking and routing/navigation**: LBS, as a special case of m-commerce, can help the users to track the location of people and objects. When integrated with real time traffic data, LBS can also guide the mobile users among the best route contingent on the current traffic condition. Tracking can also be combined with navigation service to be employed in route optimization for delivery services.

- **Resource management**: These applications are targeted to employees, including activity scheduling, staff management, or email management and so on. When users predefined which people are allowed to know their location, this service can help scheduling the ‘ad-hoc’ gathering when those predefined people are in the proximity.

### 2.3 Behavioural impacts

Recent developments in mobile technology have been so rapid that the relevant studies focusing on its implication in demand for transport are relatively limited. Although there has long been a number of research about the impact of Information and Communication Technologies (ICTs) on activity and travel behaviour (Hensher and Golob, 2000; Kwan, 2002; Mokhtarian and Salomon, 2002), most of the work focuses on the fixed internet related influences, such as tele-working, e-shopping behaviour. More recently, attention has been given to the role of mobile technology as researchers realise that mobile technology has increasingly given people virtual accessibility to various activities, which dramatically change people’s lifestyle. Golob and Regan (2001) distinguish the overall effect of ICT including mobile technology on travel behaviour between the substitution effect, generation effect and modification effect. This implies
that the use of ICT can not only substitute existing physical travel (e.g. in the context of e-commerce, m-commerce), but also lead to extra travel for additional activities (e.g. mobile promotion leads to extra shopping), or modify the existing way of travelling (e.g. the provision of real time travel information). Modifications of travel often occur when the pre-planned activity and associated travel are rescheduled through mobile services while on the move. Couclelis (2000) uses the concept of ‘fragmentation’ to describe the disintegration of activities with use of mobile technology. ‘Fragmentation’ occurs when mobile technology releases the conventional temporal and spatial constraints such that segmentation of activity participation occurs. This is embodied in three different perspectives, i.e. time, space and manner. For example, involving the use of mobile technology, individuals can work when travelling on the train to somewhere rather than constrained by the official working hours at the office. Also individuals can conduct shopping online via mobile devices as opposed to visit a physical shop. Townsend (2001, 2003, 2004) attributes the resulting behavioural impacts of mobile technology to three levels: individual, group and unbans life. He mentioned (Townsend, 2003):

“What little information we do have regarding the possible consequences of mass mobile communications use by urban dwellers suggests changes in activity patterns at three scales:

- Individual – increased flexibility to manage commitments, respond to changes in urban environment in real time
- Group – increased coordination of households, social networks, and firms
- Urban – smart mobs, increased efficiency/metabolism within existing physical extent, other unknown emergent phenomena” (page 30).

Recently, Srinivasan and Raghavender (2006) have found that mobile phones affect both travel dimensions and activity participation significantly. They observed that mobile technology provide individual users with a greater degree of control over location and
timing of activities, which bring about more frequent activity reorganization and the interaction and coordination with other individuals on the move. The use of mobile technology also enables to participate in a variety of virtual activities and services such as chatting, messaging, games, music, shopping etc. According to a recent market survey for NTT DoCoMo mobile phone users in Japan in 2005, people often conduct activities via mobile when they are inside the train or waiting for a train or bus at the station. They surf i-mode sites, see advertisements, email and talk with other persons, which changes the conventional waiting and meeting behaviour (IT media news, cited by Ohmori, 2006). As have been recognised by early studies (Mokhtarian and Salomon, 2001; Redmond and Mokhtarian, 2001), the use of mobile phones and miniaturized digital devices (such as portable computers and music players) increases opportunities for conducting activities while on the move. In UK, in terms of a national questionnaire survey of rail passengers conducted in 2004, a longer travel time may be perceived as increasingly beneficial as travel environment become more equipped with mobile technologies for working and entertainment (Lyons et al., 2007; Jain and Lyons, 2008). In these cases, utility of travelling may appear to be positive.

Based on the above empirical studies from existing literature, the individual characteristic behaviour patterns with use of mobile technology can be summarised from the following two perspectives.

- **Conventional activity modification**: The mobile technology enables users to keep access to various context-based information services, which leads to more frequent reorganizing conventional activities and more frequent interaction and coordination with individuals on the move (Golob and Regan, 2001; Townsend, 2003; Srinivasan and Raghavender, 2006).

- **Virtual activity participation**: The mobile technology provides mobile users with strong functional services that allows for the replacement of conventional
activities for virtual activities (Mokhtarian and Salomon, 2001; Redmond and Mokhtarian, 2001; Ohmori, 2006; Srinivasan and Raghavender, 2006). In these cases, the use of mobile technology is derived from the demand of activity participation, while the associated travel in conventional activity is substituted. The adoption of mobile technology opens the limits to individual action and enables these activities to be performed at new times and places in a new way.

2.4 Modelling implications

In activity-based travel behaviour analysis, although a number of studies have been proposed to examine the impact of mobile technology empirically, none of the existing modelling frameworks has accommodated either of the above characteristic behaviour patterns theoretically.

In order to model the above characteristic behaviours, some key underlying elements need to be identified. Regarding the first perspective, a substantial number of studies have characterised the acquisition of information in travel choice behaviour (i.e. departure time, route choice) (Denant-Boemont and Petiot, 2003; Kenyon and Lyons, 2003; Chorus et al., 2006) and its overall effect on the whole pattern of rescheduling behaviour (Arentze and Timmermans, 2005; Sun et al., 2005). Based on these existing studies, it can be concluded that modelling the decision process in conventional activity modification behaviour under mobile information use requires the following key components:

- Acquisition of various context-based mobile information services
- Relevant perception updating process
- Activity schedule choice process.

A comprehensive modelling framework that incorporates all the above relevant elements is included as Appendix A.
In this thesis, most of our efforts have been concentrated to modelling the virtual activity participation. In activity-based travel demand analysis, modelling the activity participation requires the measurement of utility of an activity. In the past few years, a number of models have been proposed to represent the utility of conventional activities and associated activity pattern in a physical, face-to-face context. Classical approach relies on the strong connection between utility of an activity and the attributes of activity, such as timing, duration and location. However, in the context of mobile commerce, mobile technology may serve as a substitute to physical travel. Individuals can pursue activities anytime anywhere so that the temporal and spatial constrains imposed to conventional activity, are relaxed. Hence new modelling frameworks may need to be developed, which would be both important and challenging to us. Now the problems exist here include:

- How does the existing literature measure the utility of conventional activity?
- Can these existing utility models be extended to the context of virtual activities (e.g. m-shopping, m-banking) involving the use of mobile services?
- If not, how to formulate a new approach to measure the utility of activities, which can not only be applied in conventional activities, but also extended to a broader context, such as mobile commerce

2.5 Summary

This chapter first provided a brief introduction to mobile commerce services. The relevant studies on behavioural impact of underlying mobile technology were then reviewed, based on which the characteristic behaviour patterns involving the use of mobile technology are summarised. Finally the subsequent modelling implications resulting from these characteristic behavioural patterns were discussed.

The description in this chapter showed that the advent of mobile commerce, as
well as Location-based services is due to recent advancements in wireless communication technologies. M-commerce services provide mobile users with accessibility and connectivity to various information and services, through which individuals’ conventional travel behaviour has been revolutionised. Two characteristic behavioural patterns were identified, including more frequent rescheduling behaviour and more interactive coordination with individuals on the move, together with participation in substitute virtual activities anywhere anytime. These two behavioural impacts brought new challenges to our researchers. In this thesis, we concentrate on the modelling the second effect. The existing literatures and future model development are presented in later chapters.
3 Review of utility models of activities

3.1 Introduction

Using utility to represent individual satisfaction associated with choice alternative originates from microeconomics (Varian, 2006b). The study of the utility of activities has a long history in a variety of disciplines. In the field of travel demand modelling, existing utility models can be classified into two broad groups: explicit microeconomic models and activity-based travel demand models. Microeconomic researchers have pursued the classical economic question of long-term decisions of how consumers allocate time and goods between different activities or aggregate activity classes, such as work, leisure, and travel. The consumption outcomes of goods and time expended on various activities are the primary sources of utility. In activity-based travel analysis, the focus is on the short-term activity scheduling and rescheduling decisions in the course of a day or a week. Utility derives directly from activity participation, mainly through the available time allocated in specific activity episode and secondarily activity timing, sometimes modified by contextual and/or personal characteristics. In both groups of models, individuals are assumed to maximise the utility under constraints of time, money, and [sometimes] technology. The review presented in this chapter looks at the existing works in these two areas. Although these utility models have been widely applied by transport researchers to perform various empirical analyses (such as interpretation of value of time and mode choice behaviour etc.), in this review we principally concentrate on the issue of model specification, namely the interpretation of the relevant variables that enter the utility function and the role of constraints.

The discussion in this chapter is structured as follows. Section 3.1 describes the explicit microeconomic models. Section 3.2 reviews the activity-based travel behaviour
models. Section 3.3 provides the summary of this chapter.

### 3.2 Microeconomic models

Recently, a number of reviews have been proposed in this area for the purpose of evaluating empirical parameter values, such as the value of time and travel time savings (Gonzalez, 1997; Jara-Diaz, 2000; Perez et al., 2003). Based on these reviews, existing microeconomic models are considered to be sustained by two powerful frameworks. One includes consumer theory, the subsequent household production theory and general time allocation theory that explicitly incorporate the time dimension into the utility function in various forms. Utility in this framework is defined as ‘direct utility’, representing people’s preference for different consumption bundles of time and goods. It does not depend on other variables, such as price of goods and individual income. The other is a goods/leisure/activity framework that connects time allocation theory with discrete choice theory. This framework is originally applied to model the decision to acquire one unit of a certain generic good (e.g. car, fruit) followed by the decision of a specific type (car mode, fruit type). Later on, it has been widely applied to model travel choice behaviour. When combined with discrete choice techniques, utility in this framework is termed ‘conditional indirect utility’ and represents the maximum utility obtained conditional on a certain choice having been made. It incorporates the effect of the constraints faced by individuals as well as their previous decisions.

#### 3.2.1 Household production models and general time allocation models

Traditional consumer theory assumes that consumption is an activity and that an individual attempts to maximise the utility of their economic activities through consuming a bundle of goods. In this formulation, the specification of utility depends on the continuous consumption amount $x$ under time and money constraints. Since the
mid-1960s, the use of time has received increasing attention mainly due to the issue of better understanding the supply of working hours (Becker, 1965; Johnson, 1966; De Serpa, 1971; Evans, 1972). The time variable became explicitly incorporated into the consumer theory framework, which leads to the formulation of the household production theory and time allocation theory. The only difference between these two is that time allocation theory assumes that the time and goods dimension enter the utility function directly, whereas household production theory incorporates the dimensions of time and goods into the utility function through the intermediate concept of a ‘commodity’ via household production function. In both contexts, time is considered as an economic resource. Each individual has an identical and fixed amount of time to consume [24 hours in a day, 7 days in a week, etc.]. Unlike money, time cannot be stored, and as such can only be transferred among different activities. The allocation of time to different activities leads to differential values accruing to the individual, measured in money terms. Individuals are assumed to allocate their time to the various activities so that they will obtain the maximum level of utility subject to certain constraints. In terms of the source of utility and which component of time entering the utility function, existing time allocation models can be specified in various ways.

3.2.1.1 Household production models

Becker’s model (1965) pioneered this school of thought. He first proposed an intermediate concept of final ‘commodity’ and explicitly incorporated it as an argument of utility function. Household members purchase market goods and combine them with non-working time to produce non-market final ‘commodities’ (e.g. dinner at home), which are defined as household production activities. From this point of view, a household is regarded as a ‘small firm’. Household members are both producers and

---

In this thesis, the use of time is examined from two perspectives: the time allocation to the activities and the timing (i.e. start time) of these activities.
consumers. Input time $T$ and goods $x$ are treated as finite resources allocated to household activities, and enter the utility as necessary input through production functional relationship with $Z$. The transformation of input $T$ and $x$ to output $Z$ depends on the household production function $h(\ )$. In modelling terms, it can be expressed as:

$$Z = h(x,T)$$  \hspace{1cm} (3.1)

Where $h(\ )$ is determined by the structure of household production technology. Generally, the partial derivatives of $Z$ with respect to $T$ and $x$ are non-negative, i.e.

$$\frac{\partial Z}{\partial x} \geq 0$$ \hspace{1cm} (3.2)

$$\frac{\partial Z}{\partial T} \geq 0$$ \hspace{1cm} (3.3)

The household is assumed to assign their total input resources (time $T$ and goods $x$) optimally to maximise the utility of household activities under time and money constraints. Becker’s framework is expressed as:

$$\text{Max } U(Z_1, Z_2, \ldots, Z_n) = U(h_1, h_2, \ldots, h_n) = U(x_1, x_2, \ldots, x_n; T_1, T_2, \ldots, T_n)$$ \hspace{1cm} (3.4)

s.t. \hspace{0.5cm} D = T_w + \sum_{i=1}^{n} T_i = T_w + T_c \hspace{1cm} (3.5)

$$wT_w + y = \sum_{i=1}^{n} p_i x_i$$ \hspace{1cm} (3.6)

Where $Z_i$ ($i=1, \ldots, n$) is ‘commodity’ $i$ produced with input market goods $x_i$ and non-working time $T_i$; $p_i$ is price of goods $x_i$; $U(\ )$ is the utility function. The total time resource $D$ is divided into working time $T_w$ and nonworking time allocated to household productions $\sum_{i=1}^{n} T_i$. $\sum_{i=1}^{n} T_i$ is also defined as ‘consumption time’ $T_c$, which is
the total time spent in obtaining the commodity \( Z \), but Becker does not distinguish between ‘consumption time’ and the time allocated purely to the household production process. The financial constraint in Equation (3.6) indicates that the sum of income earned in work hours \( T_w \) at wage rate \( w \) plus the unearned income \( y \) must cover the total costs of the input goods \( x_i \) at their corresponding current price \( p_i \) in total time period \( D \). As Becker points out, the above constraints are not independent and can be merged into one if the production function is reformulated as:

\[
T_i = a_i Z_i \quad (3.7)
\]

\[
x_i = b_i Z_i \quad (3.8)
\]

where \( a_i \) and \( b_i \) are fixed coefficients of converting ‘final commodity’ into input factors, representing the requirements of market goods and non-working time per unit of \( Z_i \). It should be noted that Becker’s model requires the assumption that the market goods serving as input in one commodity cannot be used for the production of another, which implies a one-to-one relationship between market goods, non-working time and ‘commodity’. It also suggests constant returns in producing \( Z_i \) (Please refer to Section 4.3.1.1). As working hours are considered to be flexible, then \( T_w \) in Equation (3.6) may be substituted in equation (3.5) yielding,

\[
wD + y = \sum_{i=1}^{n} (p_i b_i + w a_i) Z_i \quad (3.9)
\]

This equation implies that if an individual devotes all their time to work, the maximised amount of money earned by doing this can be spent on the commodities \( Z_i \) through both direct expenditure on market goods \( \sum_{i=1}^{n} p_i b_i Z_i \) and indirect loss of income due to the expenditure on the ‘consumption time’ rather than on work \( \sum_{i=1}^{n} w a_i Z_i \). Becker’s model does not explicitly address the relationship between input time and market goods.

It has been recognised that Becker introduces a series of new features to
contemporary consumer theory. He proposes the concept of a particular type of ‘commodity’ as the output of household production activities. He also emphasises the role of household technology in determining the household behaviour, which permit us to attribute the variation of household behaviour to the changes in household technology. However, as pointed out by Pollak and Wachter (1975), the application of the household production function requires a strong assumption regarding the structure of household technology, such as the one-to-one production relationship leading to absence of joint production, and the presence of constant returns to scale. All these assumptions only occur in special cases. Also, in Becker’s model, the duration of working hours is assumed to be flexible and does not enter the utility functions. Furthermore, the time required for the consumption of ‘commodities’ are not clearly defined and distinguished from ‘consumption time’ $\sum T_i = T_c$. This has been noted and taken into account in the specifications of later researchers (DeSerpa, 1971; Evans, 1972). From these perspectives, Becker’s model may not be considered as a fully-appropriate framework for time allocation analysis.

A number of researchers subsequently made contributions by extending Becker’s model (Lancaster, 1966; Winston, 1982; Graham and Green, 1984; Gronau, 1986). Their work gives rise to the formulation of household production theory. Following Becker, Lancaster (1966) presented a study that brought an important change to conventional consumer theory. He introduced the concept that the characteristics of a ‘commodity’ are the primary source of utility rather than the ‘commodity’ itself. This assumption gives rise to a new form of utility model. In his specification, a household is assumed to choose the ‘commodities’ that can maximise their utility, which is derived from the desired characteristics of the commodities. Hence $x_i$ becomes the characteristic $i$ of the ‘commodities’. $x_i = \sum_f B_{ij} Z_j$ transforms the ‘commodities’ to the desired characteristic
and the coefficient $B_{ij}$ is termed ‘consumption technology’. Unlike in Becker’s model, Lancaster relaxes the assumption of a one-to-one relationship between $x_i$ and $Z_j$, which implies the existence of joint production. Lancaster’s model constitutes a significant contribution to later travel demand modelling, as transport researchers assume that utility of an activity derives from qualitative and quantitative attributes of activities, for example, activity duration, activity timing, activity type and location.

Gronau (1986) extended Becker’s model by distinguishing between the ‘commodities’ produced through work activity at home (called ‘home production time) and leisure (called ‘home consumption time’). His model can be expressed as:

$$\text{Max } U(z_1, z_2, \ldots, z_n, z_w)$$

s.t. $D = T_w + \sum_{i=1}^{n} T_i$

$$wT_w + y = \sum_{i=1}^{n} p_i x_i + p_w x_w$$

Where $z_i (i = 1, \ldots, n)$ and $z_w$ are ‘commodities’ produced through leisure and work activity at home; $p_w$ and $x_w$ are respectively the price and consumption amount of goods associated with $z_w$. $z_w$ and $z_i$ relate to the corresponding goods and time via different production functions, namely that:

$$z_i = h_i (x_i, T_i)$$

$$z_w = h_w (x_w, T_w)$$

Where $h_w$ and $h_i$ are respectively the production functions for work and leisure activity at home.

As a merger of time of day specific analysis and household production theory, Winston (1982) developed a more dynamic formulation of utility by introducing a
marginal utility function to examine household activities. The problems of how much
time is spent, as well as the timing of activities, are solved in his framework. He
considered two tiers of household behaviour: one as pure production behaviour and the
other as pure consumption behaviour. Utility is correspondingly separated into two
components: process utility and outcome utility. Process utility derives from production
process which spreads out during the entire activity duration, during which the household
combines the purchased goods and their labour to produce the consumption ‘commodity’.
Outcome utility derives directly from consuming the home-made ‘commodity’ which is
obtained in a limited time interval following the completion of production. Both process
utility and outcome utility are represented as integrals of corresponding marginal utility.
Namely, the utility function is generalised as:

\[
U = \int_{t}^{T} u_{p}(\tau) d\tau + \int_{t}^{T} u_{o}(\tau) d\tau \tag{3.15}
\]

Where \(\tau\) is time of day; \(u_{p}(\tau)\) is the marginal process utility and \(u_{o}(\tau)\) is marginal
outcome utility; \(T\) is the activity duration and \(t\) is activity timing (i.e. start time of activity).
He proposes a marginal process utility \(u_{p}(\tau)\) as a function of activity intensity \(q(\tau)\), the
elapsed time \(t-\tau\) and time-of-day \(\tau\), namely that:

\[
u_{p}(\tau) = u_{p}(\tau, t-\tau, q(\tau)) \tag{3.16}\]

He also assumes the existence of a production function for each activity type which
describes the relation between the labour \(l\), goods inputs \(x\) and the resulting intensity of
activity at the same moment \(\tau\) modified by the production environment. Stated formally,

\[
q(\tau) = q(x(\tau), l) E(\tau) \tag{3.17}
\]

Where \(E(\tau)\) is defined to measure the quality of production environment of household
activity (e.g. weather, the opening hours of shops and the presence of friends); \( q() \) is the production function, characterised by a ‘satiation effect’ and a ‘diminishing marginal effect’ with relates to \( x(\tau) \) and \( I \). This implies \( \frac{\partial q}{\partial x} > 0, \frac{\partial^2 q}{\partial^2 x} < 0 \) and \( \frac{\partial q}{\partial I} > 0, \frac{\partial^2 q}{\partial^2 I} < 0 \).

The proposition of production function \( q() \) assumes the presence of underlying technologies of production for specific commodities and for the performance of certain activities. In terms of marginal outcome utility, it is written as:

\[
 u_o(\tau) = \frac{u_o(Z)}{T} \quad (3.18)
\]

He suggested \( u_o(\tau) \) as an average rate across the whole activity duration \( T \), which is derived directly from consumption of total output \( Z \).

As can be concluded from the above discussions, household production theory relies on intermediate artefact of some ‘commodity’ to derive the utility of activities. The idea of ‘production’ plays a central role in analysis of time allocation.

3.2.1.2 General time allocation models

In general time allocation theory, the terms ‘household production’ and ‘commodity’ are not mentioned. The consumption of goods and various components of time enter the utility function directly.

De Serpa (1971) proposed a model that can deal with some of the shortcomings of Becker’s model. He explicitly defined the time necessary for the consumption of market goods, as well as the consumption amount, as the direct source of utility. He also included working time in the utility function. The utility of spending a given amount of time on an activity depends on the particular type of activity. We note that De Serpa is considered to be the first to specify ‘technical constraints’ in his framework, which captures the insight that there may be a minimum time requirement for the consumption of market goods. De
Serpa’s model can be written as:

$$\begin{align*}
\text{Max } & \quad U(x_1, x_2, \ldots, x_n; t_1, t_2, \ldots, t_n; T_w) \\
\text{s.t. } & \quad wT_w + y \geq \sum_{i=1}^{n} p_i x_i \\
& \quad D = T_w + \sum_{i=1}^{n} t_i \\
& \quad t_i \geq a_i x_i \quad \forall i
\end{align*}$$

(3.19) \hspace{1cm} (3.20) \hspace{1cm} (3.21) \hspace{1cm} (3.22)

Where $t_i$ is the time allocated to a given activity $i$; $x_i$ is the continuous amount of consumption of this activity; and $a_i x_i$ represents the minimum time period. The technical constraint in Equation (3.22) states that the required minimum time is proportional to the consumption amount $x_i$. This gives rise to the classification of two types of activities: those that individuals have to spend more time than desired and those that individuals would like to spend as much as possible (defined as ‘pure leisure’ activity). Additional technical constrains have been developed recently by Jara-Díaz (2003) with the aim to strength the insight that consumption of goods requires time. He establishes the conceptual structure of the technical constraints through two general functions defined as the ‘activity possibility frontier’ (i.e. $t_i \geq f(x_i)$) and ‘consumption possibility frontier’ (i.e. $x_i \geq g(T_i)$).

Another important model in this literature is proposed by Evans (1972). In his model, the only argument of the utility function is the time allocated to different activities. It seems reasonable in the sense that certain activities, such as work, must be measured in units of time. But for other types of activities, such as going to the cinema, Evan’s model supposes that utility depends on amount of time spent in the cinema rather than the number of visits to the cinema. Individuals aim to arrange their activities optimally under constraints of time and money. Although the amount of time assigned to an activity is
considered to be the only source of utility, activity participation requires goods and hence a transition function between assigned time and input goods was introduced. His framework is formulated as:

\[
\begin{align*}
\text{Max} & \quad U(T_1, T_2, \ldots, T_n) \\
\text{s.t.} & \quad \sum_{i=1}^{n} T_i = D \\
& \quad \sum_{i=1}^{n} c_i T_i \geq 0
\end{align*}
\]

Where \( T_i \) is time allocated to activity \( i \); \( c_i \) is the cost per unit of time and \( c_i = \sum_j p_j q_{ji} \); \( q_{ji} \) represents the amount of goods \( j \) required per unit time of \( T_i \); \( p_j \) is price of goods \( j \).

The explicit representation of the relationship between input goods and time is ignored in Becker’s earlier model. With regards to the interpretation of \( c_i \), it is positive when an individual pays for the activity, negative when individual is paid (e.g. working hours) and zero when the activity is unpaid but costless.

The above time allocation models discussed so far calculated only the optimal amount of resource allocation between various activities or aggregate activity classes in a long time horizon under certain constraints; they do not incorporate the effect of how time is used. Until the early 1980s, time-varying demand analysis received attention spurred by policy guidance in various areas such as energy pricing and traffic management. For transport researchers, how to measure the scheduling effect has become of significant academic interest. Based on Becker (1965) and Johnson’s models (1966), Small (1982) added the scheduling decision \( s \) in both utility function and constraints to formulate a scheduling model of consumer activities in consideration of work trips. The scheduling term \( s \) includes all characteristics of the timing of activity and associated travels, which could be the time the trip begins, the time of arrival at work, or the time entering a specific geographic area (such as for congestion charging purposes). He divides the total time
resource $D$ into three components: work time $T_w$, leisure time $T_l$, and ‘consumption’ time. The ‘consumption’ time is defined as the time that is complementary to $T_w$ and $T_l$, relying on the scheduling decision $s$. Small’s model is written as:

$$\text{Max } U(x_1, x_2, \ldots, x_n, T_w, T_l, s) \quad (3.26)$$

$$\text{s.t. } wT_w + y = \sum_{i=1}^{n} p_i x_i + c(s) \quad (3.27)$$

$$D = T_w + T_l + T_i$$

$$F(s, T_w; w) = 0 \quad (3.29)$$

Where $D$ is ‘consumption’ time; $c(s)$ is scheduling cost; $F(\ )$ relates the wage rate $w$ and working hours $T_w$ to schedule decision $s$ (i.e. arrival time at work and departure time after work). In order to be applied in a discrete choice framework, he also derives an indirect utility function from the direct utility function achieved at the optimal solutions of $T_w^*$, $T_l^*$ and $x^*$ conditional on $s$. Stated explicitly, it is expressed as:

$$V(c(s), T(s), s) = U(x^*, T_w^*, T_l^*, s) \quad (3.30)$$

This indirect utility function in Equation (3.30) relies on the term $s$ and associated variables: schedule cost $c(s)$ and ‘consumption time’ $T(s)$. An empirical specification was further developed, in which the effect of a scheduling decision $s$ is modelled by accommodating the ‘schedule delay’ which represents the difference between actual arrival time and some ‘ideal’ activity start time.

3.2.2 Goods/Leisure/Activity choice models

The other powerful framework in microeconomic models combines the above general time allocation theory with discrete choice theory. These models have been
widely adopted in the transport literature to capture mode choice behaviour. Hence the
direct utility function employed in time allocation models is transformed in this
framework to derive the indirect utility function, which generally includes both travel
time and travel cost in an additive linear specification and sometimes are modified by
some representation of income (wage rate, aggregate income, etc.). Indirect utility
represents the maximised utility when a certain mode of travel is chosen. The
specification of indirect utility in this class of models is related to the role of working
hours $T_w$, which is treated as exogenous or endogenous, depending on whether it is
assumed that individuals can choose their working hours freely given a certain wage rate.

### 3.2.2.1 Models with endogenous working hours

In late 1970s, Train and McFadden (1978) postulated the goods/leisure trade-off
framework to analyse mode choice behaviour. This approach rests on a utility function
that increases with the general consumption of goods and time allocated to leisure
activities. Total time resource is divided into aggregate time components: work time,
leisure time and travel time. Given a single trip to be performed, this is summarised as:

\[
\begin{align*}
\text{Max } & \quad U(G, T_L) \\
\text{s.t.} & \quad T_L + t_i + T_w = D \\
& \quad G + c_i = wT_w + y
\end{align*}
\]

where $G$ is the consumption of goods (in monetary terms); $T_L$ is leisure time; $T_w$ is
working time; $w$ is the wage rate; $y$ is unearned income; $D$ is the total available time; $t_i$
and $c_i$ are the travel time and travel cost of mode $i$; $i \in M$ and $M$ is choice set of mode;
$U(\ )$ is the direct utility function.

In this model, travel time and travel cost indirectly influence utility through the
consumption of goods $G$ and leisure time $T_L$. By virtue of the constraints introduced in
Equation (3.32) and (3.33), an individual’s working hours is considered to be flexible. Increasing \( T_w \) implies consuming more G but reducing \( T_L \), while decreasing \( T_w \) implies consuming less G but increasing \( T_L \). This yields the trade-off effect between goods and leisure. Hence this problem is solved in two steps. First, utility is maximised conditional on choosing mode \( i \). Substituting the variable \( G \) and \( L \) in Equation (3.31) with constraints in Equation (3.32) and (3.33) as a function of \( T_w \), we have:

\[
\text{Max } U(G, T_L) = U(wT_w + y - c_i, D - t_i - T_w)
\]

(3.34)

The optimal solution of \( T_w \) is achieved by taking the first order differentiation of Equation (3.34), namely that:

\[
\frac{\partial U}{\partial T_w} = \frac{\partial U}{\partial G} w - \frac{\partial U}{\partial T_L} = 0
\]

(3.35)

This produces that optimal solution of \( T_w^* \) depends on \( c_i \), \( t_i \) and \( w \) (i.e. \( T_w^* = W(w, c_i, t_i) \)). Substituting this condition into Equation (3.34), indirect utility representing the maximised utility conditional on mode \( i \) is ultimately written as a function of \( c_i \) and \( t_i \) given the preferred wage rate \( w \), i.e.:

\[
V_i = V_i(c_i, t_i, w)
\]

(3.36)

Where \( V_i \) is the indirect utility conditional on the chosen mode \( i \). This indicates that the trade-off between goods and leisure only depends on the choice of travel mode, which is characterised by some combination of travel time and travel cost. The second step is the discrete optimisation among the entire modes \( M \). The chosen mode is the one with the highest indirect utility in the form of Equation (3.36).

Train and McFadden (1978) also propose that the direct utility function can be specified as classical Cobb-Douglas form, i.e.
\[ U = \alpha G^\beta T_k^{1-\beta} \]  

(3.37)

Where \( \alpha \) and \( \beta \) are parameters of Cobb-Douglas utility function. \( \alpha \) is a positive utility constant. \( \beta \) represents the relative preference for goods relative to leisure and \( 0 < \beta < 1 \) (Train, 2003). After some algebraic derivation, the indirect utility of choosing mode \( i \) in Equation (3.36) can be rewritten as the following specification (Jara-Diaz, 2007):

\[ V_i = \alpha (1 - \beta)^{1-\beta} \beta^\beta \left[ w^{1-\beta} (D - t_i) + w^{-\beta} (y - c_i) \right] \]  

(3.38)

Empirical evidence suggested that the value of \( \beta \) is between 0.7 to 1 (Train and McFadden, 1978). However, in extreme cases when \( \beta \) approaches 0, mode choice is determined by \( -\frac{c_i}{w} - t_i \), while when \( \beta \) approaches 1, mode choice is determined by \( \frac{-c_i}{w} - t_i \).

Following De Serpa (1971), Jara-Dias and Guevara (2003) proposed a unified model system encompassing all types of activities and goods (work, sleep, travel and so on). As opposed to the constraint imposed on the exponent of leisure time in Equation (3.37), they specify the direct utility function as a more general Cobb-Douglas form. Technical constraints on goods and activity time are also taken into account. Statedly formally,

\[
\begin{align*}
\text{Max } & U = \alpha T_w^{\beta_w} \prod_{i \in I} T_i^{\beta_i} \prod_{k \in K} X_k^{\beta_k} \\
\text{s.t. } & w T_w + y - \sum_{k \in K} P_k X_k \geq 0 \\
& D - T_w - \sum_{i \in I} T_i = 0 \\
& X_j - X_j^{\text{min}} \geq 0 \quad \forall j \in J
\end{align*}
\]  

(3.39) (3.40) (3.41) (3.42)
\[ T_r - T_r^{Min} \geq 0 \quad \forall r \in R \]  

(3.43)

Where \( \beta_w, \beta_i \), and \( \beta_k \) are exponents corresponding to work, non-work activities and goods; \( \alpha \) is also a positive utility constant; \( T_j \) is time assigned to non-work activities; \( T_w \) is work time; \( I \) is the set of all activities except work, \( K \) is the set of all goods. \( R \) is the set of constrained activities and \( J \) is the set of mandatory goods; \( T_r^{Min} \) is minimum time requirement of constrained activities and \( X_j^{Min} \) are minimum consumption amount of mandatory goods.

Constructing the Lagrange objective function of above model and taking first order partial differentiation with respect to \( T_i \) where \( i \not\in R \), \( T_i^{min} \), \( X_k \) where \( k \not\in J, X_j^{Min} \) and \( T_w \), yields the optimal solutions of \( T_w^*, T_i^* \) where \( i \not\in R \) and \( X_k^* \). Consider that one of the non-work activities is travel with travel time \( t_i \) and travel cost \( c_i \), the indirect utility function can be obtained by replacing the optimal values in the direct utility function, which leads to the following specification, i.e.

\[ V_i = V_i(t_i, c_i, w, G_j, T_j) \]  

(3.44)

Where \( G_j = \sum_{j \in J} P_j X_j^{Min} - y - c_i \) and \( T_j = \sum_{r \in R} T_r^{Min} - t_i \). For more details about the algebraic derivation, please see (Jara-Diaz, 2007).

It should be noted that the above models are built on a strong assumption that an individual can freely choose the number of hours which they work and receive a predefined wage rate. In many cases, this may be an unrealistic assumption. Researchers have more recently made contributions by addressing this issue (Bates and Roberts, 1986; Jara-Diaz and Farah, 1987; Jara-Diaz, 1994)
3.2.2.2 Models with exogenous working hours

Contrary to the specification of Train and McFadden’s model (1978), Bates and Roberts (1986), building on works by DeSerpa (1971) and Train and McFadden (1978), presented a model in which the number of working hours is considered as an exogenous constant. This model is formulated as:

Max \( U(x, q, t_1, t_2, \ldots, t_n) \) \hspace{1cm} (3.45)

s.t. \( Y = px + \sum_{i=1}^{n} c_i \delta_i \) \hspace{1cm} (3.46)

\( D - T_w = q + \sum_{i=1}^{n} \delta_i t_i \) \hspace{1cm} (3.47)

\( t_i \geq t_i^0 \quad \forall i \) \hspace{1cm} (3.48)

where \( x \) is the consumption of a generalised good, \( q \) is the time spend on a generalised activity, \( t_i \) is travel time by mode \( i \), \( c_i \) is travel cost by mode \( i \), \( \delta_i \) is a binary variable taking a value of 1 when mode \( i \) is chosen, otherwise 0, and \( t_i^0 \) is the minimum travel time for mode \( i \). As with De Serpa’s model, this minimum time constraint does not apply to leisure activities.

To obtain the specification of the indirect utility function, Bates made a first order Taylor series expansion of the above direct utility function which yields the following relationship:

\( U_i \approx U(x = 0, q = 0, t_1 = 0, \ldots, t_n = 0) + \frac{\partial U}{\partial x} x + \frac{\partial U}{\partial q} q + \sum_{i=1}^{n} \frac{\partial U}{\partial t_i} t_i \) \hspace{1cm} (3.49)

Denoting the Lagrange multiplier of the above constraints in Equation (3.46), (3.47) and (3.48) respectively as \( \lambda, \mu, \phi \), the first order partial differentiation of the Lagrange objective function is performed with respect to \( x, q \) and \( t_i \), which yields the following values:
\[
\begin{align*}
\frac{\partial U}{\partial x} &= \lambda p \quad (3.50) \\
\frac{\partial U}{\partial q} &= \mu \quad (3.51) \\
\frac{\partial U}{\partial t_i} &= \mu \delta_i - \delta \phi_i \quad (3.52)
\end{align*}
\]

Given the constraints in Equation (3.46)-(3.47), replacing the partial derivative terms in Equation (3.49) with Equation (3.50)-(3.52) produces the following expression:

\[
U_i \cong U(x = 0, q = 0, t_i = 0, \ldots, t_n = 0) + \lambda \left( Y - \sum_{i=1}^{n} \delta c_i \right) + \mu (D - T_w) + \sum_{i=1}^{n} \delta \phi t_i \quad (3.53)
\]

Thus the indirect utility function that applies when mode \( i \) is chosen simplifies to a linear function of, i.e.

\[
V_i \cong \lambda c_i + \phi t_i \quad (3.54)
\]

Similarly, Jara-Díaz and Farah (1987) then modified Train and McFadden’s model by specifying the same form of direct utility function with different constraints.

\[
\begin{align*}
\text{Max } U &= \alpha G^\beta T_L^{1-\beta} \quad (3.55) \\
\text{s.t. } G + nc_i &= wT_w + y \quad (3.56) \\
T_L + nt_i &= D - T_w \quad (3.57)
\end{align*}
\]

where \( t_i, c_i \) are respectively travel time and travel cost using mode \( i \); \( n \) is number of trips made during certain period. Given that \( T_w \) is also considered to be exogenous, there is nothing to optimise in this framework. Thus the conditional indirect utility can be obtained simply by replacing \( G \) and \( T_L \) in Equation (3.55) with the constraints in (3.56) and (3.57), namely that:

\[
V_i = \alpha \left( wT_w + y - nc_i \right)^\beta (D - T_w - nt_i)^{1-\beta} \quad (3.58)
\]
Taking the first order Taylor series of Equation (3.58) leads to the linear approximation.

\[ V_i \approx c_i e^{-\beta_i} - t_i e^{1-\beta_i} \tag{3.59} \]

Where \( e = \frac{wT_w + y}{D - T_w} \) is defined as the expenditure rate. This implies that the indirect utility of mode \( i \) is a linear function of travel time and travel cost, adjusted by the expenditure rate.

Jara-Díaz (1994) proposed a model which extended the representation of leisure time \( L \) and goods \( G \) consistent with the assumption established by Evans (1972). He considers the basic source of utility to derive entirely from time spent on different activities. The dependence among activities through the allocation of time and the shared use of goods is also incorporated. His model is formulated as:

Max \( U(T, T^F_w, T^V_w, t) \) \tag{3.60}

s.t. \[ \sum_i T_i + T^F_w + T^V_w + \sum_{j=1}^{N} \sum_{i \in M_j} \delta_{ij} t_{ij} = D \tag{3.61} \]

\[ \sum_{i} \sum_{d} p_{id} x_{id} + \sum_{j=1}^{N} \sum_{i \in M_j} \delta_{ij} t_{ij} = Y_F + wT^V_w \tag{3.62} \]

\[ F(X,T) \geq 0 \tag{3.63} \]

\[ N = N(x) \tag{3.64} \]

where \( T \) is vector of time \( T_i \) allocated to different activities; \( T^F_w \) is fixed work duration; \( T^V_w \) is variable working hours; \( t \) is a vector of travel times \( t_{ij} \) of trip \( j \) in mode \( i \); \( N \) is the number of trips during certain period; \( \delta_{ij} \) is binary variable indicating whether trip \( j \) is chosen to use mode \( i \); \( M_j \) is choice set of modes for trip \( j \); \( Y_F \) is a fixed income level; \( w \) is the individual’s wage rate; \( F(\ ) \) is the technical transformation function between
goods \( X \) and time \( T \); \( X_{id} \) is good \( i \) bought in zone \( d \); \( P_{id} \) is the price of good \( i \) bought in zone \( d \). In this model, all activities directly impact the individual’s utility. As denoted in Equation (3.62), a set of goods \( X \) can be purchased in different places with different prices. In Equation (3.64), the number of trips depends on the choice of goods. \( F(\ ) \) indicates an implicit relationship between \( X \) and \( T \).

Jara-Díaz (1994) also explores the implication of his model by considering the mode choice problem in the case of a specific journey \( k \). For simplicity, all decisions (e.g., the number of journeys \( N \) and choice of destination \( d \)) are assumed to be given, such that the fourth constraint is dropped. In this way, his model is rewritten as:

\[
\begin{align*}
\text{Max} & \ U \left( T, T_w, T_w', t_1, \ldots, t_{ik}, \ldots, t_w \right) \\
\text{s.t.} & \sum_j T_i + T_w^F + T_w' + \sum_{j,k} t_j + t_{ik} = D \\
& \sum_i P_i X_i + \sum_{j,k} C_j + C_{ik} = Y_F + wT_w' \\
& F(X, T) \geq 0
\end{align*}
\]

(3.65)

(3.66)

(3.67)

(3.68)

Hence the corresponding conditional indirect utility function is obtained by replacing the conditional solution \( T, T_w' \) in Equation (3.65) with constraints in Equation (3.66) and (3.67), namely that:

\[
V_{ik} = V \left( D - T_w^F - \sum_{j,k} t_j - t_{ik}, T_w', \frac{1}{w} \left( Y_F - \sum_i P_i X_i - \sum_{j,k} C_j - C_{ik} \right), t, t_{ik} \right)
\]

(3.69)

In this specification, travel time \( t_{ik} \) does not only enter the utility function directly as an argument, but also influences the available time to perform other activities (i.e. the first term in Equation (3.69)). Making the linear approximation of the above equation by taking a first order Taylor series, for choosing mode \( i \), yields the following specification:
\[ V_i = \lambda + \alpha \left( D - T_w^F - \sum_{j=1}^{n} T_j - t_{ik} \right) + \beta T_w^F + \gamma \frac{1}{w} \left( Y_F - \sum_i P_i X_i - \sum_{j=1}^{n} C_j - C_{ik} \right) + \eta_{ik} \] (3.70)

where \( \alpha, \beta, \gamma, \eta \) are parameters. The indirect utility that matters in mode choice is:

\[ V_i = (\eta - \alpha)t_{ik} - \gamma \frac{1}{w} C_{ik} \] (3.71)

As can be seen in Equation (3.71), the utility of choosing mode \( i \) is a linear specification of travel time and travel cost. Equations (3.54) and (3.59) also show that the indirect utilities of mode \( i \) are all represented as a linear specification characterised by different parameters. These linear specifications of indirect utility function facilitate the calculation of the ‘value of time’ as the marginal rate of substitution between travel cost and travel time. When applied to assess travel time savings, the interpretation of the coefficients differs among these models.

3.2.3 Summary

Section 3.2.1 and section 3.2.2 provide a detailed review on microeconomic models which are broadly classified into two groups: household production models as well as time allocation models on the one hand, and goods leisure/activity tradeoff models on the other. The evolution of these model classes has been examined mainly from two perspectives. The first is the utility specification relating to the variables or the sources considered to influence utility. Conventional consumer theory assumes that utility derives purely from the consumption amount of goods \( x \). Household production models assume that non-market ‘commodity’ is the direct source of utility. Market goods \( x \) and time \( T \) are input resource to produce \( Z \). They enter the utility function indirectly through the production function \( h(\cdot) \) relating to \( Z \). General time allocation models and goods leisure/activity models suggest that utility derives directly from the consumption of
market goods (i.e. either via continuous amount \( x \) or monetary value \( G \)) and different elements of time vector \( T \), such as leisure.

The second is the constraints imposed to the utility function. The traditional consumer theory and household production framework included money and income constraints only (e.g. Becker, 1965; Johnson, 1966). An important conceptual extension to the literature was to postulate the additional schedule and technical constraints (e.g. DeSerpa, 1971; Bates, 1987; Jara-Diaz, 1994; Jara-Diaz and Guevara, 2003). Table 3.1 summarises the existing studies from these perspectives.

Table 3.1 Summary of existing microeconomic models

<table>
<thead>
<tr>
<th>Model type</th>
<th>Source of utility</th>
<th>Additional Constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer theory</td>
<td>( U=U(X) )</td>
<td>---</td>
</tr>
<tr>
<td>Household production models</td>
<td>( U=U(Z)=U(x,T) ) with ( Z=h(x,T) )</td>
<td>---</td>
</tr>
<tr>
<td>Time allocation models</td>
<td>( U=U(x,T) ) e.g.</td>
<td>- De Serpa (1971) first proposed a basic technical constraint</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Small (1982) populated a schedule constraint</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Evans (1972) merges the technical with money constraints</td>
</tr>
<tr>
<td>Goods/activity models</td>
<td>( U=U(GT_L) ) e.g.</td>
<td>- Bates and Roberts (1987), Jara-Diaz (1994, 2003) and Jara-Diaz and Guevara (2003) include technical constraints</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Jara-Diaz (1994) populated a constraint on total number of trips</td>
</tr>
</tbody>
</table>
3.3 Activity-based travel demand models

3.3.1 Trip-based models and activity-based models

When we refer to ‘travel demand modelling’, we consider an individual’s decision process regarding travel choices. In classical trip-based models, it has been modelled as a series of discrete decisions, which typically consisted of four parts:

1) whether to travel,
2) when and where to travel,
3) by what means of travel, and
4) Route assignment

These give rise to the trip generation, trip distribution, mode choice and route assignment dimensions of travel behaviour, respectively. The trip-based approach concentrates on analysing trip-level decisions, explicitly neglecting (in many cases due to limited computing power and/or data resources) the broader context in which activity participation and travel decisions are made.

In recent years, there has been a distinct paradigm shift from the trip-based approach to activity-based approach, with the aim of better understanding people’s behavioural motivations of participating in a given activity in a certain place and at a particular time. Compared with the classical trip-based approach, the theoretical advantage of the activity-based school primarily depends on the possibility of capturing an individual’s travel behaviour more realistically, with the promise of then extending the analysis to better understand people’s behavioural responses to network or policy changes.

Since the advent of activity-based modelling, a series of reviews of the developing literature have been published (Axhausen and Garling, 1992; Bhat, 1996; Ettema and
Timmermans, 1997; Bhat and Koppelman, 2000). In this framework, the decision process is specified to include lower-level choices of allocating time to activities within a fixed time frame, such as a day or a week. The rationale behind is that the demand for travel is derived from an individual’s participation in activities distributed across geographic space.

In activity-based travel analysis, the utility of an activity is principally discussed in the context of an individual’s whole activity pattern, of which the utility is represented as the sum of the utility of each constituent activity. The utility of each activity is specified through a mathematical function based on a set of quantitative and qualitative activity attributes (such as activity type, duration, timing, activity location etc.). In most cases, transport researchers have intuitively represented the utility of an activity as a function of its timing and duration, sometimes modified by contextual and personal characteristics. Existing activity models can be broadly classified into three groups: duration-dependent models, timing-dependent models and hybrid duration/timing-dependent models. In the remainder of this section, we will examine these classes of models in some detail.

### 3.3.2 Duration-dependent models

Duration-dependent models consider the utility of an activity to be derived from completion of this activity. In this view, an individual’s scheduling decision is an optimisation problem of distributing time to different activities under the restriction of a fixed time resource (e.g. the number of hours within a day). Duration dependent models are broadly divided into two categories based on the assumption regarding the shape of utility function: conventional duration-dependent models and S-shape duration dependent model.
3.3.2.1 Conventional duration-dependent model

Conventional duration-dependent models are built on the structure of classical time allocation theory, which characterise the utility of a limited number of discrete activity classes (e.g. in-home discretionary activities, out-of-home discretionary activities etc. and occasionally including multiple episodes), as a function of the duration of these activities (Kitamura, 1984; Kitamura et al., 1996; Bhat and Misra, 1999; Yamamoto et al., 2000). The utility functions are typically represented as a linear or logarithmic function of activity duration. These duration-dependent models, also termed as activity-time allocation models, are often combined with activity choice models in a discrete-continuous modelling framework, within which activity time allocation is the continuous decision while the activity type decision constitutes a discrete choice.

Kitamura (1984) examined people’s daily time allocation between discretionary and mandatory activities. He derived a model of discrete activity choice and continuous time allocation based on the random utility maximisation. The behavioural assumptions underlying the model formulation can be summarised as:

- if engagement in a discretionary activity does not increase total utility, then the activity will not be chosen and no time will be allocated to it at all;
- if it contributes to total utility in a positive way, then the discretionary activity will be allocated with an optimal amount of time.

The random utility of an activity is specified as a multiplicative function of independent random variables and a natural logarithm of the allocated amount of time. Suppose there are \( J \) types of activities to which a given amount of time is allocated by individual. Let utility of activity \( i \) be:

\[
U_i(t_i, x_i) = e^V(t_i, x_i) 
\]

(3.72)

where \( t_i \geq 0 \) \((i = 1, 2, ..., J)\) is the amount of time allocated to activity \( i \); \( x_i \) is the vector
of exogenous variables; $V_i$ is the deterministic utility of activity $i$; $\varepsilon_i > 0$ is the random variable assumed to be independent of $x_i$ and $t_i$.

With these assumptions, the individual’s time allocation behaviour can be expressed as the following problem:

$$\text{Max } U(t_1, t_2, t_3, t_4) = \sum_{j=1}^{J} \varepsilon_j V(t_j, x_j)$$

s.t. $\sum_{j=1}^{J} t_j = D$ \hspace{1cm} (3.73)

With $V(t_j, x_j) = f_j(x_j) \ln t_j \gamma_j$ \hspace{1cm} (3.75)

where $D$ is the total amount of time to be allocated; $f_j(\ )$ is a positive function and $\gamma_j$ is an unknown coefficient with $\gamma_j > 0$. The logarithmic function satisfies the plausible assumption that the utility of an activity increases, but the marginal utility diminishes, as the amount of time allocated increases. Replacing $V(t_j, x_j)$ in Equation (3.75) with Equation (3.73) and taking the first order partial derivative with respect to $t_j$, the optimal solution of time allocation for activity $j$ is:

$$t_j^* = \frac{\varepsilon_j \gamma_j f_j(x_j)}{\sum_{j=1}^{J} \varepsilon_j \gamma_j f_j(x_j)} D \hspace{1cm} j = 1, 2, ..., J$$

(3.76)

We note that the above discussion is based on the assumption that time is allocated to all $J$ types of activities. This is most certainly not always the case in a person’s daily time budgeting. An individual may or may not take part in particular discretionary activities in a given day. This discreteness of such behaviour is not represented by the above utility functions. Hence, the utility functions of discretionary activities are redefined as:
\[
U_j(t_j, x_j) = \begin{cases} 
\varepsilon_j V(t_j, x_j) & \text{if } t_j > 0 \\
0 & \text{if } t_j = 0 
\end{cases}
\]  \hspace{1cm} (3.77)

Hence activity \( j \) does not contribute to total utility if no time is allocated to it, whereas an insufficient amount of time allocation may yield negative utility. The probability of each individual engaging in an activity can be expressed as a Tobit model (Tobin, 1958).

Later on, Kitamura et al. (1996) extended this discrete-continuous choice model to study activity participation and time allocation to in-home and out-of-home discretionary activities. They found that individuals working several days per week allocate a larger proportion of their daily out-of-home time to discretionary activities than those working less. They also showed that the proportion of time allocated to in-home discretionary activities increases with commuting time. Lastly, Yahamoto et al. (2000) built on this framework to analyse the trade-off between in-home and out-home activities separately for workdays and weekends.

Bhat and Misa (1999) formulated a model for the allocation of total weekly discretionary time between in-home and out-of-home locations and between weekdays and the weekend. The model formulation takes the form of a continuous utility-maximising resource allocation problem. The authors’ specification assumes that total weekly discretionary time is exogenously predetermined, and discretionary activities are classified into four categories:

1) in-home weekdays,
2) in-home weekend,
3) out-of-home weekdays, and
4) out-of-home weekdays.

Hence, time allocation to each of the four categories is examined as the fraction of total weekly discretionary time allocated to the particular category.

Let \( i \) be an index for the discretionary categories (\( i = 1, 2, 3, 4 \)). Consider that the
utility of category \( i \) is a logarithmic function of the fraction of total discretionary time allocated to it, which satisfies the assumption of increasing utility of category \( i \) with diminishing marginal utility as the fraction of time allocated to category \( i \) increases. The utility of category \( i \) is related to a positive category-specific functional term. With the above assumptions, Bhat and Misa’s specification is expressed as:

\[
\text{Max } U(f_1, f_2, f_3, f_4) = \sum_{i=1}^{4} e^{\beta_i} \ln(f_i) \quad (3.78)
\]

subject to:

\[
\sum_{i=1}^{4} f_i = 1 \quad f_i > 0 \quad i = 1, 2, 3, 4 \quad (3.79)
\]

Where \( f_i \) is the fraction of total discretionary time allocated to category \( i \), \( e^{\beta_i} \) is the exponential function; \( x_i \) the vector of exogenous individual socio-demographic.

Equation (3.79) indicates that all fractions must sum up to unity, implying that all discretionary time is allocated. Expressing the Lagrange multiplier of the constraint as \( \lambda \), the Lagrangian function becomes,

\[
L = \sum_{i=1}^{4} e^{\beta_i} \ln(f_i) + \lambda \left(1 - \sum_{i=1}^{4} f_i \right) \quad (3.80)
\]

Taking the derivative of this function with respect to each fraction \( f_i \), we obtain the optimum fractional allocation:

\[
f_i^* = \frac{e^{\beta_i}}{\sum_{i=1}^{4} e^{\beta_i}} \quad (3.81)
\]

In the models discussed above, the utility specifications (i.e. logarithmic functional forms) satisfy the ‘saturation effect’ through an increasing utility function and ever-diminishing marginal utility, similar to the assumption in microeconomic theory. However, this assumption may be violated, especially for particular types of activities (such as leisure and information acquisition) where there may be other types of variation in the utility and marginal utility function among the whole range of possible activity
duration. As introduced by Supernak (1992) and Joh et al. (2002), other plausible shapes of the utility function with respect to time duration may be more appropriate.

3.3.2.2 S-shape duration dependent model

Joh et al. (2002) introduced an S-Shape utility function in the development of the ‘Aurora’ model - a dynamic activity-based scheduling model (Timmermans et al., 2001; Joh et al., 2003; Joh, 2004). They paid particular attention to the possibility of increasing marginal utility due to a negative saturation effect on activity duration in the beginning phase of certain activities. The initial increase of marginal utility to a certain point in time can be conceived as a ‘warming-up’ period and the length of this period was specified as variable dependent on activity type. Based on these considerations, their utility function of a single activity was formulated as:

\[ U = U_{\text{min}} + \frac{U_{\text{max}} - U_{\text{min}}}{(1 + \exp[-\beta(T - \alpha)])} \]  

(3.82)

where:

- \( T \) is the duration of whole activity;
- \( U_{\text{min}}, U_{\text{max}} \) are unknown parameters, \( U_{\text{min}} \) is the minimum utility of an activity and \( U_{\text{min}} \leq 0 \), \( U_{\text{max}} \) is the maximum utility of an activity and \( U_{\text{max}} > 0 \);
- \( \alpha, \beta, \gamma \) are activity-specific parameters;
- \( \alpha \) positions the function on the time-of-day axis and \( \alpha > 0 \) always;
- \( \gamma \) influences the position of saturation point: \( 0 < \gamma < 1 \) implies the saturation point is later than \( \alpha \) and the warming up period is longer than cooling down period, whereas \( \gamma > 1 \) when saturation point is earlier than \( \alpha \) and warming up period is shorter than cooling down period;
- \( \beta \) represents the steepness of the rate of change around the saturation point.
and $0 < \beta < 1$.

The marginal utility of Equation (3.82) is S-shaped, first increasing until a point of inflection, and then decreasing. This implies $dU/dT > 0$ and $d^2U/d^2T < 0$, with the sign of the second derivative dependent on the location on the duration axis.

3.3.2.3 Discussion

Although different functional forms of duration-dependent models have been proposed, a consensus has yet to emerge regarding the most appropriate shape of the utility function for activity duration. Also duration-dependent models do not take into account a person’s preference for the timing of activities, resulting in a specification where the marginal utility of an activity is independent of time-of-day. This is contrary to the studies on the time-of-day choice, which indicate that timing of activity influence the utility of activity patterns.

3.3.3 Timing-dependent models

A substantial body of evidence exists, derived from both theoretical and empirical studies, indicating that the utility of an activity is dependent on the timing of an activity. For instance, the quality and range of goods available to purchase may vary by time-of-day (e.g., a morning newspaper), which could give rise to differential levels of utility at different hours of the day. Timing-dependent models ignore the influence of activity duration, but rather relate the utility of a single activity to the activity timing choice (either between discrete time intervals or at a specific time-of-day on a continuous time scale). Depending on the underlying decision-making mechanism, this category of models is classified into two subgroups: time choice models and schedule delay models.

3.3.3.1 Time period choice models

Time choice models regard the timing of activities as a choice between a limited
numbers of time intervals (Ben-Akiva and Bowman, 1998; Arentze and Timmermans, 2005). Time period choices are one possibility, where the individual chooses among several coarse time intervals of continuous time (e.g. 7:00 AM – 9:00 AM, 9:00 AM to 12:00 noon, etc). The utility of an activity is specified as a function of the characteristic of several variables – time period, travel time, travel cost, and the socio-demographic profile of the individual.

Ben-Akiva and Bowman (1998) presented an integrated discrete choice model system of an individual’s daily activity and travel behaviour which consists of their decisions on tours, destination, travel modes and time of day. The duration of each activity is regarded as exogenously fixed. They assume that particular activities are associated with higher utility in certain periods than in others. In this view, the timing of an activity is treated as the choice among intervals including the morning, afternoon, and evening, rather in continuous time scale. The nested logit model is used to represent various decisions on different dimensions (i.e. time of day, activity choice, location choice, travel mode choice).

3.3.3.2 Schedule delay models

The second group of models in this category are schedule delay models, which have mostly been employed to model trip departure time choice in a single activity tour (such as a work-related tour). The key insight is that the timing of activities may be guided by particular constraints. The schedule delay approach focuses on modelling the impact of such constraints on the timing of activity and trips. This approach assumes the existence of a preferred start time associated with each activity. Likewise, a trip to access an activity hence has a preferred arrival time (PAT). Deviations from the preferred arrival time, which is termed as ‘schedule delay’, give rise to negative utility.

Vickrey (1969) was the first person to propose this idea to model peak period commuter scheduling behaviour. He suggested that individual travellers are assumed to
minimise the indirect utility which is a deterministic function of travel time and schedule delay (the difference between the official work time and actual arrival time) at departure time \( t \). Small (1982) also applied this concept to model commuting travel. In his model, trip utility is expressed as:

\[
V(t) = \mu r(t) + \nu \max(0, (PAT - t - r(t))) + \zeta \max(0, (t + r(t) - PAT))
\]  

(3.83)

where \( V(t) \) is the utility of travel starting at time \( t \), \( r(t) \) is the travel time departing at time \( t \), \( PAT \) is the preferred arrival time and \( \mu \) is a travel time parameter, and \( \nu \) and \( \zeta \) are schedule delay parameters. This framework was subsequently applied by other researchers to model similar commuter behaviour (Arnott et al., 1988, 1994).

3.3.3.3 Discussion

As pointed out by Ettema et al. (2007), timing-dependent models ignore the variation of utility derived from the length of activity duration, which lead to a specification where marginal utility of an activity is independent of elapse time. This might be possible in the activity with a short duration. However for activities with extended duration (such as sleep and work and so on), this is contrary to the studies in activity-based duration dependent models and time allocation models. For example, in the case of a work activity, working productivity may vary over the working period due to fatigue effect, which leads to varying utility at different times.

3.3.4 Duration- and Timing-dependent models

Duration-dependent models and timing-dependent models make strong assumptions that people’s decisions regarding the timing and duration of activities are separate from each other. However, both theoretically and intuitively, the choice of timing and duration of activities are closely related. In recent years, researchers have started to explore the relationship between activity timing and duration. In the category of both
timing- and duration-dependent models, the utility derived from an activity depends on both its duration and timing. These models provide the possibility of analysing these decisions holistically, accompanied by the introduction of the marginal rate of utility which gives a more sophisticated treatment to choices of both duration and timing. The central idea is that there exists a function for marginal utility which may vary over the course of a day (Ettema et al., 2007). The marginal rate of utility expresses the utility derived from activity participation per unit of time, which primarily depends on the time-of-day and elapsed time since the beginning of the activity. The utility of an activity is expressed in terms of the integral of the various components of marginal utility over the activity duration.

Earlier models in this category fall within the ‘PJETA’ framework, which principally consists of models proposed by Polak and Jones (1994), Ettema and Timmermans (2003) and Ashiru et al. (2004), and were extended by Ettema et al. (2004) This is implemented by various specifications of marginal utility functions. Contrary to the specification of the pure timing-dependent models, the PJETA class of models acknowledges that timing decisions take place on a continuous time scale.

Polak and Jones (1994) first introduced this idea of marginal utility, based on the earlier work by Winston (1982) and Koenker (1979). They suggested a general specification of utility of activity \( j \) which is specified as:

\[
U_j(t,T) = \int_t^{t+T} u_j(\tau) d\tau
\]

(3.84)

Where \( t \) is the timing (i.e. start time) of activity \( j \); \( u_j(\tau) \) is the marginal rate of utility associated with activity \( j \); \( T \) is the duration of the activity, and \( \tau \) is the time-of-day. The first derivative of utility for the timing of activity \( t \) is expressed as:
\[
\frac{\partial U_j(t,T)}{\partial t} = u_j(t + T) - u_j(t)
\]  

(3.85)

Based on this utility specification, they proposed a framework to model the impact of road pricing charges on the timing of people’s travel based on the consideration of a home-based tour (i.e. home-destination-home). The timing decision of the journey is examined in the context of the individual’s activity schedule, in which the timing of travel follows as a consequence of the relationship between the time varying pattern of destination utility and travel cost. They also conclude that when the optimal decisions of departure time are made, the marginal utility derived from the last unit of time in the current activity equals the marginal utility derived from the first unit of time in the next activity. A more empirical specification is also obtained when the utility of activity \( U_j(t,T) \) is approximated by using a first order Taylor series. This specification implies that travellers may trade off the ‘schedule delay’ of travel and the ‘duration penalty’ of destination activity participation (i.e. the difference between the actual duration and optimal duration) to adjust their behaviour when travel time and cost change.

Following Polak and Jones, Ettema and Timmermans (2003) proposed an alternative model, in which the marginal utility of an activity is represented as a direct function of the time-of-day \( \tau \), while activity participation choice, mode choice and destination choice are assumed to be exogenously fixed. The formulation of the marginal utility of an activity is based on the derivation of the S-shape functional form by Equation (3.82) proposed by Joh et al. (2002).

\[
u(\tau) = \frac{\gamma \beta U_j^{\text{max}}}{\exp[\beta(\tau - \alpha)] \{1 + \exp[-\beta(\tau - \alpha)]\}^{\gamma+1}}
\]  

(3.86)

where the parameters in Equation (3.86) have the same interpretation as for Equation (3.82).
We note that the above PJET models allow for more complex forms of utility generation relating to activity timing decisions, as opposed to the relatively basic linear specification in pure timing-dependent models. However, the duration component is neglected in the marginal utility function. For activities subject to saturation and fatigue effects, marginal utility decreases with increasing activity duration, whereas PJET models assume that marginal utility remains constant at time-of-day $\tau$ irrespective of activity duration (Ettema et al., 2007).

Recently, Ashiru et al. (2004) and Ettema et al. (2004) have proposed empirically tested models that combine the above time-of-day-dependent marginal utility of PJET models and the duration-dependent models. Hence, marginal utility in this specification depends on both time-of-day $\tau$ and elapsed time $\tau - t$ (where $t$ is the start time of activity). The general functional form for the marginal utility of activity $j$ is expressed as an additive specification of the above two components, namely that:

$$U_j(t, T) = \int_t^{\tau} u_j(\tau, \tau - t) d\tau = \int_t^{\tau} u_j(\tau) d\tau + \int_t^{\tau} u_j(\tau - t) d\tau$$  \hspace{1cm} (3.87)

Ettema et al. (2004) explored the timing and duration of activities and trips within the context of people’s responses to road pricing policies. In this framework, marginal utility encompasses two components for duration and timing. They draw on concepts from both PJET models and the work of Yamamoto et al. (2000) and formulate the problem as:

$$\text{Max } U = \max \left( \sum_m U^T_m + \sum_j U^A_j \right)$$  \hspace{1cm} (3.88)

Where $U^A_j$ is utility of activity $j$ and $U^T_m$ is utility of trip $m$. Equation (3.88) implies that individuals seek to maximise the total utility derived from both activities and trips. Hence the utility of trip $m$ at current time clock $t$ is defined as a linear function of travel
time $R_t(t)$ and travel cost $C_m(t)$, that can vary over time to reflect changing travel conditions at different times of the day. The utility of activity $j$ at current time clock $t$ is expressed as:

$$U_j^A = U^A(t, t_j') = \int_{t_j}^{t_j'} u^A(\tau, t - \tau)d\tau = \int_{t_j}^{t_j'} u^{AT}(\tau)d\tau + \int_{t_j}^{t_j'} u^{AD}(t - \tau)d\tau$$  \hspace{1cm} (3.89)$$

Where $t_j'$ is the start time of activity $j$, $u^A$ is the marginal utility function of activity, which is expressed as an additive form of time-of-day component $u^{AT}(\tau)$ and elapsed time component $u^{AD}(t - \tau)$. $u^{AT}(\tau)$ is represented as an S-shaped marginal utility function, as initially shown in Equation (3.86):

$$u^{AT}(t) = \frac{\gamma \beta U_{\max}}{\exp[\beta(t - \alpha)] \left[1 + \exp[-\beta(t - \alpha)]\right]^{\gamma+1}}$$  \hspace{1cm} (3.90)$$

An alternative specification is also proposed by using a Cauchy distribution:

$$u^{AT}(t) = \frac{U_{\max}}{c \pi \left(\frac{t - b}{c}\right)^2 + 1}$$  \hspace{1cm} (3.91)$$

where $b$ reflects the peak of the distribution (i.e. the time-of-day with the highest marginal utility), $c$ reflects the deviation (the extent to which an activity is bound to a specific period in the day), and $U_{\max}$ is the scale of the distribution. The elapsed time component of marginal utility is based on the assumption that cumulative utility follows a logarithmic function (Bhat and Misra, 1999; Yamamoto et al., 2000). Stated explicitly, it is represented as:

$$u^{AD}(t) = \frac{\eta}{t - t_j'}$$  \hspace{1cm} (3.92)$$
Ettema et al. (2004) applied the above utility specification to evaluate a road pricing scheme. They compare the estimation result of a utility model with \( u^{AT}(\tau) \) based on a Cauchy distribution as in Equation (3.91) and \( u^{AT}(\tau) \) based on the derivation of an S-shaped function as in Equation (3.90) using SP data set for an ‘activity-work-activity’ pattern. Their results indicate that the marginal utility of work may consist of both a time-of-day component and an elapsed time component, whereas the marginal utilities of pre-work and after-work activities are primarily composed of the elapsed time component. Ettema et al. (2004) also reported that an estimated model with a time-of-day component based on a symmetric Cauchy distribution best reproduced their data.

Recently, Ashiru et al. (2004) proposed a similar framework for modelling the utility of an activity schedule, drawing on the results of previous studies (Winston, 1982; Joh et al., 2002). This particular framework assumes a continuous time scale, such that the entire model is formulated in terms of marginal utility arising from participation in a series of linked activities. The disutility arising from travel and activity participation (such as travel time, egress/access time, route delay, facility wait time, activity wait time, late start time and travel time variability and so on), together with the utility derived from the consumption of a generalised good, are also taken into account by introducing corresponding marginal terms. Each of these utility terms are either functions of the departure time, the duration of the activity or both, with the utility of activity participation also a function of the intensity of activity participation.

Most recently, Ettema et al. (2007) extended this early specification by incorporating a third component into the utility function based on previous studies (Small, 1982; Ashiru et al., 2004; Ettema et al., 2004). They pointed out that both duration- and timing-dependent models assume that the timing of an activity is based entirely on the activity’s continuous marginal utility, which imply that activities can be scheduled at any time of the day. Their insight is that this specification overlooks the strong possibility that
some activities are subject to strict time constraints, perhaps such as work or school arrangements. To account for this possible discontinuity in the marginal utility function, they incorporated a schedule delay component into the utility function based on the schedule delay models (Vickrey, 1969; Small, 1982). Thus the utility of activity $j$ is rewritten as:

$$U_j^A = U^A(t, t', t_{sp}) = \int_{t_j}^{t'_j} u^{AT}(\tau)d\tau + \int_{t_j}^{t'_j} u^{AD}(t - \tau)d\tau + V_j^S(t, t_{sp})$$

(3.93)

where $t_{sp}^j$ is the preferred starting time of activity $j$; $V_j^S(t, t_{sp})$ is the schedule delay utility component which is defined as a linear function of early schedule delay (EDL) and late schedule delay (SDE) as described in Small’s work (1982). This utility framework was embedded in an error component logit model to account for individual heterogeneity in the evaluation of activity attributes and tested empirically using an SP dataset relating to a hypothetical work tour. Their estimation results suggest that the time-of-day and schedule delay component are the most important factors influencing the scheduling of work activities. Considerable unobserved heterogeneity with respect to schedule delay and mode choice was also found by the authors.

3.3.5 Summary

Based on the activity-based transport literature described above, activity duration and/or timing are the main attributes associated with the utility of an activity. The research emphasis of activity-based travel demand modelling has focussed on activity scheduling in addition to time allocation. Different assumptions have been made to derive various model specifications. A brief summary of the existing activity-based utility models is provided in Table 3.2.
Table 3.2 Summary of existing activity-based utility models

<table>
<thead>
<tr>
<th>Model type</th>
<th>Assumptions</th>
<th>Source of utility</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Duration-dependent models</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conventional duration models</td>
<td>- Saturation effect over the entire range of duration</td>
<td>Duration</td>
</tr>
<tr>
<td>S-shape duration model</td>
<td>- More flexible form of marginal utility depending on the characteristics of activity</td>
<td></td>
</tr>
<tr>
<td><strong>Timing-dependent models</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Timing choice models</td>
<td>- Timing decisions is made among coarse time intervals</td>
<td>Timing</td>
</tr>
<tr>
<td>Schedule delay models</td>
<td>- There exists a preferred timing decision for each activity under constraints</td>
<td></td>
</tr>
<tr>
<td><strong>Timing- and duration-dependent models</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PJET models</td>
<td>- Marginal utility is independent of elapsed time</td>
<td>Timing and duration</td>
</tr>
<tr>
<td>Ashiri et al. (2004) and</td>
<td>- Marginal utility depends on both time-of-day and elapsed time</td>
<td></td>
</tr>
<tr>
<td>Ettema et al. (2004)</td>
<td>- Marginal utility depends on both time of day and elapsed time</td>
<td></td>
</tr>
<tr>
<td>Ettema et al. (2007)</td>
<td>- Scheduling constraints</td>
<td></td>
</tr>
</tbody>
</table>

3.4 Conclusions and discussions

Existing theories in microeconomics and transport generally assume that individuals derive utility directly or indirectly from participating in activities. The utility functions are related to some selected attributes of activities and also varied by characteristics of individuals and household. In microeconomic theory, utility is a monotonically-increasing function with a diminishing marginal utility among the entire range of explanatory variables, such as goods consumption and time allocation. For transport researchers, activity-based utility functions have been developed to address activities undertaken in a physical, face-to-face context, where timing and duration characteristics are likely to be the most important beneficial factors that individual derived from participation. This reflects both the importance of scheduling considerations in most activity-based frameworks and the likelihood that for activities where an individual must be present at a particular location, duration and timing are likely to be major components of the overall benefit that individuals derive from participation.
However, when applying the existing literatures directly to model the virtual activity participation in the context of m-commerce, some weaknesses can be identified. Firstly, undertaking a virtual activity while travelling is more likely to be a spontaneous decision than a long term economic decision as indicated in microeconomic models. Besides the time allocation to virtual activity itself and goods consumption derived from activity participation, other explanatory variables, such as travel time and the characteristics of technology, are also related to the individual’s decision to undertake these mobile activities. Secondly, the tight connection between the scheduling decision and the spatio-temporal characteristics of activities that are assumed in activity-based models, are weakened in the case of mobile commerce. Thirdly, the use of mobile technology may play a role of substitution to the traditional inputs of time and money. The trade-off effect between time, money and technology which might be quite salient in a mobile-electronic activity context, are not well-accommodated in existing modelling frameworks. All of these constitute the main challenge in modelling virtual activity participation while on the move.

On the other hand, although none of existing modelling frameworks is adequate enough to be directly applied to the characterisation of utility of virtual activities in a mobile context, there are some important and useful concepts that can be borrowed from existing literature. These concepts are listed as follows:

- Conventional consumer behaviour is stated in terms of the continuous consumption amount of goods \( (X) \) chosen by individual in an attempt to maximise the utility; later, Lancaster (1966) introduces the goods characteristic as the primary source of utility
- Utility derives from general consumption of goods and time allocation to out of work activity (‘leisure’) (Train and McFadden, 1978)
- Household production theory assumes that household activities can be considered
as production process, in which time and goods are the input resources allocated to these activities (Becker, 1965; Lancaster, 1966; Winston, 1982; Graham and Green, 1984)

- Utility of activity is separated into process component and outcome component (Winston, 1982)
- In activity-based models, travel derived from activity participation (Axhausen and Garling, 1992; Ettema and Timmermans, 1997)
- Activity-based utility models assume individuals aim to maximize the utility of whole activity pattern/schedule in a short term period, such as a day (Polak and Jones, 1994; Ettema and Timmermans, 2003; Ashiru et al., 2004; Ettema et al., 2004)
4 The activity production approach

4.1 Overview of activity production approach

The aim of this chapter is to present a novel approach to measure the utility of an activity which can be applied in a broader context, such as m-commerce and e-commerce. The proposition of this idea is built on the concept of activity production, which combined some basic assumptions in both microeconomic and transport literatures as described in Section 3.4. In this approach, activity is regarded as ‘small firm’. Individual transforms the input time, money and technology into the output of goods through activity production process. Both production process and outcome of consumption are sources of (dis)utility. We show how a unified activity utility model based on this approach generalises existing activity utility models and demonstrate how it can easily be extended to deal with activities performed in electronic and mobile contexts.

This chapter starts with the description of a unified theoretical modelling framework based on the activity production approach. The various specifications of utility functions are then provided. The conclusion is presented in the end.

4.2 Theoretical modelling framework

In this section, we formulate a unified activity utility model in the presence/absence of various technologies based on activity production approach, from which a model of technology choice behaviour in activity participation can be further derived.

In our activity production approach, each activity is regarded as Becker’s archetypal ‘small firm’ (Becker, 1965). Based on the assumption in conventional activity-based models (see review Ettema and Timmermans, 1997), travel is induced by
the needs of activity participation. In our context, travel is considered to be a necessary input into activity production in the absence of substituting technology. An individual transforms the input time (including activity time and associated travel time in the absence of technology) and money (including travel cost in the absence of technology or technology cost) into the outputs (goods) through a production process characterised by certain technology.

In order to provide insight into the potential effects of different technology on the whole activity pattern and motivate the empirical specification of utility function, a unified theoretical framework was developed on a simple work related pattern. We consider an individual pursues an activity using technology \( k (k = 1, 2, \ldots, K) \) characterised by attributes vector \( W(k) \) during the non-work time. The individual aims to maximize the utility of whole work-related activity pattern (Polak and Jones, 1994; Ettema and Timmermans, 2003; Ettema et al., 2004), which derived directly from the trade-off between consumption of goods produced through non-work activity and the ‘leisure time’, as formulated in the goods/leisure framework by Train and McFadden (1978). The utility of consumption of goods is obtained through both the consumption amount as stated in conventional consumer theory and general attributes as introduced by Lancaster (1966). The leisure time is defined specifically as the complementary time to the work time and input time to the activity participation. Given fixed working hours and associated travel and fixed wage rate, the problem is formulated as:

\[
\text{Max } U(X, Q, T_L) \quad (4.1)
\]

s.t. \( p'X + c[W(k)] = I \quad (4.2) \)

\( T_L + T[W(k)] \leq D - T_w \quad (4.3) \)

\( k = 1, 2, \ldots, K \text{ and } k \in M \quad (4.4) \)
Where $X$ is the consumption amount vector of various goods obtained through non-work activity production; $p$ is corresponding price vector of various goods; $Q_k$ is the qualitative attributes vector of goods obtained using technology $k$, including the flavour, nutrient, warmth, beauty and so on; $Q_k$ depends not only the type of technology used but also the type of goods purchased, for example, in the case of online shopping for grocery, the purity and freshness of goods might be inferior to that of conventional shopping at a supermarket, whereas for the purchase of goods like a CD or a book, there may exist no difference between the two shopping activities; $M$ is the set of discrete technology alternatives; $K$ is the total number of technology alternatives in the choice set $M$; the attributes vector of substituting technology $W(k)$ characterises the activity production process; for example in case of mobile technology, $W(k)$ includes the connection speed, network security and network connectivity and so on; $T[W(k)]$ and $c[W(k)]$ are respectively the input time and input money to activity production, both depending on attributes vector of technology $W(k)$; $T_L$ is leisure time specified as complementary time to working hours $T_w$ and input time $T[W(k)]; D$ is total available time; $I$ includes both earned and unearned income. Assuming utility increases with consumption of goods and leisure time as formulated in Train and McFadden’s model (1978), less input time $T[W(k)]$ and lower input cost $c[W(k)]$ in the activity production lead to higher overall utility of activities. In the absence of substituting technology, $T$ represents the travel time plus activity time and $c$ corresponds to the travel cost. Hence Equation (4.1)-(4.4) generalise the existing goods/leisure framework given fixed working hours by adding the concept of technology.

In the above model, individual can be viewed as choosing both the trade-off between goods and leisure and the one of the discrete technology alternative. As the choice of technology $k$ is discrete and of $X$ and $T_L$ are continuous, the problem can be
solved in two steps. Firstly find the optimal solution of $X$ and $T_L$ conditional on discrete choice of technology $k$. Substituting $X$, $T_L$ in Equation (4.1) with the constraints in Equation (4.2) and (4.3) yields the conditional solutions $X(I - c[W(K)], p)$ and $T_L(D - T_w - T[W(K)])$. Secondly, optimize over all $k$ among the entire choice set $M$ and obtain the overall maximum of utility. In our context, working hour and wage rate are considered to be determined. Thus income becomes an exogenous variable. Given fixed price vector, conditional demands $X$ and $T_L$ entirely rely on $c[W(k)]$ and $T[W(k)]$ underlined by the use of technology $k$. Hence the indirect utility $V_k$, representing the maximum utility that the individual would derive if technology $k$ is chosen, is formulated as:

$$V_k = V(I - c[W(k)], p, Q_k, D - T_w - T[W(k)])$$ (4.5)

Thus the chosen technology $k$ can be interpreted as that which realizes $V_k > V_l$, $\forall l \neq k$ and $l \in M$ such that the maximum $V_k$ becomes the unconditional utility among the entire choice set $M$. It is desirable to note that not all arguments in Equation (4.5) will influence the discrete choice for a single person. Given fixed $p$ and $D$ and predetermined value of $I$ and $T_w$, Equation (4.5) for a single person in discrete choice modelling can be simplified as:

$$V_k = V(c[W(k)], T[W(k)]; Q_k)$$ (4.6)

Following the theoretical considerations of activity production approach described above, Equation (4.6) implies that both activity production process and outcome of consumption relate to the utility. In order to better understand the substitution effect between input variables during activity production, the utility can be rewritten as process component incorporating the input time $T[W(k)]$ and money $c[W(k)]$ characterised.
by the production technology $k$ and outcome component relying on $Q_k$ (Winston, 1982). Thus Equation (4.6) is reformulated as:

$$V_k = V^p_k \left( e[W(k)], T[W(k)] \right) \otimes V^o(Q_k)$$

(4.7)

Where $V^p_k$ is process component of utility characterized by technology $k$; $V^o$ is outcome component of utility; $\otimes$ is combination operator which may be addition or multiplication.

The theoretical concepts of activity production approach applied to single activity participation are illustrated in Figure 4.1.

As we can see, Equation (4.7) explicitly identifies the inputs (e.g., time and money) necessary to perform an activity and the outputs derived from the activity production (consumption of goods via the general attributes). Utility of an activity consists of process utility component and outcome utility component. When defining the process utility, individuals act as a pure producer. They combine necessary input time and money to produce the output goods. This process utility component represents the individual satisfaction or dissatisfaction (depending on the type of activity) from activity production process within certain technological environment. When defining utility of outcome, individuals act as a pure consumer. They obtain satisfaction from consuming the general attributes of goods obtained through the activity production. The characteristics of the goods are the primary source of outcome utility.

To better understand how this empirical model in Equation (4.7) can be applied
to capture the technology choice behaviour in activity participation, we consider a given shopping activity where an individual has a choice between a conventional shopping activity (in a physical shop) and an online shopping activity via fixed computer or mobile device. For a conventional shopping, an individual spends travel time and travel cost to arrive at the physical shop, in which activity time is further consumed to search for the goods, queue and pay at the cashier. In this case, the total input time $T$ includes both travel time and activity time, while the input money mainly includes the travel cost. For an online shopping activity, the individual requires a relatively small amount of time (online connection time) to access the retailer’s website and may also need to pay for the online access when in a mobile environment (e.g. on the travel). By use of mobile technology, activity time is used in searching, browsing the website and online payment. Thus total input time mainly depends on the activity time, whereas the input money relies on the technology cost (such as connection payment). The presence/absence of different technologies is characterised by different functional forms of process utility in these two shopping activities. In a broader context, for each production technology, a unique process utility is constructed to represent the efficiency of activity production. The different substitution effects between input time and money in given technological contexts can also be identified. The goods obtained through both shopping activities might be the same (for example, the purchase of book, CD, electronic equipment) or different in some attributes (such as price or quality). The outcome utility also differs corresponding to the changes of these attributes in different technological contexts.

### 4.3 Utility function

#### 4.3.1 Process utility function

The problem addressed here is how the process utility function $V_k^p( )$ in
Equation (4.7) can be empirically specified with relates to the input variables. As described in Chapter 3, production functions, initially proposed in firm production theory, have arisen as direct utility functions in microeconomic models. For example, in goods leisure/activity framework, production function forms of utility are constructed to represent the satisfaction derived from consumption of various goods and time, and the substitution effects between the various types of consumption (Train and McFadden, 1978; Jara-Diaz and Farah, 1987). In household production framework, firm production functions are employed to describe the relationship between output of non-market ‘commodity’ and the inputs of preparation time and ‘market goods’ in the participation of household activities (Becker, 1965; Winston, 1982).

In our activity production model, with an aim to characterise the consumption of input time and money and substitution effects between these factors, process utility function $V^p_k(\cdot)$ is also regarded to exhibit as a production function form. In this thesis, we trace back to firm production theory to examine more production functions such that the variety of technical efficiency and substitution effects between production factors can be captured. Built on the specifications of these production functions, corresponding process utility functions $V^p_k(\cdot)$ are also presented. Some technical attributes relating to our interest are also examined so that the empirical implications derived from these attributes can also be obtained.

4.3.1.1 Brief review of firm production function

In firm production theory, production functions describe how a firm converts all combination of inputs (defined as ‘production factors’) to the output (Varian, 2006a). For a given technology, it is defined as a relationship between the maximal feasible output and the inputs necessary to produce the output. The inputs of the production refer to labour ($L$), capital ($C$), land ($N$), and raw materials and so on. For each production
technology, a unique production function can be constructed.

It is generally assumed that Wicksteed (1894) first proposed a general algebraic relationship between a single output $y$ and multiple input $x$, namely that:

$$y = f(x_1, x_2, \ldots, x_n)$$  \hspace{1cm} (4.8)

Where $x_1, x_2, \ldots, x_n$ are inputs of production; $y$ is the maximum output with all the combinations of inputs. In this section, we introduce some important technical concepts of production function using the general specification in Equation (4.8), as based on these concepts empirical implications of various process utility functions can be measured. Further derivations of these concepts from various specific functional forms are combined with the analysis of process utility function in the coming section.

The first technical concept that we explain in this thesis is marginal product, which is described as the additional units of output by adding a particular unit of input and keeping all the other inputs remain constant (Varian, 2006a). In firm production theory, it is defined as:

$$\frac{\partial f}{\partial x_i} \geq 0$$  \hspace{1cm} (4.9)

Equation (4.9) implies that adding one unit of input will always increase or at least not decrease the output of production. Based on this definition, the law of diminishing return states that in the short run the marginal product decreases with additional unit of input variable (Varian, 2006a), namely that:

$$\frac{\partial^2 f}{\partial^2 x_i} \leq 0$$  \hspace{1cm} (4.10)

It should be noted that household production theory is built on these basic assumptions. Becker (1965) firstly mentioned that in household production function, the partial derivatives of final ‘commodity’ with respect to market goods and time in
preparation for ‘commodity’ are always non-negative (i.e. Equation (3.2) and Equation (3.3)). Gronau (1977) and Winston (1982) also proposed that production function is subject to diminishing marginal productivity, which satisfies (4.10). Also in consumer theory, it is generally assumed that there is an increasing utility and decreasing marginal utility with the consumption of goods and time allocation to activities (Train and McFadden, 1978; Jara-Diaz and Farah, 1987).

Another technical property of production function introduced here is return to scale. It explains how the resulting output will change by certain proportion change of each input (Varian, 2006a). A production function is said to be homogeneous of degree $n$, if for any scalar $l$, it can be specified as the following form:

$$f(lx_1, lx_2, \ldots, lx_n) = l^n f(x_1, x_2, \ldots, x_n) \quad (4.11)$$

Correspondingly, we can characterize the ‘return to scale’ property as the homogeneity properties of the production function. The outcome can be identified as increasing return to scale, constant return to scale and decreasing return to scales. When $n > 1$, $l^n > l$ and the production function exhibits increasing return to scale. It indicates that when each input increases by same proportion $l$, the output will increase more than proportionally. When $n < 1$, $l^n < l$ and the production function exhibits decreasing return to scale. It implies that when each input increases by $l$, the output will increase less than proportionally. When $n = 1$, $l^n = l$ and the output will increase by same scale as the input, the production function exhibits constant return to scale. As reviewed in Chapter 3, in household production framework and goods leisure/activity framework, a constant return to scale is a frequently imposed assumption on household production function and direct utility function (Becker, 1965; Michael and Becker, 1973; McFadden, 1978; Jara-Diaz and Farah, 1987).

Marginal rate of technical substitution ($MTS$) is another important technical
attributes that deserves our attention. It can be measured by:

\[ MTS = -\frac{\partial f}{\partial x_1} / \frac{\partial f}{\partial x_2} = -\frac{\partial x_2}{\partial x_1} \]  

(4.12)

Although \( MTS \) has a negative sign, economists often refer to its absolute value to imply that maintaining the same level of output, how much units of one input may be substituted for another (Varian, 2006a). \( MTS \) constitutes the theoretical basis to construct the value of travel time savings in transport demand modelling (Jara-Diaz, 2007).

To date, various forms of production functions have been proposed. The simplest version is to represent the output as a linear additive function of various inputs. A more complicated version is Cobb-Douglas function (Cobb and Douglas, 1928). Assuming only two factors of production, it is expressed as:

\[ y = AL^\alpha C^\beta \]  

(4.13)

Where \( L \) is labour input; \( C \) is the capital input; \( y \) is the output of total production; \( \alpha, \beta \) are parameters determined by the applied technology. \( A \) is total factor productivity. Based on the previous definition of scale of return, we can derive that when \( \alpha + \beta > 1 \), the function has increasing scale of return; when \( \alpha + \beta < 1 \), it has decreasing scale of return and constant scale of return when \( \alpha + \beta = 1 \).

A generalization of Cobb-Douglas function is Translog production function (Christensen et al., 1973), which is formulated as:

\[ \log y = A + \alpha \log L + \beta \log C + \gamma \log L \log C \]  

(4.14)

Compared with log form of Equation (4.13), Equation (4.14) allows for the interaction between log form of input factors.

Another function specification is constant elasticity of substitution (CES) function as illustrated in Equation (4.15) (Arrow et al., 1961). It permits to vary the elasticity of
substitution between zero and infinity. The elasticity of substitution is quite an important technical attributes of production function in microeconomic theory. Due to reason that this technical concept is beyond the range of our research, a detailed explanation will not be provided in this thesis. Consider the two factor CES function, it is written as:

\[ y = \alpha \left( \beta L^\gamma + (1-\beta)C^\gamma \right)^{\frac{1}{\gamma}} \quad (4.15) \]

Where \( \alpha \) is the parameter that describes the production scale; \( \beta \) is the share of input; \( \gamma \) determines the substitution effect between input \( L \) and \( C \). \( \mu \) decides the scale of return of the production function. With \( \mu > 1 \), it exhibits increasing return of scale. With \( \mu < 1 \), it has decreasing return of scale and \( \mu = 1 \) with constant return of scale.

Leontief production function (Leontief, 1941) assumes that inputs of production are used in fixed proportion and there is no substitution effect between different factors. The two factor Leontief production function is expressed as:

\[ y = \min \left( \frac{L}{\alpha}, \frac{C}{\beta} \right) \quad (4.16) \]

Where \( \alpha \) and \( \beta \) are respectively constants determined by the technology. The generalized version of Leontief production function has a more flexible functional form (Diewert, 1971). Two-factor Generalised Leontief production function is represented as:

\[ \frac{1}{y^\gamma} = \alpha \gamma L + \beta \gamma C + \gamma \sqrt{LC} \quad (4.17) \]

Like Translog production function proposed in Equation (4.14), generalize Leontief, allowing for the partial elasticity of substitution between inputs to vary.

Among all the formulations discussed so far, Cobb-Douglas function is most widely used to formulate the direct utility function in microeconomic utility models (Train and McFadden, 1978; Jara-Diaz and Farah, 1987; Jara-Diaz and Guevara, 2003). Train and McFadden (1978), as well as Jara-Diaz and Farah (1987), assume a constant
scale of return on the utility function, i.e. $U = \alpha G^\beta L^{1-\beta}$ where $\alpha > 0$ and $0 < \beta < 1$. $\beta$ represents the importance of goods relative to leisure in direct utility. Recently, as shown in Equation (3.39), Jara-Diaz and Guevara (2003) propose a more general Cobb-Douglas form of utility function without giving constraint on the exponential parameters.

4.3.1.2 Process utility function

As previously described, existing literatures assume that direct utility function arises as the production function form, while in the context of our study, it is the indirect process utility that is considered to exhibit the production function form. Therefore, the basic assumptions (such as increasing utility, decreasing marginal utility, and constant scale of return) applied in existing literature by adding constraints to the relevant coefficients, are not imposed in our modelling framework.

Based on various formulations of production functions described in Section 4.3.1.1, several plausible forms of process utility functions are specified here. Also the definitions of technical attributes in Equation (4.9)-(4.12) provide us a theoretical basis to investigate the empirical implications of various specific process utility functions. Starting from the simplest production function, the process utility function can be written as a linear additive form of input variables, i.e.:

$$V_k^p(T,c) = \alpha_k + \beta_k T + \gamma_k c \tag{4.18}$$

Where $\alpha_k, \beta_k, \gamma_k$ are parameters depending on the substituting technology of activity production. According to Equation (4.11), multiplying each input variable by a scalar $l$, $V_k^p(T,c)$ changes by the same proportion $l$. Hence Equation (4.18) implies that linear process utility function displays a property of constant scale of return. According to the definition of marginal product in Equation (4.9), the marginal process utility of input
time is calculated by \( \frac{\partial V^p_k}{\partial T} = \beta_k \). Thus process utility changes \( \beta_k \) unit corresponding to one unit change of input time \( T \). When \( \beta_k > 0 \), an individual derives utility from the consumption of input time; otherwise, an individual derives disutility from the consumption of input time. Similar interpretation is obtained with regards to input cost \( c \).

With \( \frac{\partial V^p_k}{\partial c} = \gamma_k \), process utility changes \( \gamma_k \) unit corresponding to one unit change of input money \( c \). When \( \gamma_k > 0 \), an individual derives utility from the consumption of input money; otherwise, an individual derives disutility from the consumption of input money.

With regards to the marginal rate of technical substitution (MTS) in Equation (4.12), the technical substitution effect between input time and money is measured by:

\[
MTS = \frac{\frac{\partial V^p_k}{\partial T}}{\frac{\partial V^p_k}{\partial c}} = \frac{\beta_k}{\gamma_k}
\]  

(4.19)

Equation (4.19) indicates that this linear additive form of process utility function allows for a perfect substitution effect between input factors, which means that \( T \) can be substituted freely by constantly rate \( \frac{\beta_k}{\gamma_k} \) given same level of process utility. The alternative constant \( \alpha_k \) accommodates the individual intrinsic preference of technology \( k \).

Another formulation is built on Equation (4.13) so that the process utility function is written as:

\[
V^p_k (T, c) = \alpha_k T^{\beta_k} c^{\gamma_k}
\]  

(4.20)

Following the same steps as above, in Equation (4.20), multiplying each input by same scalar \( l \) leads to the following equation:

\[
l^{\beta_k + \gamma_k}V^p_k (T, c) = \alpha_k (lT)^{\beta_k} (lc)^{\gamma_k}
\]  

(4.21)

In Equation (4.21), \( \beta_k + \gamma_k \) explains how the process utility will change by certain
proportion change of input time and money. When $\beta_k + \gamma_k > 1$, process utility exhibits increasing return of scale. Namely, when input time and money each increases by same proportion, the process utility will increase more than proportionally. When $\beta_k + \gamma_k < 1$, it is contrary that process utility exhibits decreasing return of scale. It implies that when input time and money each increase by same proportion, the process utility will increase less than proportionally. And when $\beta_k + \gamma_k = 1$, process utility will increase by same scale as the input and exhibits constant return to scale. As $\frac{\partial V_k^p}{\partial T} = \alpha_k \beta_k T^{\beta_k-1}c^{\gamma_k}$, the marginal process utility of input time relies on both the parameter estimations and the value of input variables. When $\alpha_k \beta_k > 0$, an individual derives utility from the consumption of input time in activity participation; otherwise the individual obtains disutility from the consumption of input time. As $\frac{\partial V_k^p}{\partial c} = \alpha_k \gamma_k T^{\beta_k}c^{\gamma_k-1}$, the marginal process utility of money also relies on both the parameter estimation and the value of input variables. When $\alpha_k \gamma_k > 0$, an individual derives utility from the consumption of input money and obtains disutility when $\alpha_k \gamma_k < 0$. The $MTS$ between input variables is also derived by:

$$MTS = \frac{\partial c}{\partial T} = \frac{\partial V_k^p}{\partial T} = \frac{\partial V_k^p}{\partial c} = \frac{\beta_k c}{\gamma_k T}$$ (4.22)

Equation (4.22) represents that marginal rate of substitution between input time $T$ and input money $c$ depends on both the technology $k$ and the ratio between two variables. Therefore, as opposed to linear process utility, Cobb-Douglas form of process utility cannot accommodate a perfect substitution effect. As $MTS$ tends to be infinity when $T$ is close to zero, thus $T$ can be substituted freely by $c$ and vice versa.

Another tentative form of process utility function is based on CES function in Equation (4.15), namely that:
Where $\alpha_k$ is the overall scale parameter; as $\left(\beta_k T^{\gamma_k} + (1 - \beta_k) c^{\gamma_k}\right)^{\frac{\mu_k}{\gamma_k}}$ is always positive, $\alpha_k$ determines whether an individual obtain utility ($\alpha_k > 0$) or disutility ($\alpha_k < 0$) from the production process. The share parameter $\beta_k$ indicates which input factor plays more important role than the other in activity production process. If each input variables in Equation (4.23) changes by scalar $l$, it yields the following form:

$$l^{\mu_k} V_k^p (T, c) = \alpha_k \left(\beta_k (lT)^{\gamma_k} + (1 - \beta_k)(lc)^{\gamma_k}\right)^{\frac{\mu_k}{\gamma_k}} \text{ (4.24)}$$

Thus $\mu_k$ decides the scale of return of the process utility function. When $\mu_k > 1$, process utility exhibits increasing return of scale; When $\mu_k < 1$, process utility exhibits decreasing return of scale; and When $\mu_k = 1$, process utility exhibits constant return of scale. Taking the first order differentiation in Equation (4.23) relating to $c$ leads to the following equation:

$$\frac{\partial V_k^p}{\partial c} = \alpha_k \mu_k \left(1 - \beta_k\right) \left(\beta_k T^{\gamma_k} + (1 - \beta_k) c^{\gamma_k}\right)^{\frac{\mu_k}{\gamma_k} - 1} \gamma_k c^{\gamma_k - 1} \text{ (4.25)}$$

Equation (4.25) implies that the marginal process (dis)utility of input money relies on both the parameter estimation underpinned by the substituting technology $k$ and the value of input variables. As $\left(\beta_k T^{\gamma_k} + (1 - \beta_k) c^{\gamma_k}\right)^{\frac{\mu_k}{\gamma_k} - 1} c^{\gamma_k - 1}$ remains to be positive, thus when $\alpha_k \mu_k \left(1 - \beta_k\right) > 0$, an individual derives utility otherwise obtains disutility from the consumption of input money in activity production process. Following the same procedure with relates to $T$, we have:

$$\frac{\partial V_k^p}{\partial T} = \alpha_k \mu_k \beta_k \left(\beta_k T^{\gamma_k} + (1 - \beta_k) c^{\gamma_k}\right)^{\frac{\mu_k}{\gamma_k} - 1} T^{\gamma_k - 1} \text{ (4.26)}$$

Equation (4.26) denotes that marginal process utility of input time also depends on the
substituting technology \( k \) and the value of input variables. Similarly, as

\[
\left( \beta_k T^{\gamma_k} + (1 - \beta_k) c^{\gamma_k} \right)^{\frac{\beta_k}{\gamma_k} - 1} T^{\gamma_k - 1}
\]

maintains to be positive, \( \alpha_k \mu_k \beta_k \) determines whether the individual obtain utility (\( \alpha_k \mu_k \beta_k > 0 \)) or disutility (\( \alpha_k \mu_k \beta_k < 0 \)) from the consumption of input time in activity production process. In terms of \( MTS \) between input variables, we obtain:

\[
MTS = \frac{\partial c}{\partial T} = \frac{\partial V_i^p}{\partial T} = \frac{\beta_k}{\beta_k - 1} \left( \frac{c}{T} \right)^{\gamma_k - 1}
\]

Equation (4.27) indicates the substitution effect between input \( T \) and \( c \) relies on both the ratio between them and parameters determined by technology \( k \). Accordingly, CES form of process utility function also cannot incorporates the perfect substitution effect between inputs as when \( T \) tends to be zero, \( \frac{\partial c}{\partial T} \) becomes infinitive.

In summary, each production technology is characterised by a unique process utility function. In each specification, the parameter estimates and the derived empirical values capture the specific technological effect on individual’s activity behaviour.

In terms of other production functions described above, Leontief function assumes no substitution effect between different production factors, thus it does not enable us to accommodate the substitution effect between input factors in process utility function. The propositions of Translog and Generalized Leontief function are to capture the varying partial elasticity of substitution between inputs, which are beyond our concentration. With these considerations, the examination of process utilities built on these specifications is not provided in this thesis.
4.3.2 Outcome utility function

The problem addressed in this part is how to specify $V^o$ in Equation (4.7) with relates to the general attributes vector $Q_k$. Under separability assumption, the total outcome utility $V^o$ can be represented as the sum of component derived from each attribute dimension, i.e.:

$$V^o(Q_k) = \sum_j V^o_j(Q_{kj})$$  \hspace{1cm} (4.28)

Where $V^o_j$ is the component of outcome utility determined by attribute $j$, $Q_{kj}$ is the value of attribute $j$ obtained via technology $k$. Given continuous attribute $j$, the formulation of $V^o_j$ is considered to comply with microeconomic rules: increasing utility and decreasing marginal utility with respect to certain attribute $Q_{kj}$. Namely, $V^o_j$ satisfies the condition $\frac{\partial V^o_j}{\partial Q_{kj}} > 0$, $\frac{\partial^2 V^o_j}{\partial^2 Q_{kj}} < 0$, representing the ‘saturation effect’ in consumer behaviour theory. The log form or exponential form function are applied to capture this effect, namely that:

$$V^o_j = d \log(Q_{kj})$$  \hspace{1cm} (4.29)

$$V^o_j = d \exp(Q_{kj})$$  \hspace{1cm} (4.30)

Where $d$ is the parameter. With regards to the discrete attribute (such as color), $Q_{kj}$ is represented as a dummy variable and $V^o_j$ is simply a linear function of $Q_{kj}$.

4.4 Conclusions

This chapter introduces activity production approach to measure the utility of an activity. Based on this new paradigm, a unified activity utility model is formulated. We
demonstrate how this model can be easily extended to deal with activities in the presence of substituting technology, e.g. mobile technology. We show how this model can generalize existing goods/leisure models in the absence of technology.

Compared with existing activity-based models, this model concentrates on modelling the impact of technology on activity participation. It is intended to better identify the substitution effect between input time and money to activity participation using different technologies and explicitly separate process utility and outcome utility, which are merged in conventional activity-based models. A number of specifications of process utility functions arising from production functions are provided. In most cases, performing an activity involving the use of technology (for example e-shopping, e-banking, mobile game) is spontaneous. Individuals may not be strongly guided by conventional spatio-temporal constraints. Based on these considerations, an explicit treatment of timing decisions is not necessary in this framework, as opposed to activity-based travel demand models.
5 Data collection: Stated Choice (SC) survey

In chapter 4, a unified modelling framework for technology choice and activity participation decisions, based on the activity production approach is described. With an aim of applying this framework to model virtual activity participation in mobile context, we require the estimation of the derived indirect utility function in Equation (4.7). This chapter describes the methodology used to collect the necessary data to obtain the appropriate specification and parameters. In section 5.1, the methodological background is explored. The data requirements and existing procedures to collect the data in travel demand analysis are outlined. Section 5.2 describes the proposed survey methodology. Section 5.3 presents a brief descriptive analysis of the characteristic of the sample. Section 5.4 provides a preliminary analysis of data collected, focusing on investigating the internal validity of the data. The final section presents a summary of this chapter.

5.1 Methodological background

The estimation of the indirect utility function in Equation (4.7) requires data regarding activity participation in the presence of mobile technologies. The key sets of variables include, input time and input cost to activity production, and the attributes of final goods. In addition, recent studies on the impact of ICT on travel behaviour (e.g. Mokhtarian and Salomon, 2002; Ohmori, 2006; Srinivasan and Raghavender, 2006) suggest that data on general use of internet, mobile internet, and particular socio-demographic and socioeconomic status are also required.

At present, pursuing activities involving the use of mobile services (e.g. m-shopping and m-banking) is not as common as participating in conventional activity (e.g. conventional shopping at a physical shop) and activity using fixed online service (e.g. e-shopping). These mobile activities are still new to many people. To the best of our
knowledge, few studies in travel demand modelling concentrate on this area; hence existing datasets do not contain the necessary information on these variables, or components which would allow them to be generated.

In travel demand analysis, procedures for acquiring activity-travel data are generally divided into two categories: revealed preference (RP) approaches and stated preference (SP) approaches. In some cases, combinations of SP and RP approaches are also adopted (Morikawa, 1989). RP approaches require observing and recording actual behaviour of each respondent, whereas in an SP approach the respondent is presented with hypothetical situations. A number of studies have provided detailed discussions of advantages and disadvantages of SP and RP data (Louviere et al., 1980; Kores and Sheldon, 1988; Louviere et al., 2000; Adamowicz and Deshazo, 2006). According to these studies, the main advantage of using RP data is that it reflects individuals’ real decision given various constraints (such as the budget of time and money), while SP data reflects the potentially stated decisions in hypothetical contexts. However, two principle drawbacks of using RP data are identified. Firstly, the explanatory variables in the real situation generally have low variability such that the resulting estimated coefficients are only valid in a narrow data range. Thus RP data provides limited or invalid prediction to the potential changes. Secondly, using RP data may generalise collineararity among the explanatory variables in real situation, which leads to implausible estimation results.

In recent years, SP approaches has received increasing attention and become one of the key techniques of travel demand analysis. The growth in the popularity of SP approaches mainly relies on the advantages in the context of assessing individual response to new technologies, products or services, where RP data cannot be collected. Also SP approaches are more economical to be applied in the context when observable data is expensive and time consuming to be obtained using RP approaches. In an SP approach, each respondent is normally asked to answer more than one question and
researchers have more control over the experimental design. Thus the variability of attribute levels and the correlation between the attributes can be adjusted to specific purpose of research. However, the validity of using SP approaches has been criticised because the expressed preference in a hypothetical scenario might not be consistent with their real behaviour as certain types of real constraints may not be taken into account. Further, as SP approaches relies on respondents’ ability to understand the experiment and present reliable answers, thus the generated SP data may not be consistent internally due to some systematic errors relating to experiment procedure.

In the case of our study, an SP approach is employed to obtain the data necessary to estimate the model. This is mainly due to two reasons. Firstly, the aim of this research is to model the individual response to mobile technology for activity participation, which is relatively new in travel demand modelling. Hence no available RP datasets exist. Secondly, collecting the RP data based on our activity production framework requires each respondent to be equipped with mobile internet in activity participation, which is expensive and time consuming.

In terms of how to design an overall SP survey, more details will be discussed in the next section. In this section, we mainly introduce three options of response scale in constructing an SP questionnaire, namely ranking, rating and choice questionnaires (Hensher, 1994). In a choice questionnaire, a respondent is simply asked to choose the preferred alternative among the entire choice set; in ranking questionnaire, a respondent is required to arrange the alternatives in order of preference; whereas in a rating questionnaire, a respondent is required to express the preference of each alternative using a category of rating scale (such as 5 or 10 point scales). Although ranking and rating questionnaires provide richer information about the order and the degree of preference than choice questionnaire, they increase the task complexity to respondents. In reality, an individual makes the decision by comparing the alternatives and selecting one. A major
concern in travel demand modelling is to predict the behavioural responses to new services or changing policies and choice responses are directly translated into these predictions (Hensher, 1994). In the past decades, stated choice (SC) approach has become increasingly important accompanied by the extensive application of discrete choice models in examining behavioural response of individual, household and road authorities in various choice situations and contexts, such as forecasting mode and route choice behaviour (Hensher, 2001a; Hensher, 2001b; Jou, 2001; Hensher and Rose, 2007) and testing the effects of proposed policies (Hensher and King, 2001; Van der Waerden, 2002; van Amelsfort and Bliemer, 2005). Based on these considerations, in this research, the stated choice (SC) approach is adopted to collect the data necessary to estimate our model.

In a typical SC experiment, the researcher creates a number of hypothetical choice situations (i.e. choice sets) which consist of several alternatives defined by a number of attribute dimensions with assigned levels. Each sampled respondent is presented with these choices sets and required to specify their preferred alternative within each choice set. These response data are pooled together over these hypothetical choice sets and sampled respondents in later estimation.

5.2 Proposed SC survey methodology

5.2.1 Proposed computer-aided personal survey

An SC survey questionnaire can be implemented in one of four methods classed by the survey instruments: a paper and pencil survey, a computer-aided personal interviewing (CAPI), a computer-aided telephone interviewing (CATI), or an internet-based survey (Bonnel, 2003). A paper and pencil survey involves posting the questionnaire to the respondent and asking him to complete it and return it to the
responsible person. An internet-based survey requires respondents to complete a questionnaire online. Both paper and pencil survey and internet-based survey are administered by the respondent himself. A CAPI survey involves inviting respondents to attend a face-to-face interview at a designated place, whereas in a CATI survey, the interview is conducted over the phone. Both CAPI and CATI surveys are administered by the interviewers.

Each survey methodology has inherent advantages and disadvantages. Bonnel and Le Nir (1998) and Bonnel (2003) summarised their performance based on the criteria of response speed, response rate, survey cost, quality of data, geographical representation, and complexity of the questionnaire. In comparison with conventional survey instruments (i.e. paper-pencil formats), computer-based application (including CAPI, CATI and internet-based survey) are more flexible in the area of data processing and questionnaire construction. These advantages are demonstrated in enabling direct data entry, an automatic consistency check and implementing more advanced surveys, in which later choice situations can be adaptive to responses in earlier ones and choice situations can be automatically tailored to each respondent. In terms of the sample base, both CATI and internet-based surveys bring about some bias in that CATI survey excludes the respondents without telephone while internet-based survey excludes the respondents without internet access. As both CAPI and CATI surveys are under the interviewers’ control, they provides higher response rate, quicker response speed and the better quality of data, as opposed to self-administered internet-based survey as well as paper and pencil survey. However taking into account the journey derived from conductin the interview, CAPI yields the most expensive cost and smallest sample size.

Based on these interpretations, a comparison is made in Table 5.1 to illustrate which survey methodology is most appropriate in the context of our study.
Table 5.1 Comparisons of survey methodologies

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Paper and pencil</th>
<th>CAPI</th>
<th>CATI</th>
<th>Internet-based survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response rate</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Response speed</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Survey cost</td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Quality of data</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Data processing</td>
<td>1</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Sample base</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Sample size</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Complexity/flexibility of questionnaire</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>14</strong></td>
<td><strong>28</strong></td>
<td><strong>24</strong></td>
<td><strong>20</strong></td>
</tr>
</tbody>
</table>

Note: 4 very good performance, 3 good performance, 2 moderate performance, 1 poor performance

The results show that the CAPI approach has the highest total score among all the methodologies given the context of our study. Therefore, it was selected to collect the data needed in order to estimate the proposed activity production model. This is mainly due to three reasons. Firstly, considering the complexity of this survey, it was decided that the experiment would be carried out in an entirely controlled environment in the interests of the quality of data collected. Thus only CATI and CAPI become feasible survey methodologies. Secondly, the objective of this research is to better understand individual’s activity participation behaviour in the presence of mobile technology. As suggested by Bonnel (2003), the selection of an appropriate survey methodology is dependent on the objective of the survey. Particularly, in a survey aiming to understand individuals’ activity travel behaviour, a face-to-face interview is preferable to telephone interview. Thirdly, as our sample frame was staff and students at Imperial College London, the generally high CAPI survey cost induced by the journey to conduct the interview can be avoided in this research.

5.2.1.1 Selection and recruitment of SC sample

The sampling frame was staff and students at Imperial College London. This is due to several reasons, such as ready access to the sample, convenience in recruiting on campus and relatively low costs for recruitment. Although the sampling strategy cannot
represent the whole population, it was deemed appropriate for the research purposes considering the limited time and other available resources. A number of selection and recruitment methods for participants were considered, including the use of email, posting advertisement on campus and direct approach of individuals. The initial stage involved sending email invitations to all staff and students in Centre for Transport Studies (CTS) at Imperial College London and asking them to make an interview appointment within two weeks via an online website (called ‘Survey Monkey’). However, the response rate was quite low (less than 3%). Therefore, later, a direct approach was adopted as the principal recruitment procedure. Staff and students, mainly research students, were contacted in person to schedule an interview and our research objective and interview process were also briefly explained. Potential respondents were then re-contacted to attend the scheduled interview at a pre-specified location.

5.2.1.2 Selection of target scenario

The SC survey consisted of hypothetical pair-wise activity choice situations involving the comparison between mobile activity and conventional activity. It is clearly important that the target scenario should be one in which respondents might have seriously considered undertaking the activity with a mobile device, had the mobile technology been available to them. For example, we may employ a scenario of an individual travelling by train or waiting for a train or a bus at the station. Broadly speaking, there were two aspects to be considered in determining the scenario: the type of activity episode to be conducted and the broader activity pattern in which the choice between activity with and without use of mobile technology is made. Firstly, a work related schedule is chosen due to the fact that associated commute to work by train may present an appropriate environment to perform a mobile activity, including adequately long journey times and access to the mobile internet while on the train. Hypothetical activity episodes were designed which could be undertaken in the presence/absence of
mobile technology. Thus mobile banking and mobile shopping were considered to be suitable candidates. Over the past couple of years, great interest has arisen in analysing e-shopping and in-store shopping behaviour (Bhat, 2003a; Farag, 2003, 2007). Thus, it is reasonable to assume that mobile shopping, as an alternative shopping mode employing different technologies than e-shopping and in-store shopping, would be a good target of activity episode. A further advantage of choosing mobile shopping is that the existing body of research on shopping activities (i.e. e-shopping and in-store shopping) can provide valuable insights into understanding various factors that influence a person’s choice between online shopping and conventional shopping. The related empirical results can also be taken into consideration in the development of the proposed experimental design, such as setting values of attributes levels in the SC exercises, and adding additional questions to gather the socio-economic demographics and attitudinal factors relating to shopping choice behaviour. In order to enhance the realism of this survey, the choice of hypothetical scenario are based on the constraint that other shopping alternatives (such as e-shopping at home or a fixed location) cannot be performed based on the activity schedule which we provide to respondents. Mobile shopping and conventional shopping are therefore the only two alternatives in their choice set. In a normal situation where there is no time constraint, a respondent might tend to use e-shopping (e.g. regular grocery shopping at home) as an alternative to conventional shopping, whereas the occurrence of some unexpected event might result in mobile shopping being accepted as the only alternative to conventional shopping to obtain the required goods due to the time and scheduling constraint. Meanwhile, factors known to influence mobile shopping behaviour, e.g. delivery time slot, delivery place, are also taken into account in our survey design.

Based on these considerations, a hypothetical flower-shopping scenario embedded in a work-related pattern is chosen. The details of this scenario are shown in Figure 5.1.
In this experiment, each respondent was asked to envision himself or herself on the train travelling to work, which departed from the station at 7:30am. The respondent is informed that they have pre-arranged plans to go to a friend’s birthday party after work and that he wants to buy some flowers as a present. The respondent is told that online shopping during work time is not possible, thus he is informed of two ways of buying flowers: either conventional shopping after work or mobile on-line shopping on the train.

If the respondent decides to choose conventional shopping, he would need to travel to the shopping area at around 6pm from his office after finishing work. He may find that he has to visit several flower shops until he gets his preferred flowers. It will also take some time to browse, select and pay for the flowers in the flower shops. Finally, he can carry the flowers with him and arrive at the party. The scenario of conventional shopping is described in Figure 5.2.
If he chooses mobile shopping, he pursues the shopping activity using his mobile phone on the train during his journey to work, instead of going to the shop after work. Later on, the flowers he ordered will be delivered to his office. And after work, he can leave for the party directly from his office with flowers ordered online early in the morning. The scenario of mobile shopping is shown in Figure 5.3.

Initially, it was thought not to specify the type of present purchased; only a general ‘birthday present’ was presented to the respondents. However, a paper-based preliminary study (within CTS in September 2006) suggested that had this strategy been pursued, a
large portion of respondents would have been preoccupied with the type of present bought online, thus distracting their attention from essential decision process of the SC exercise. As most mobile retailers do not provide same-day delivery service for grocery shopping or the purchase of goods such as compact discs or books, the delivery of these ‘presents’ would constitute a problem according to the specified activity pattern. Also we need goods where the quality is potential variable so that the impact of consumption outcome on making shopping choice decisions can be examined, while the goods such as CDs and books have the same qualities between mobile shopping and conventional shopping. With these considerations, we specified a specific flower shopping episode which included same day delivery service in our scenario.

5.2.1.3 Computer-aided survey structure

All survey work was carried out using CAPI procedures. A program written in VB.net was installed on a laptop computer to implement the survey. A full source code listing of the interview program is included as Appendix B. The generated choice design matrix was saved in an Access data file linked to the VB program. The SC data and personal information data collected were automatically output to a text data file to be formatted for estimation. The interview process consisted of three distinct parts as shown in Figure 5.4.
The screenshots of the main elements of the interview are included as Appendix C.

The first section is the introduction about the survey and background information covering how to conduct online shopping using a mobile device, for the benefit of respondents unfamiliar with the service model.

In the second part, respondents were asked to imagine themselves in a hypothetical scenario of a typical workday pattern as described in section 5.2.1.2, in which a shopping activity must be conducted to buy flowers for a friend’s birthday party that night. Respondents are informed that they have two different ways to conduct this shopping activity: mobile shopping or conventional shopping. Based on the previous model specification in Chapter 4, each shopping activity was fully described by the combination of 4 variable values of activity attributes as referred to in Section 5.2.2.1. For mobile shopping activity, online time and online cost correspond to the input time and money expenditure within our activity production framework. Journey time was included as an additional activity attribute with an aim to investigate the time use in simultaneous ...
activities (i.e. mobile shopping and associated travel). For conventional shopping activity, extra travel cost corresponds to the input money expenditure, whereas extra travel time together with shopping time corresponds to the input time within our activity production framework. In the interest of simplicity, the general descriptions on the quality of flowers in both shopping activities represent the outcome utility within our framework. Respondents were repeatedly shown a series of choice situations between the two shopping activities and asked to choose between them.

The final portion of the survey collected basic demographic and socio-economic characteristics, as well as information regarding the respondent’s internet usage and experience with online shopping. With an aim of exploring attitudinal factors influencing technology usage, a general personality test based on Big-Five Personality (BFP) Theory (John et al., 1991) was added at the end of this survey. BFP theory postulates that individuals can be characterised using five broad factors, namely openness, conscientiousness, extraversion, agreeableness and neuroticism. Researchers have prepared a number of measurements within BFP theory (Robins et al., 2001; Rammstedt and Rammsayer, 2002; Gosling et al., 2003). A recently-developed short version (Rammstedt and John, 2007) was adopted. The interview process lasted about half an hour for each respondent.

5.2.1.4 Survey piloting

A pilot study was undertaken in the Centre for Transport Studies (CTS) at Imperial College London in the first two weeks in August 2007. A total of 12 pilot interviews were conducted with students and staff in CTS. Each respondent was presented with 12 choice situations which were randomly drawn from an efficient SC design consisting of 180 observations (for the details of efficient SC designs are included in Section 5.2.2.). The pilot survey’s procedures were similar to those presented in Section 5.2.1.3. The major difference was that the questions presented in part three were based on the empirical
studies on mobile-commerce (Niina et al., 2006; Yi-Shun Wang, 2006).

The preliminary results of data analysis using multinomial logit model (MNL) with linear utility function is outlined in Table 5.2.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>MNL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td>Extra travel cost</td>
</tr>
<tr>
<td></td>
<td>Extra travel time</td>
</tr>
<tr>
<td></td>
<td>Shopping time</td>
</tr>
<tr>
<td></td>
<td>Quality of flowers</td>
</tr>
<tr>
<td>Mobile shopping</td>
<td>Journey time</td>
</tr>
<tr>
<td></td>
<td>Online cost</td>
</tr>
<tr>
<td></td>
<td>Online duration</td>
</tr>
<tr>
<td></td>
<td>Quality of flowers</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.631</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-38.0162</td>
</tr>
</tbody>
</table>

* indicates that the corresponding parameters was not significant at 5% level

In Table 5.2, the model was estimated using $12 \times 12 = 144$ choice observations and BIOGEME 1.5 for parameter estimation. The description of these activity attributes and associated levels is provided in the following section. As shown above, the parameters for journey time and extra travel time were found to be statistically insignificant, which may be due to either inappropriate SC design or intrinsic individual indifference.

At the end of pilot interview, respondents participated in a debriefing session to provide feedback regarding improvement of the survey design. Most respondents indicated that survey participation was interesting, instructions were clear and well understood, and the idea of presenting complex information visually (i.e. via graphs and images) was thought to be successful.

Nevertheless, some refinements were identified. Firstly, the physical layout required improvements, as it was found that each page should be formatted in the same structure including a title and description of the content. The key information regarding the description of activity attributes required modification to improve clarity. The sequences of mobile shopping participation were rearranged so as to be described in
separated graphics step-by-step for ease of comprehension, rather than included in one single graphic. Two graphics incorporating all information regarding the sequence of shopping scenarios were inserted in the pages describing shopping activity attributes, as respondents tended to forget key points of the shopping scenarios after clicking away from the introduction pages. In the portion including the SC questions, the design was refined by randomly arranging a flipped sequence of shopping activities on some choice situations, due to respondents’ heterogeneity in their reading habits.

Secondly, it was decided to rephrase some of the survey’s questions. For example, although the notion of online cost given in the pilot study was well understood by the respondents, some of them were confused whether the delivery cost of mobile shopping is included in it. Also, when defining the quality of flowers, a general description was given, whereas the assumption of equal price in the two shopping activities was not mentioned. At the final part of pilot interview, it was decided to replace the questions relating to the individual attitudinal factors of mobile technology adoption with a more general personality test in later collection, as some questions were too implicit to be well understood.

Thirdly, with regards to the experimental design, the “duration” attributes of mobile shopping were chosen to be 5 levels, namely from 10 minutes, 15 minutes, 20 minutes, 25 minutes to 30 minutes, whereas the attributes of “conventional shopping” duration were set to 5 levels equally spaced from 10 minutes to 50 minutes. In a number of instances, it was found that respondents chose mobile shopping and did not choose conventional shopping at all, because they felt the conventional shopping duration was too long. The preliminary data analysis as described in Table 5.2 also found an insignificant parameter for the attribute of extra travel time in conventional shopping, which was set to 3 levels ranging from 10 minutes, 20 minutes and 30 minutes. According to the feedback from respondents, this was thought to be due to the small variations in
corresponding attribute values as presented in the exercise. This problem can be addressed by either reducing the attributes levels or increasing the level difference. Also it was found that it was necessary to provide oral reiterations before answering choice questions as some respondents tended to confuse the different activity attributes, such as journey time and online shopping duration. Hence an additional sample question was added at the beginning of SC choice questions to show the respondents the process of making shopping choices based on the given attributes values. Each respondent was then asked to reflect on the initial key information regarding activity attributes before stating their choice. Another problem found was that some respondents displayed behavioural inconsistency in the same choice situations. Thus it was necessary to add repetitive choice questions to test survey fatigue effects to ensure the quality of the data collected. The number of iterations, which was set to be 12 in pilot study, was increased to 16 according to the respondents’ feedback and consistency with existing studies employing SP surveys.

Later on, further minor modifications were made to the interview programme and the survey was finalized in April 2008. The survey re-commenced in May 2008 and was concluded in the first week of August 2008. A total of 67 interviews were successfully completed. Respondents were recruited via email and direct approach among staff and students at Imperial College London as described in section 5.2.1.1 above.

5.2.2 Design of SC survey

5.2.2.1 Characteristics of alternative

In the second part of the SC survey, respondents were presented with a number of hypothetical scenarios involving a choice between mobile and conventional in-store shopping activities. In these choice scenarios, each shopping alternative was described by 4 attributes based on the model specification described in the previous chapter. Activity attributes for conventional in-store shopping activities were:
• Extra travel cost
• Extra travel time
• Shopping time
• Quality of flowers

Referring to Figure 5.2, extra travel cost and extra travel time were the extra cost and time incurred in the travelling from office to shop to buy the flowers, shopping time covered time spent in the shop browsing, selecting and paying at the cashier. In the interests of parsimoniousness, the overall effects of multiple quality attributes of flowers were expressed as a single general value. For mobile shopping, the activity attributes for mobile shopping were:

• Journey time
• Online cost
• Online duration
• Quality of the flowers

As for Figure 5.3, journey time was the duration of the journey from station to the office, online cost represented the cost of internet access during the journey plus the cost of delivery, online time was the time required during the journey to connect to the internet, browse and select the flowers and to book the delivery and pay. The description of quality of flowers was the same as the one in conventional shopping. Thus each binary choice scenario was completely defined by the values of \(4 \times 2 = 8\) attributes.

In any experimental design, two issues must be addressed: the number of attribute levels and attribute level range. According to recent studies (Rose and Bliemer, 2005, 2006), the number of attribute levels depends on the model specification. If linear effects are expected for a certain attribute, then only two levels are needed for this attribute, whereas if nonlinear effects are expected, more than two levels are required to estimate any such nonlinearity. In terms of the dummy coded attributes, the attribute levels are
predetermined. As more levels of attributes are used the number of choice situations to be generated grows. For any experiment design, it is generally considered desirable to maintain activity level balance (Rose and Bliemer, 2006). That is to say that each attribute level should appear the same number of times for each attribute so as to insure that parameters can be estimated on the whole range of attribute levels. Therefore, it is undesirable to mix too many different numbers of attributes levels (e.g. the mixture of odd numbers and even numbers) as this will yield a larger number of choice situations under the constraint of attribute level balance. With regards to the attribute level range, existing studies on SC experimental design (Rose and Bliemer, 2005) advocate using a wider rather than narrower range as this tends to lead to more reliable parameter estimates. A wider range leads to wider application as model estimations are directly applicable only to the data range on which it is estimated. From a practical perspective, the attribute levels must make logical sense to the respondents. Based on these considerations and the resulting refinement in pilot study, attribute identification and the corresponding levels are outlined in Table 5.3

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conventional shopping</strong></td>
<td></td>
</tr>
<tr>
<td>Extra travel cost</td>
<td>£1, £5</td>
</tr>
<tr>
<td>Extra travel time</td>
<td>10min, 30min</td>
</tr>
<tr>
<td>Shopping time</td>
<td>10min, 15min, 20min, 30min, 35min</td>
</tr>
<tr>
<td>Quality of flowers</td>
<td>I got the flowers I preferred..</td>
</tr>
<tr>
<td></td>
<td>I settled for an alternative</td>
</tr>
<tr>
<td><strong>Mobile shopping</strong></td>
<td></td>
</tr>
<tr>
<td>Journey time</td>
<td>35min, 60min</td>
</tr>
<tr>
<td>Online cost</td>
<td>£3, £8</td>
</tr>
<tr>
<td>Online duration</td>
<td>10min, 15min, 20min, 35min, 30min</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>I got the flowers I preferred..</td>
</tr>
<tr>
<td></td>
<td>I settled for an alternative</td>
</tr>
</tbody>
</table>

In Table 5.3, the number of levels of shopping time in conventional shopping and online duration in mobile shopping are set at five due to the assumption of a nonlinear process utility function. To yield a manageable number of choice situations, the attribute levels of extra travel time, extra travel cost, and online cost, which are input variables within the
activity production framework, are set to two. The attributes values and attribute level range are based on the feedback from the pilot study. Figure 5.5 shows the presentation of a typical choice scenario.

Figure 5.5 A screenshot of typical choice scenario from the SC survey

It should be noted that the key issue in the statistical experiments of SC exercises is how attribute levels are constructed into choices presented to respondents. This is the area in which there have been significant theoretical developments in recent years, especially in the context of SC exercises. The next section provides an overview of the relevant theory and applies it to the design of the current exercise.

5.2.2.2 Existing design for stated choice

Experiment design theory is the underlying mechanism of generating the design matrix (i.e. a matrix of explanatory attribute values). Various theories assume different combinations of attribute values to be assigned to the respondents in a systematic manner. Traditionally, researchers have employed orthogonal designs (Louviere et al., 2000). This design aims to minimize the correlations between attributes levels shown to the respondent. The simplest example of orthogonal design is the full-factorial design which consists of all combination of levels of attributes. For linear models, all main effects,
two-way interactions, or higher-order interactions can be estimated. In most practical situations, it is cost-prohibitive and tedious for the respondents to answer all the choice sets. For this reason, fractional factorial design which only comprises a proportion of all the combination is an alternative option, though this is at the cost of possible confounding effects. A number of recent studies (Huber and Zwerina, 1996; Kanninen, 2002; Sandor and Wedel, 2002; Rose and Bliemer, 2005, 2006) have raised questions regarding the relevance of orthogonal designs and found that the orthogonal property is unrelated to the desirable properties of the choice models that are widely applied to analyse the SC data. Unlike in linear models, within which the orthogonal structure between attributes is important to determine the independent effects, in discrete choice models we are principally concerned with the correlations of difference between attributes. Therefore, according to these studies, it is generally assumed that in cases where some combinations of factor level are infeasible (such that the deletion of these combinations may violate the orthogonality of the survey design), there are different numbers of levels within each factor, or a non-linear model requires interaction or polynomial effects (especially when the number of runs is limited) orthogonal designs may not be necessary or appropriate.

Recently, given budget constraints and attempts at limiting any fatigue effect, identifying methods to reduce the number of choice situations presented to each respondent has become increasingly relevant. For this reason, a new research area in efficient choice (EC) design has emerged as researchers have recognised that introducing such designs can produce more reliable parameter estimates with lower sample sizes (Rose and Bliemer, 2005, 2006). The overall aim of EC design is to maximise the efficiency of the experiment which can be quantified as a function of the asymptotic variance-covariance matrix of the parameter estimates. These designs can provide the maximum amount of information to us regarding the parameters estimates on these data from a statistical perspective. Huber and Zewerina (1996) played an important role in
linking the statistical property (minimisation of different functions of asymptotic variance-covariance matrix) of the stated choice experiment design to choice models that are estimated with SC data. They suggest that this procedure can produce more reliable parameter estimates at a fixed sample size, and also reduce sample sizes with a fixed level of desired reliability of parameter estimates using the SC data.

In EC designs, a number of different criteria identified with different functional forms of asymptotic variance-covariance of parameter estimates have been employed to both define and measure the statistical efficiency (Rose and Bliemer, 2006). One of the most widely applied measures in the literature is $D$-error and the corresponding EC design that yields a minimum D-error is called $D$-optimal design. In practice, a $D$-efficient design that has sufficiently low D-error is often applied. $D$-error is defined as the determinant of the asymptotic variance-covariance matrix of parameter estimates. In the case of a single respondent, we have:

$$D-error = \left( \det \Omega \right)^{1/2}$$  \hspace{1cm} (5.1)

Where $\Omega$ is the asymptotic variance-covariance matrix of parameter estimates; $Q$ is the total number of generic attributes to be estimated from the design. $\Omega$ is written as:

$$\Omega = X'PX = \sum_{s=1}^{S} \sum_{j=1}^{J} x'_{njs} P_{njx} x_{njs}$$  \hspace{1cm} (5.2)

Where $X$ is the value of the design matrix which consists of the combinations of attributes values of alternatives; $x_{njs}$ is the value of alternative $j$ ($j = 1, 2, ..., J$) in choice set $s$ faced by individual $n$; $P$ is a $J \times S$ by $J \times S$ diagonal matrix with elements equal to the choice probabilities of alternative $j$ over choice set $s$; $J$ is the total number of alternatives and $S$ is the total number of choice scenarios faced by individual $n$. We note that the specification of the choice probability matrix $P$ requires assumed values of the parameter estimates. Different types of $D$-errors have been proposed depending on the prior
information of parameters. Generally speaking, three cases can be distinguished as follows:

\[ D_z \text{- error} = \left( \det \Omega(X, 0) \right)^{\frac{1}{\beta}} \]  \hspace{1cm} (5.3)

\[ D_p \text{- error} = \left( \det \Omega(X, \tilde{\beta}) \right)^{\frac{1}{\beta}} \]  \hspace{1cm} (5.4)

\[ D_b \text{- error} = \int_{\beta} \left( \det \Omega(X, \tilde{\beta}) \right)^{\frac{1}{\beta}} \phi(\beta | \theta) d\beta \]  \hspace{1cm} (5.5)

\( D_z \text{- error} \) (‘z’ from zero) in Equation (5.3) assumes that the prior values of parameter \( \tilde{\beta} \) are set to zero. Designs that are optimized with \( D_z \text{- error} \) have no available information regarding the parameters, including both the sign and magnitude. \( D_p \text{- error} \) (‘p’ from priors) in Equation (5.4) suggests a specific fixed non-zero prior parameter, whereas \( D_b \text{- error} \) (‘b’ from Bayesian) in Equation (5.5) assumes the prior parameters \( \tilde{\beta} \) to be random variables with a joint probability density given parameters \( \theta \). Besides D-error, another well-known efficiency measure is \( A \text{- error} \) which is the trace of the variance-covariance matrix (i.e. the summation of all diagonal elements of the matrix). Therefore, it is the variance rather than covariance that actually influences the \( A \)-error. Correspondingly, the design with the lowest \( A \)-error is called \( A \)-optimal design. \( A \)-error is specified as:

\[ A \text{- error} = \frac{tr(\Omega)}{K} \]  \hspace{1cm} (5.6)

Similar to D-error, different \( A \text{- error} \) calculations are defined based on the availability of information on the parameters, namely that:

\[ A_z \text{- error} = \frac{tr(\Omega(X, 0))}{K} \]  \hspace{1cm} (5.7)
In order to avoid parameters with large values overshadowing others, a weighted summation is used instead to allocate more importance to certain parameters to ensure that an accurate estimation of these parameters is obtained.

Rose and Bliemer (2006) concluded that EC designs may outperform other methods when there exists prior knowledge regarding the parameter values, most such parameters tend to be alternative-specific and researchers attempt to keep attribute balance for all design attributes. The applications of efficient designs in such situations, which may not be orthogonal, are effective to the degree that the variance-covariance parameters are minimized. Rose and Bliemer also posited a close match between orthogonal design and D-optimal design: in cases where all parameters are alternative specific, a $D_{z}$-optimal design is orthogonal. However it is not straightforward to compare EC and orthogonal designs when no information is available about the parameter values. In the case of no prior information regarding the parameters, it is possible to collect a pilot sample to obtain initial information regarding parameter estimates and thus generate an efficient design. We note that an SC design which is created for a specific model might not be efficient for other models when using the same data.

Referring to Equation (5.2), the problem of generating an EC design can be formulated as given feasible attribute levels $x_{njs}$ for all alternative $j$, given the number of choice situation $S$ and the prior values of parameter estimates $\hat{\beta}$, with a resulting level-balanced design matrix $X$ that minimizes the efficiency error based on different criteria in Equation (5.3)-(5.9). Theoretically, in order to address this problem, one
could determine the full factorial design and evaluate each combination of $S$ choice situations, with the knowledge that the combination with the lowest efficiency error is the optimal design. In the cases when the full factorial design implies a large number of choice situations, it becomes infeasible to evaluate each combination. Various computerised search algorithms have therefore been developed to achieve this aim. The existing algorithms can be divided into two classes: row-based and column-based algorithms. In a row-based algorithm, an initial design, incorporating all the constraints that apply to the final design (such as attribute level balancing), is randomly selected from a set of predefined candidates (i.e. either the full factorial design for small problems or a fractional factorial design for large problems). Then it is iteratively refined with addition and deletion of choice sets. In each iteration, if the design has a lower efficiency error in terms of the above efficiency criterion, it will be stored and the final efficient design would be the one that increases the efficiency most in all iterations. A row-based algorithm could easily eliminate any utility-dominated choice situations, but it is difficult to maintain the balance of different attribute levels. The modified Federov algorithm (Cook, 1980) is the most widely used algorithm of this kind. Column-based algorithms, such as the Relabeling, Swapping & Cycling algorithm (Huber and Zwerina, 1996; Sandor and Wedel, 2001), create a design by selecting attribute levels over all choice situations for each attribute. In each iteration, different columns for each attribute are created, which together form a design. The design with the lowest efficiency error is stored. As opposed to row-based algorithms, column-based algorithms have more flexibility in designs which require the balance of different attributes levels, but have limitations in finding desirable combinations of attribute levels.
5.2.2.3 Proposed SC design

5.2.2.3.1 Efficient Choice (EC) design

In this research, an efficient design was adopted in the SC experiment. This decision was made for several reasons. Firstly, nonlinear utility functions are suitable specifications in the context of our study, within which the orthogonal structure of design matrix $X$ between attributes is not required. Secondly, the attributes of alternatives, namely the input time and cost in the presence/absence of mobile technology, are considered to be alternative-specific. Thus an orthogonal design may not necessarily be applicable in this case. Thirdly, given an available amount of time and resources, an EC design can produce more reliable parameter estimates at a fixed sample size.

5.2.2.3.2 Total number of choice observations

In order to formulate an EC design we require feasible attribute levels for two shopping activities, the number of shopping choice situations and a priori estimates of parameter values. In Section 5.2.2.1 we presented a definition of attributes levels. The estimation results of pilot data provide some evidence regarding expected parameter values (Louviere et al., 2000), although this is obviously limited by the available sample size in the pilot. In terms of the number of choice situations, Bliemer and Rose (2006) suggested that $S$ should mainly depend on the intuition of how many choice situations each respondent can handle, as long as $S$ is equal to or larger than the number of parameters. They also proposed that although more choice situations will automatically increase the efficiency, compensating for this effect by normalising the efficiency error, the number of choice situations makes little difference. In this research, the optimal number of choice scenarios was calculated using an autocall macro (%mktruns) in the SAS software package (SAS Support, 2009). In the context of current experiment, with 2
five-level and 4 two-level attributes in both shopping alternatives (as referred to Table 5.3), the command can be specified as \%mktruns (2 2 5 2 2 5 2), which reported that the optimal numbers of choice observations $S$ can be 100, 200, 400, 500, 800 or more given 8 attributes with $2 \times 2 \times 5 \times 2 \times 2 \times 2 \times 5 \times 2 = 1600$ levels.

To test the impact of these numbers of choice situations on the efficiency of a design, the following procedures were undertaken. Firstly, a design matrix $X$ consisting of $S$ choice observations was generated using a R inbuilt function (optFederov) (Wheeler, 2004) based on a Fedorov’s exchange algorithm (Fedorov, 1972). Secondly, a synthetic dataset was generated given the MNL model and prior values of parameters listed in Table 5.2. A full source code of generating this synthetic dataset using R is included as Appendix D. Although several plausible forms of nonlinear utility functions have been described in preceding chapters, we cannot distinguish which is applicable for each particular shopping activity. Hence, a linear utility function is assumed at this stage in the interests of parsimoniousness. Thirdly, parameters were estimated using BIOGEME 1.5 software. Fourly, in order to obtain the average values of parameter estimations for each number of choice observations $S$, the above procedures are repeated 10 times. The average estimation results were calculated as the sum of estimated coefficients divided by 10. Finally, for each number of choice observations $S$, the average estimation results were compared with the prior values. The one matching the prior values most closely was chosen as the number of choice situations in our experiment. The average estimation results of choosing different $S$ using linear MNL model, as well as the prior value of parameters, are outlined in Table 5.4.
Table 5.4 Estimation results for choosing different numbers of choice situations using linear MNL model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Prior value</th>
<th>N=100</th>
<th>N=200</th>
<th>N=400</th>
<th>N=500</th>
<th>N=800</th>
<th>N=1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Journey time</td>
<td>-0.007</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.004</td>
<td>-0.096</td>
<td>-0.005</td>
<td>-0.008</td>
</tr>
<tr>
<td>Online cost</td>
<td>-1.347</td>
<td>-1.6</td>
<td>-1.584</td>
<td>-1.43</td>
<td>-1.4</td>
<td>-1.4</td>
<td>-1.38</td>
</tr>
<tr>
<td>Online time</td>
<td>-0.281</td>
<td>-0.357</td>
<td>-0.311</td>
<td>-0.27</td>
<td>-0.298</td>
<td>-0.29</td>
<td>-0.287</td>
</tr>
<tr>
<td>Quality of flower</td>
<td>2.256</td>
<td>3.02</td>
<td>2.652</td>
<td>2.2</td>
<td>2.4</td>
<td>2.4</td>
<td>2.232</td>
</tr>
<tr>
<td>Extra travel cost</td>
<td>-1.57</td>
<td>-1.94</td>
<td>-1.8</td>
<td>-1.7</td>
<td>-1.69</td>
<td>-1.62</td>
<td>-1.6</td>
</tr>
<tr>
<td>Extra travel time</td>
<td>-0.018</td>
<td>-0.006</td>
<td>-0.016</td>
<td>-0.019</td>
<td>-0.02</td>
<td>-0.0168</td>
<td>-0.02</td>
</tr>
<tr>
<td>Shopping time</td>
<td>-0.122</td>
<td>-0.169</td>
<td>0.153</td>
<td>0.1378</td>
<td>-0.107</td>
<td>-0.125</td>
<td>-0.12</td>
</tr>
<tr>
<td>Quality of flower</td>
<td>1.24</td>
<td>1.8</td>
<td>1.49</td>
<td>1.395</td>
<td>1.254</td>
<td>1.219</td>
<td>1.27</td>
</tr>
</tbody>
</table>

* indicates that corresponding parameters insignificant at 5% level

In Table 5.4, all the average parameter estimations for different number of choice observations have the same sign as the prior values. In order to better compare these results with the prior values, a variable termed \( \text{error rate} = \frac{\text{average-priors}}{\text{priors}} \) was calculated. The error rate results of different number of choice situations are found in Table 5.5

Table 5.5 Results of error rate of choosing different number of choice observations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>N=100</th>
<th>N=200</th>
<th>N=400</th>
<th>N=500</th>
<th>N=800</th>
<th>N=1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Journey time</td>
<td>1.43</td>
<td>0.71</td>
<td>0.43</td>
<td>0.38</td>
<td>0.29</td>
<td>0.14</td>
</tr>
<tr>
<td>Online cost</td>
<td>0.19</td>
<td>0.18</td>
<td>0.06</td>
<td>0.05</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Online time</td>
<td>0.27</td>
<td>0.11</td>
<td>0.04</td>
<td>0.06</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Quality of flower</td>
<td>0.34</td>
<td>0.18</td>
<td>0.02</td>
<td>0.02</td>
<td>0.06</td>
<td>0.01</td>
</tr>
<tr>
<td>Extra travel cost</td>
<td>0.24</td>
<td>0.15</td>
<td>0.08</td>
<td>0.08</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Extra travel time</td>
<td>0.67</td>
<td>0.11</td>
<td>0.06</td>
<td>0.11</td>
<td>0.07</td>
<td>0.11</td>
</tr>
<tr>
<td>Shopping time</td>
<td>0.39</td>
<td>0.25</td>
<td>0.13</td>
<td>0.12</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Quality of flower</td>
<td>0.45</td>
<td>0.20</td>
<td>0.13</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
</tr>
</tbody>
</table>

As we can see in Table 5.5, the error rates have general decreasing patterns with increase of number of observations. For each estimated parameter, the error rate of choosing the above number of choice observations is plotted in Figure 5.6.
(a) Error rate of journey time

(b) Error rate of online cost

(c) Error rate of online time

(d) Error rate of quality of flowers for mobile shopping

(e) Error rate of extra travel cost

(f) Error rate of extra travel time
In general, the figure shows that error rate displays a rapid decreasing pattern when the number of choice observations approach 400. After that, error rate decreases consistently in a flat pattern when the number of choice observations continue to increase. Trading off the increase in data set with the accuracy in parameter estimation, 800 is chosen as the appropriate number of choice observations. Based on the above analysis, a D-efficient design matrix with 800 choice observations was generated.

5.2.2.3.3 Repetition for each respondent

In terms of the maximum number of repetition for each respondent, Bliemer and Rose (2006) suggested that depending on the complexity of each choice situation, roughly 10 to 20 choice situations should be feasible. In this experiment, the number of choice situations was initially set to 12 in pilot study. Respondents felt it would be reasonable to increase the number of choice situations. In order to maintain the balance between respondent burden and sufficiency for examining the dynamics of individual choice behaviour, the maximum number of repetitions was set to 18, among which 15 choice scenarios was generated by previous procedure and in addition three further scenarios were added to the design (Polak, 1994). The first additional choice scenario was
always presented as the first scenario to the respondents. This scenario served both as a sample and a ‘warm-up' for the main SC exercise. The remaining two additional choice scenarios were inserted respectively in the middle and at the end of SC exercise to investigate the consistency of respondents’ choice behaviour. These additional deliberately-repeated choice scenarios were presented earlier:

- The first additional scenario is a repeat of the first non-sample scenario and was presented as the 8th scenario in total
- The second additional scenario is a repeat of the 8th non-sample scenario, and was displayed as 15th scenario.

This construction enables us to directly test for behavioural consistency and to identify and if necessary for controlling fatigue effects. The proposed overall statistical design is summarised in Table 5.6.

<table>
<thead>
<tr>
<th>Scenario number</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Random subset of replications from D-efficient design</td>
</tr>
<tr>
<td>3</td>
<td></td>
</tr>
<tr>
<td>…</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Repeat of number 2</td>
</tr>
<tr>
<td>9</td>
<td>Random subset of replications from D-efficient design</td>
</tr>
<tr>
<td>14</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Repeat of number 9</td>
</tr>
<tr>
<td>16</td>
<td>Random subset of replications from D-efficient design</td>
</tr>
<tr>
<td>17</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td></td>
</tr>
</tbody>
</table>

5.3 Descriptive analysis of SC sample characteristics

5.3.1 Main demographic characteristics of the SC sample

Of the 67 interviews carried out, 62 of them were considered to pass validity checks
through the diagnostic analysis applied to the SC data as referred to in Section 5.4. Table 5.7 summarises the key characteristics of the valid records after data filtering.

Table 5.7 Main personal characteristics of SC sample

<table>
<thead>
<tr>
<th>Personal characteristic</th>
<th>Percentage of sample (N=62)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>73%</td>
</tr>
<tr>
<td>Female</td>
<td>27%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
</tr>
<tr>
<td>20-25</td>
<td>23%</td>
</tr>
<tr>
<td>25-29</td>
<td>50%</td>
</tr>
<tr>
<td>30-34</td>
<td>16%</td>
</tr>
<tr>
<td>35-40</td>
<td>8%</td>
</tr>
<tr>
<td>&lt;50</td>
<td>3%</td>
</tr>
<tr>
<td>Qualification</td>
<td></td>
</tr>
<tr>
<td>PhD</td>
<td>85%</td>
</tr>
<tr>
<td>Master</td>
<td>8%</td>
</tr>
<tr>
<td>Bachelor</td>
<td>7%</td>
</tr>
<tr>
<td>Other qualifications</td>
<td>0%</td>
</tr>
<tr>
<td>Employment</td>
<td></td>
</tr>
<tr>
<td>Full-time paid employment</td>
<td>35%</td>
</tr>
<tr>
<td>Part-time paid employment</td>
<td>2%</td>
</tr>
<tr>
<td>Full-time self employment</td>
<td>0%</td>
</tr>
<tr>
<td>Part-time self employment</td>
<td>0%</td>
</tr>
<tr>
<td>Full-time student</td>
<td>63%</td>
</tr>
<tr>
<td>Part-time student</td>
<td>0%</td>
</tr>
<tr>
<td>No currently employed</td>
<td>0%</td>
</tr>
<tr>
<td>Income</td>
<td></td>
</tr>
<tr>
<td>Less than 4k</td>
<td>10%</td>
</tr>
<tr>
<td>4k-8k</td>
<td>5%</td>
</tr>
<tr>
<td>8k-15k</td>
<td>31%</td>
</tr>
<tr>
<td>15k-30k</td>
<td>32%</td>
</tr>
<tr>
<td>30k-75k</td>
<td>15%</td>
</tr>
<tr>
<td>Over 75k</td>
<td>0%</td>
</tr>
<tr>
<td>Decline to answer</td>
<td>8%</td>
</tr>
</tbody>
</table>

As shown in Table 5.7, the broad classifications of qualification, employment and income are based on the definitions of National Travel Survey (NTS) data. The results are generally as we would expect. The majority of valid respondents are male, and the average age is 28.4 years with standard deviation of 4.6 years. Most are highly-educated, with 93% of them holding postgraduate degrees. In terms of employment status, 35% are full-time research assistants with income below 40k and 63% are full-time students. These results indicate that there is a large concentration of students and staff with higher qualifications, young, male, and lower-to-moderate incomes. Although our sample is not representative of the entire population, they constitute active potential users of mobile services. It is therefore more important to ensure that that the sample is representative in
terms of the variation of activity choice behaviour in the presence of technology, particularly with use of mobile services. We also considered internet usage of the SC sample. Table 5.8 presents the corresponding results.

<table>
<thead>
<tr>
<th>General use of Internet</th>
<th>Percentage (N=62)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet Access</td>
<td></td>
</tr>
<tr>
<td>At home, at work and when travelling</td>
<td>18%</td>
</tr>
<tr>
<td>At home and at work</td>
<td>70%</td>
</tr>
<tr>
<td>Only at work</td>
<td>12%</td>
</tr>
<tr>
<td>Only at home</td>
<td>0%</td>
</tr>
<tr>
<td>Don't have access to the internet at all</td>
<td>0%</td>
</tr>
<tr>
<td>Internet usage</td>
<td></td>
</tr>
<tr>
<td>Regularly use several hours per day</td>
<td>97%</td>
</tr>
<tr>
<td>Regularly use several hours per week</td>
<td>1.5%</td>
</tr>
<tr>
<td>Only use occasionally</td>
<td>1.5%</td>
</tr>
<tr>
<td>Never use</td>
<td>0%</td>
</tr>
<tr>
<td>Online shopping</td>
<td></td>
</tr>
<tr>
<td>Regularly use</td>
<td>30%</td>
</tr>
<tr>
<td>Occasionally use</td>
<td>69%</td>
</tr>
<tr>
<td>Never use</td>
<td>1%</td>
</tr>
<tr>
<td>Mobile internet</td>
<td></td>
</tr>
<tr>
<td>Regularly use several hours per day</td>
<td>0.03%</td>
</tr>
<tr>
<td>Regularly use several hours per week</td>
<td>0.08%</td>
</tr>
<tr>
<td>Only use occasionally</td>
<td>37%</td>
</tr>
<tr>
<td>Never use</td>
<td>52%</td>
</tr>
<tr>
<td>Mobile shopping</td>
<td></td>
</tr>
<tr>
<td>Regularly use</td>
<td>1%</td>
</tr>
<tr>
<td>Occasionally use</td>
<td>11%</td>
</tr>
<tr>
<td>Never use</td>
<td>88%</td>
</tr>
</tbody>
</table>

The results in Table 5.8 show that all respondents have internet access, with 18% also having mobile internet access. A significant number of respondents are heavy internet users with several hours per day, and only 1% of them have never shopped online. However, in terms of the mobile internet, half of respondents have used it, mostly for browsing and seeking information, whereas only 10% of them have used the mobile internet for shopping.

5.3.2 Personality characteristics

In the final part of the SC survey, a ten-item short version of the Big Five Inventory (BFI), was applied to measure the respondents’ personality (Rammstedt and John, 2007). BFI consists of 5 personality traits, i.e. openness, conscientiousness, extraversion,
agreeableness and neuroticism. Each dimension is measured using two selected items rated on a 5-step scale, in which one term is true-scored and the other is reversed-scored (as referred to Appendix B). The average score represented as the sum of two selected items and the standard deviation of the score for each BFI dimension, are presented in Table 5.9.

<table>
<thead>
<tr>
<th>Personality traits</th>
<th>Average scores</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFI-1(Openness)</td>
<td>6.49/10</td>
<td>1.7</td>
</tr>
<tr>
<td>BFI-2(Conscientiousness)</td>
<td>7.34/10</td>
<td>1.6</td>
</tr>
<tr>
<td>BFI-3(Extraversion)</td>
<td>6.81/10</td>
<td>1.9</td>
</tr>
<tr>
<td>BFI-4(Agreeableness)</td>
<td>4.98/10</td>
<td>1.8</td>
</tr>
<tr>
<td>BFI-5(Neuroticism)</td>
<td>7.29/10</td>
<td>1.6</td>
</tr>
</tbody>
</table>

5.4 Preliminary analysis of SC data

5.4.1 Diagnostic analysis

The first stage in the analysis of SP data was to carry out a series of diagnostic tests to investigate the consistency and response patterns in the dataset. Two specific type of response patterns are examined in this thesis: non-trading behaviour and lexicographic response.

5.4.1.1 Non-trading behaviour

According to early studies by Polak (1994), non-trading behaviour refers to the circumstances in which respondents select the same choice alternative in all the replication of situations. Such behaviour pattern contributes no useful information with regard to the respondent’s relative sensitivity to different activity attributes. In the case of our interview, it has been founded that some respondents displayed a strong preference for one shopping alternative over another. The occurrence of this behaviour originates from a variety of reasons including inadequate variation in the designed activity attributes,
respondents’ strong bias, and fatigue effect and so on. One aim in the design of an SC survey is generally to reduce the incidence of non-trading, consistent with the presentation of plausible hypothetical choice contexts. Overall in this research, 5 out of 67 respondents (i.e. 7.5%) were non-traders, who opt for the conventional shopping in each replication due to ‘extreme’ preference of conventional shopping for flowers in the proposed hypothetical scenario.

With an aim to exploring the effects of non-trading behaviour on the final estimation results, a basic MNL model with linear-in-parameter utility function was specified for both non-filtered sample and filtered sample without non-trading behaviour. The models were estimated using BIOGEME 1.5 and the estimation results are presented in Table 5.10.

Table 5.10 Estimation results for filtered sample and non-filtered sample

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Filtered sample (N=62)</th>
<th>Non-filtered sample (N=67)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Journey time</td>
<td>0.005(0.88*)</td>
<td>0.005(0.86*)</td>
</tr>
<tr>
<td>Online cost</td>
<td>-0.37(-10.96)</td>
<td>-0.33(-10.93)</td>
</tr>
<tr>
<td>Online duration</td>
<td>-0.02(-1.85*)</td>
<td>-0.02(-1.60*)</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>1.74(7.91)</td>
<td>1.50(7.69)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.32(2.63)</td>
<td>1.28(2.75)</td>
</tr>
<tr>
<td>Extra travel cost</td>
<td>-0.34(-8.43)</td>
<td>-0.32(-8.51)</td>
</tr>
<tr>
<td>Extra travel time</td>
<td>-0.07(-8.71)</td>
<td>-0.06(-8.14)</td>
</tr>
<tr>
<td>Shopping time</td>
<td>-0.08(-6.76)</td>
<td>-0.07(-6.45)</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>1.85(9.44)</td>
<td>1.70(9.30)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.319</td>
<td>0.273</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-778.404</td>
<td>-838.708</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-521.275</td>
<td>-600.870</td>
</tr>
</tbody>
</table>

* indicates that corresponding parameters insignificant at 5% level

Comparing the results of filtered and non-filtered sample, the estimated parameters have the same sign and close values. In mobile shopping activity, the parameters significance of filtered sample is slightly higher than that of non-filtered sample. In both dataset, the online cost and quality of flowers are most significant attributes, while journey time and online duration are insignificant attributes. A better overall level of fit was found in filtered sample with higher adjusted Rho-square and final log likelihood.
This is due to the reason that non-filtered data represent the biased information which leads to the inaccurate evaluation of overall model performance. However, given a relative small amount of non-traders (i.e. 5 out of 67), it does not significantly influence the estimation values.

In order to obtain a better insight into what factors may affect the non-trading behaviour in SC sample, we apply a standard binary probit model to investigate this issue (Polak, 1994). Stated formally, the model is written as:

$$\text{Prob}(y_n = 1) = F(\beta'X_n)$$

(5.10)

Where $y_n$ is binary variable which equals to 1 when respondent $n$ exhibits non-trading behaviour and 0 otherwise; $F()$ is standard normal distribution; $X_n$ is a vector of characteristics of individual $n$; $\beta$ is the vector of parameters.

Initially, all the variables collected through the questions in part 3 were taken into account to constitute the vector $X_n$. Due to the commonality of SC respondents in demographic characteristics, certain questions receive almost the same answers among the respondents. Finally, the following variables were included in the model specification search:

- Age and age square
- Gender
- Dummy variables for PhD and Masters’ Degree
- Dummy variable for various income categories
- Big-five personality scores

Given linear-in-parameter utility function, the binary probit model in Equation (5.10) was estimated using BIOGEME 1.5 and the estimation results are outlined in Table 5.11.
Table 5.11 Initial estimation results for model of non-trading behaviour

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient ( t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.139(-0.11 *)</td>
</tr>
<tr>
<td></td>
<td>0.00129(0.06*)</td>
</tr>
<tr>
<td>Age²</td>
<td>-0.43(-0.51*)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.397(0.02*)</td>
</tr>
<tr>
<td></td>
<td>-1.31(-0.07*)</td>
</tr>
<tr>
<td>PhD</td>
<td>-0.699(-0.08*)</td>
</tr>
<tr>
<td>Master</td>
<td>1.71(0.69*)</td>
</tr>
<tr>
<td>Dummy variable for income &lt;4k</td>
<td>-0.597(-0.08*)</td>
</tr>
<tr>
<td>Dummy variable for income 4k-8k</td>
<td>1.63(0.66*)</td>
</tr>
<tr>
<td>Dummy variable for income 8k-15k</td>
<td>0.597(-0.08*)</td>
</tr>
<tr>
<td>Dummy variable for income 15k-30k</td>
<td>1.71(0.69*)</td>
</tr>
<tr>
<td>Openness</td>
<td>-0.0554(-6.20)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>-0.282(-0.55*)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>-0.0302(-0.08*)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>0.18(0.34*)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>0.226(0.56*)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.437</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-45.748</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-11.744</td>
</tr>
</tbody>
</table>

* indicates that corresponding parameters insignificant at 5% level

As we can see, all the parameter estimates in Table 5.11 are insignificant. This may be due to the small variations in responses arising from the commonality in respondents’ demographic and socioeconomic characteristics. A variety of alternative combinations of the above variables were examined to construct the utility specification. The most successful specification is by including single variable of age, while the specification including both age and age square generalises insignificant parameter estimates. The estimation results of the most successful specification are summarised in Table 5.12.

Table 5.12 Best estimation results for model of non-trading behaviour

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient ( t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.0554(-6.20)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.648</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-45.748</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-15.101</td>
</tr>
</tbody>
</table>

The results in Table 5.12 indicate that age plays a significant role in conditioning non-trading behaviour. It was found that although the results in Table 5.11 are insignificant, the sign of the coefficient of age accords with the result in Table 5.12.
Hence despite the insignificance of parameter estimates, the results in Table 5.11 more or less provide us some insight into understanding the non-trading behaviour. A positive sign of any coefficient represents that increase in the value of corresponding variables will increase the probability of respondent being a non-trader such that the observations completed by him are more likely to be excluded from the dataset, while a negative coefficient indicates that an increase in the value of corresponding variables will decrease the probability of an individual being a non-trader so that the observations completed are less likely to be excluded from in the data set. As described in Table 5.7, all respondents are aged between 20 to 50. Hence the negative coefficient of age interprets that younger people (e.g. 20-30) display a greater tendency to be non-traders than older people. It is difficult to interpret the significance of this finding. However, one possibility is that young people in this age group (i.e. most of them are male) are more concern about their relationship with female friend than old people. Thus they always choose conventional shopping for flowers to a friend such that the quality of flowers can be guaranteed as they can see and smell the flowers by themselves.

5.4.1.2 Evidence of lexicographic choice behaviour

The basis of SP exercise relies on the idea that respondents consider the full profile of all design variables and trade-off the changes in the values of them in a compensatory manner. Lexicographic choice response leads to the departure of this response form, as in each choice situation, respondents evaluate the choice alternatives on the value of a single design variable. In this thesis, we apply the same procedure as described in Polak’s report (1994) to test for the lexicographic choice process by identifying the respondents whose choices between the two shopping alternatives appeared to be dictated by the value of a single design variable. Namely, we aim to identify the respondents who consistently choose the shopping alternative with the lowest input cost, lowest input time, or best quality of flowers. Although this way of identifying the lexicographic choice may not be
able to distinguish whether those responses result from particular configuration of tastes or genuine non-compensatory pattern (Polak, 1994), to some degree, it can more or less provide us a useful indication. In our SC experiment, the lexicographic response is not found in either input cost or input time, while only in the case of quality of flowers there exist some evidences of such lexicographic choice process. Among total 67 respondents, 16 of them were observed to choose the shopping alternative that presents better quality of flowers all the time. The proportion of lexicographic choice response is 24% (i.e. 16/67=24%)

In order to explore the effects of lexicographic response on final estimation results, the same step is taken as described in examining the non-trading behaviour. A basic MNL model with linear-in-parameter utility function was specified for both non-filtered sample and filtered sample without lexicographic response. The estimation results are presented in Table 5.13.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Filtered sample (N=51)</th>
<th>Non-filtered sample (N=67)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Journey time</td>
<td>0.003(0.5*)</td>
<td>0.005(0.86*)</td>
</tr>
<tr>
<td>Online cost</td>
<td>-0.34(-9.94)</td>
<td>-0.33(-10.93)</td>
</tr>
<tr>
<td>Online duration</td>
<td>-0.02(1.91*)</td>
<td>-0.02(-1.60*)</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>1.20(5.55)</td>
<td>1.50(7.69)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.44(2.72)</td>
<td>1.28(2.75)</td>
</tr>
<tr>
<td>Extra travel cost</td>
<td>-0.32(-7.64)</td>
<td>-0.32(-8.51)</td>
</tr>
<tr>
<td>Extra travel time</td>
<td>-0.07(-8.38)</td>
<td>-0.06(-8.14)</td>
</tr>
<tr>
<td>Shopping time</td>
<td>-0.08(-6.77)</td>
<td>-0.07(-6.45)</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>1.41(6.95)</td>
<td>1.70(9.30)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.268</td>
<td>0.273</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-645.32</td>
<td>-838.708</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-463.3</td>
<td>-600.870</td>
</tr>
</tbody>
</table>

* indicates that corresponding parameters insignificant at 5% level

The results show that there is no significant difference between parameter estimations and the value of adjusted rho-square in both non-filtered and filtered sample. This may be explained by two reasons. Firstly, as mentioned above, the test adopted here might not be infallible. Thus decisions purely evaluated by the quality of flowers may
arise from just a particular taste preference in our proposed hypothetical scenario, rather than from real lexicographic responses. Secondly, to each respondent who is considered to exhibit lexicographic behaviour using our test criteria, the lexicographic choice responses only constitute a small portion (i.e. 3 out of 18, 6 out of 18, 5 out of 18, 9 out of 18 etc.). In all the left of 18 observations, qualities of flowers are described by the same attribute value in both shopping alternatives. Hence the respondents’ responses to this attribute are left to be unknown in these choice scenarios. This is to say that their lexicographic responses are only identifiable in a relative small amount of observations, which may not constitute a strong evidence of this behavioural pattern. Overall, the estimation results in Table 5.13 suggest that lexicographic response patterns do not have a significant effect on the estimation results. Therefore, given small number of dataset, it may not be necessary to filter out these responses in model estimation in Chapter 6.

5.4.2 Analysis of the internal consistency of SC data

In section 5.4.1, diagnostic analysis was conducted to filter the raw SC data that exhibit the non-trading behaviour and lexicographic behaviour. The results in Table 5.13 suggest that lexicographic response evaluated by current criteria may not have significant influence to the final estimation results. Given the small sample size, only non-traders were excluded from total 67 respondents. Among the 18 choice observations given to each respondent, the first replication is presented as a sample case. Hence $17 \times 62 = 1054$ replications in total were remained as valid records for analysis of internal consistency.

The design of the SC survey described in Section 5.2.2.2 includes two tests on the internal consistency of SC data by repeating particular choice scenarios at different stages of the interview. In the 18 choice situations presented to respondents, No. 8 situation is identical to No. 2 (Test 1) and No. 15 situation is identical to No. 9 (Test 2). If SC data is completely internally consistent, then the choices made by the respondents in each pair of
situations would be the same. As proposed in Polak’s report (1994), the degree of disagreement in these matched choices is a measure of the internal consistency. Moreover, if the sequence and separation of replications within SC survey is unrelated to responses, then the error rate in Test1 and Test2 should be the same. Table 5.14 summarises the results.

Table 5.14 Results of tests of internal consistency of SC data

<table>
<thead>
<tr>
<th></th>
<th>Test 2: Pass</th>
<th>Test 2: Fail</th>
<th>Subtotal Test 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test 1: Pass</td>
<td>74.1%</td>
<td>9.7%</td>
<td>83.8%</td>
</tr>
<tr>
<td>Test 1: Fail</td>
<td>14.5%</td>
<td>1.6%</td>
<td>16.1%</td>
</tr>
<tr>
<td>Subtotal Test 2</td>
<td>88.6%</td>
<td>11.3%</td>
<td></td>
</tr>
</tbody>
</table>

In Table 5.14, 74% of the respondents passed both consistency checks and around 2% of them failed in both tests. Thus the overwhelming majority of the respondents behave consistently in SC survey. The rate of failure in Test 1 but success in Test 2 is higher than the rate of failure in Test 2 but success in Test 1. This indicates that the sequence order and separation of choice replication may have some influences in behavioural inconsistency.

In SC experiment, each sampled individual presents us with multiple observations on choice responses. This implies the potential of sequencing the presented choice scenarios that may results in mixtures of learning and inertia effects for individuals. The results presented in Table 5.14 suggested that responses to a particular replication within the SC experiment may have been influenced by these effects. In this section, we exert systematic differences on error component in responses to different replications of utilities so as to address these effects (Polak, 1994). Hence data from each replication is considered to have its own magnitude of error. The comparison between the relative magnitudes of these errors provides us some insight into the relationship of replication sequence to the validity of response. The estimation of models with a varying error component is computational demanding. In order to reduce the computational burden, we work with the simple linear utility specification. To identify the sequencing effect on final
estimation results, a comparison is made between basic MNL model and the extended model embodying this effect. In basic MNL model, the utility of alternative \( j \) \((j = 1,2)\) for individual \( n \) is represented as:

\[
U_{nj} = V_j(z_{nj}) + \varepsilon_{nj}
\]

(5.11)

Where \( z_{nj} \) is the vector consisting of the SC design variables listed in Table 5.3; \( V_j(\ ) \) is linear utility function for alternative \( j \); \( \varepsilon_{nj} \) is IID Gumbel distribution as referred to Section 6.1.2. By using the above MNL model, an implicit assumption is made that the error has a common variance in all the replications, which is independent of the sequence order of replication.

In this thesis, the extended specification that incorporates the sequencing and conditioning effect generalises as ML model structure as referred to Section 6.1.4, which is written as:

\[
U_{njt} = V_j(z_{nj}) + \phi_{njt} + \varepsilon_{njt}
\]

(5.12)

Where \( U_{njt} \) is the utility of alternative \( j \) \((j = 1,2)\) in replication \( t \) \((t = 1,2,...,18)\) for individual \( n \), \( \phi_{njt} \) is the specific error of replication \( t \) following normal distribution with zero mean and variance to be estimated. The error variances associated with the different replications is allowed to differ through a polynomial function of replication sequence \( t \) multiplied by the variance of a reference base. Stated formally, suppose the first replication as the reference base and the variance is represented as:

\[
\text{var}(\phi_{nj1}) = \sigma^2
\]

(5.13)

Where \( \sigma \) is parameter to be estimated, representing the standard deviation of first replication. To obtain an identifiable estimation results using BIOGEME 1.5, the specific
error variance of replication \( t \) to the reference base is normalised as:

\[
\text{var}(\phi_{ij}) = \left[ \alpha(t-1)^2 + \beta(t-1) + 1 \right] \sigma^2
\]  
(5.14)

Where \( t \) is replication sequence \((t=1,2,\ldots,18)\); \( \alpha, \beta \) are parameters, which maintain to be same among all the 16 replications. The idea to use the variance structure in Equation (5.14) aims to reduce the computational burden so as to obtain manageable estimations given our small dataset. When \( \alpha(t-1)^2 + \beta(t-1) + 1 > 1 \) implies that replication \( t \) \((t=2,\ldots,18)\) has larger normal error component than replication \( l \); when \( \alpha(t-1)^2 + \beta(t-1) + 1 < 1 \) implies that replication \( t \) \((t=2,\ldots,18)\) has smaller normal error component than replication \( l \); when \( \alpha(t-1)^2 + \beta(t-1) + 1 \) is not significantly different from one, both replication \( t \) \((t=2,\ldots,18)\) and replication \( l \) have similar amount of error.

The above ML model structure assumes that the error term of each replication composes of a common term with IID Gumbel distribution and a specific normal term with varying variance relevant to the associated replication sequence. The estimation results of both basic MNL model and the extended ML model embodying the sequence effects are outlined in Table 5.15.
Table 5.15 Estimation results for basic MNL model and the extended ML model incorporating sequencing effects

<table>
<thead>
<tr>
<th>Attributes</th>
<th>MNL</th>
<th>ML</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile Shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-1.41(-2.49)</td>
<td>-1.57(-2.40)</td>
</tr>
<tr>
<td>Journey time</td>
<td>0.002(0.32*)</td>
<td>0.002(0.28*)</td>
</tr>
<tr>
<td>Online cost</td>
<td>-0.41(-10.65)</td>
<td>-0.47(-7.55)</td>
</tr>
<tr>
<td>Online duration</td>
<td>-0.025(-2.11)</td>
<td>-0.029(-2.08)</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>1.87(7.62)</td>
<td>2.10(6.04)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extra travel cost</td>
<td>-0.36(-8.02)</td>
<td>-0.40(-6.43)</td>
</tr>
<tr>
<td>Extra travel time</td>
<td>-0.08(-8.70)</td>
<td>-0.09(-6.54)</td>
</tr>
<tr>
<td>Shopping time</td>
<td>-0.09(-7.18)</td>
<td>-0.10(-5.91)</td>
</tr>
<tr>
<td>Quality of the flowers</td>
<td>1.85(7.38)</td>
<td>2.10(6.43)</td>
</tr>
<tr>
<td>Polynomials parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>σ</td>
<td>0.823 (0.96*)</td>
<td></td>
</tr>
<tr>
<td>α</td>
<td>-0.018 (-0.58*)</td>
<td></td>
</tr>
<tr>
<td>β</td>
<td>0.174 (0.39*)</td>
<td></td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.335</td>
<td>0.333</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-636.309</td>
<td>-414.244</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-413.920</td>
<td>-412.561</td>
</tr>
</tbody>
</table>

* indicates that corresponding parameters insignificant at 5% level

Table 5.15 shows several notable observations. Firstly, by adding 3 extra parameters in ML model, no statistically significant improvement in overall model performance is obtained compared with the basic MNL model. It should be easily found that basic MNL model can be derived from ML model by imposing a set of restrictions on parameters (i.e. α=0, β=0 and σ=0). Therefore the likelihood ratio test (more details are introduced in Section 6.1.6.2) is conducted to examine the significance of difference between restricted basic MNL model and unrestricted ML model incorporating the sequence effects. With estimation results in Table 5.15, the value of the likelihood ratio test statistics equals to $-2\left[\left(-413.920\right)-\left(-412.561\right)\right] = 2.718$. The difference between the number of parameters of unrestricted ML model and restricted MNL model is 3. Given that the value of Chi-square distribution of 3 degree of freedom at the significance level of 0.05 is $\chi^2_{3,0.05} = 7.82$, the null hypothesis is accepted. This implies that the basic MNL model is more appropriate for SC data than ML model. Secondly, in ML model, all the polynomial coefficients have an obvious level of insignificance. This indicates all replications including the first reference base have similar amount of error. Hence there is no evidence of systematic change in the magnitude of errors relevant to the sequence of
replications. Thirdly, with regards to the estimated coefficients of SC designed variables, both models in Table 5.15 present comparable estimation results. The ML model has a slightly higher overall level of fit to SC data, whereas the significance levels in basic MNL model are higher than ML model.

Overall, the results from this analysis accords with Polak’s (1994), which do not support our early assumption that there were sequence effects operating in the SC responses. This might be due to the reason that respondents inherent interest in mobile shopping was strong enough to compensate for any resulting effects as SC survey goes (such as fatigue effect, learning, etc.) Therefore, it may not be necessary to incorporate the sequencing effect on the SC data in final estimation in Chapter 6.

5.5 Summary

This chapter presented the design development and diagnostic internal analysis of a stated choice survey which was undertaken to obtain the data necessary to estimate the model of our activity production framework. In this exercise, a hypothetical shopping choice scenario was chosen and a D-efficient design with 800 choice observations was generated to investigate individual’s shopping choice decisions. 67 respondents were successfully recruited among staff and students at Imperial College London and invited to a computer-based face-to-face interview. Each respondent was presented with 18 choice tasks between undertaking a shopping activity either conventionally (by personally visiting a shop) or by means of a mobile service (while travelling on public transport) and asked to identify their preferred choice of shopping method in each scenario.

Diagnostic analysis of the SC data reveals evidence of both non-trading and lexicographic response behaviour, which is related to individual characteristics. The results of direct tests of internal consistency indicate that most of SC respondents completed choice questions consistently. Moreover, there is evidence that both
lexicographic response and sequence effect do not significantly affect the SC data as oppose to the non-trading response. Overall, the internal validity of our SC dataset is high. Hence in model estimation only non-trading behaviour responses (i.e. 5 non-traders) are excluded from the raw dataset. In Chapter 6, the best model specification and appropriate estimation results will be presented using the cleaned SC data.
6 Estimation results on stated choice data

This chapter presents the estimated activity production model using cleaned SC data, from the application of discrete choice modelling techniques (Hensher et al., 2005). Several plausible forms of the basic utility functions introduced in Chapter 4 are tested. The formulation having the best fit to the empirical data is identified, from which theoretical and empirical implications are derived. Discrete choice models with various degrees of sophistication are employed to accommodate observed and unobserved heterogeneity.

This outline of this chapter is as follows: The first section presents a brief review of discrete choice models and introduces some model specification tests which are used in this thesis. The second section describes the estimation results of basic shopping choice models based on the activity production approach. The best-fit formulation built on a multinomial logit (MNL) model structure is identified and the analysis of estimation results is further derived. The third section extends the basic utility model to accommodate individual taste heterogeneity based on mixed logit model structures. A conclusion and discussion is provided at the end of this chapter.

6.1 A brief review of discrete choice models

Discrete choice models have long been recognised as an essential toolkit in travel demand modelling. Some of the early transport applications of discrete choice models were in travel mode choice (Ben-Akiva and Lerman, 1985). Recently, further progress has been made in the areas of activity-based modelling and duration modelling accompanied by advances in discrete choice modelling techniques. A number of researchers have given comprehensive reviews of the state-of-the-art and practice in applying discrete choice models to travel demand analyses (Bhat, 1997, 2000a,
6.1.1 General assumptions

In this section, we start with some basic assumptions on which the discrete choice modelling framework is based (Ben-Akiva and Bierlaire, 1999). Notations used in the remainder of this thesis are also introduced.

In discrete choice theory, a decision maker \( n \) (i.e. an individual, a household, an organisation, etc.) chooses a single alternative \( j \) among a choice set \( C_n \), which consists of a finite number of mutually exclusive alternatives \( j = 1, 2, \ldots, J \). The choice set must be exhaustive in that all available alternatives to the decision maker are included. Each alternative is described by a set of attributes, which are either generic to all alternatives or alternative-specific. The decision maker evaluates the attributes of each alternative and makes a choice decision based on different decision rules. Among these rules, utility maximization is most widely used in travel behaviour analysis. Under this rule, each alternative \( j \) faced by decision maker \( n \) is characterised by a value of utility \( U_{nj} \). \( U_{nj} \) depends on both the attributes of alternative \( j \) and the characteristics of decision maker \( n \). In the choice process, the alternative with the highest utility is chosen, namely that decision maker \( n \) will choose alternative \( j \) if and only if \( U_{nj} > U_{nk} \) for all \( j \neq k \) with \( j, k \in C_n \).

In an actual modelling analysis, analysts cannot observe all the variables that affect utility due to incomplete knowledge. Hence random utility theory is applied to capture various sources of uncertainty that must be taken into account, such as unobserved alternative attributes, unobserved individual characteristics, measurement errors and so on (Manski, 1977). Thus the utility of each alternative is represented by a systematic component, which is a function of the decision maker’s characteristics and alternative attributes, together with an error component. As such, we have:
\[ U_{nj} = V_{nj}(z_{nj}, \beta_{nj}) + \epsilon_{nj} \]  

(6.1)

Where \( \epsilon_{nj} \) is the error term representing the random part of utility; \( z_{nj} \) is a vector of variables describing the decision maker \( n \) and alternative \( j \); \( V_{nj}(\cdot) \) is the systematic part of utility represented as a function of \( z_{nj} \); \( \beta_{nj} \) is the vector of parameters representing the tastes of decision maker \( n \); \( V_{nj}(\cdot) \) is generally assumed to be linear-in-parameters with respect to the vector \( z_{nj} \) either in a generic form (i.e., \( V_{nj} = \beta_{nj}^t z_{nj} \)) or alternative specific form (i.e., \( V_{nj} = \beta_{nj} z_{nj} \)).

Under the utility maximisation assumption, the probability of decision maker \( n \) choosing alternative \( j \) is expressed as:

\[
\text{Prob}(n, j \in C_n) = \text{Prob}(V_{nj} + \epsilon_{nj} > V_{nk} + \epsilon_{nk} \forall j \neq k, j, k \in C_n)
\]

(6.2)

\[
= \text{Prob}(\epsilon_{nk} - \epsilon_{nj} < V_{nj} - V_{nk} \forall j \neq k, j, k \in C_n)
\]

Equation (6.2) can be rewritten as the cumulative distribution of the error term \( \epsilon_{nk} - \epsilon_{nj} \).

Defining \( \epsilon_n \) as the vector of \([\epsilon_{n1}, \epsilon_{n2}, \ldots, \epsilon_{nj}]\) with joint probability density function \( f(\epsilon_n) \), we have:

\[
\text{Prob}(n, j \in C_n) = \int_{\epsilon_n} I(\epsilon_{nk} - \epsilon_{nj} < V_{nj} - V_{nk} \forall j \neq k, j, k \in C_n) f(\epsilon_n) d\epsilon_n
\]

(6.3)

Where \( I(\bullet) \) is an indicator function, which equals to 1 when the term in the brackets is true and 0 otherwise. Thus the choice probability is shown as a multi-dimensional integral over the random vector \( \epsilon_n \), which only takes in a close form for certain distributions of \( f(\epsilon_n) \). For a non-closed form integral, the choice probability can be approximated using simulation technique. Equation (6.3) also indicates that only relative differences in
utilities matter; the utility scale is arbitrary. In the following part of this section, we show that various types of discrete choice models are generated by assuming different distributions of the random component of utility $f(\varepsilon_n)$.

### 6.1.2 Multinomial logit model (MNL)

Under different assumptions regarding the structure of random part of utility, various types of discrete choice models can be created. In this section, we start with the multinomial logit (MNL) model, which is traditionally considered to be the standard structure for discrete choice modelling. In the MNL model, the random component of the utility $\varepsilon_{nj}$ is assumed to be *identically and independently distributed* (IID) with a Gumbel distribution, which leads to the identical variance-covariance structure of the alternative across different decision makers (McFadden, 1973). The vector of parameters $\beta_{nj}$ whose values are the same for all decision makers, implies homogeneity of response to the attributes of alternatives across all decision makers. As a result, the choice probability of the MNL model exhibits a closed form (McFadden, 1973), which is given by:

$$\text{Prob}(n, j \in C_n) = \frac{e^{V_{nj}}}{\sum_{k \in C_n} e^{V_{jk}}} \quad (6.4)$$

The IID assumption on the error term further implies that the MNL model is characterised by the *independence from irrelevant alternatives* (IIA) property. This means that the ratio of the MNL choice probabilities of any two alternatives relies only on their systematic utilities and is unaffected by the presence or absence of other alternatives (Train, 2003). More formally, taking the ratio of choice probability of alternative $j$ and $k$ as represented in Equation (6.4) leads to:
\[
\frac{\text{Prob}(n,j)}{\text{Prob}(n,k)} = e^{v_j - v_k}
\]  \hspace{1cm} (6.5)

The IIA property can also be expressed in terms of the proportionate substitution pattern, as it implies that an increase [decrease] in the choice probability of any one alternative leads to a proportionately equal decrease [increase] in the probability of all other alternatives in the choice set. Consider Equation (6.5), and suppose that the probability of choosing alternative \( q \ (\forall q \neq j,k) \) is changed. The IIA property requires that Equation (6.5) remains constant before and after the change, which can be maintained if and only if each choice probability changes by the same proportion.

Many examples are given of circumstances in which the IIA property of MNL models can be unrealistic in empirical applications (Ben-Akiva and Lerman, 1985; Train, 2003). Perhaps the most well-known is the red-bus/blue-bus problem in the travel mode choice context. Despite its acknowledged limitations, the MNL model has the advantage of computational efficiency. In the situations when IIA property is an adequate approximation of reality, and the number of choice alternatives is large, models can be estimated with consistent parameters using a subset of alternatives, which permits efficient use of computing resources.

6.1.3 Generalisation of MNL model

In recent years, more flexible model structures have been formulated by relaxing the strict conditions imposed on MNL model, namely the IID assumption regarding the error term and fixed parameters across different decision makers (i.e. response homogeneity). Relaxing the IID assumption leads to three alternatives:

- Identical, non-independent error terms,
- Non-identical independent error terms, and
- Non-identical non-independent error terms
Table 6.1 outlines the resulting different types of models along each dimension of above relaxed assumptions (Bhat, 2002, 2007)

Table 6.1 A generalisation of MNL model structure

<table>
<thead>
<tr>
<th>Relaxed assumption</th>
<th>Resulting model types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non IID error terms</td>
<td>GEV models, MNP models</td>
</tr>
<tr>
<td>Identical, non-independent errors</td>
<td>Heteroscedastic models</td>
</tr>
<tr>
<td>Non identical, independent errors</td>
<td>ML models, MNP models</td>
</tr>
<tr>
<td>Non identical, non independent errors</td>
<td>ML models, MGEV models</td>
</tr>
</tbody>
</table>

Response heterogeneity ML models, MGEV models

The generalisation of MNL models can be broadly categorised into 4 classes: Generalised Extreme Value class of models (GEV), mixed multinomial logit class of models (ML), mixed GEV class of models, and multinomial probit models (MNP). Relaxing each dimension of assumptions on MNL model structure can generalise one or more of these categories.

Models with identical non-independent error terms arise as the GEV class of models. GEV models assume the error term to be Gumbel distributed (Ben-Akiva and Lerman, 1985; Train, 2003). We note that the MNL model is a member of the GEV class (Bhat, 2007). Other specific model structures include:

- Nested logit (NL) model (Williams, 1977; McFadden, 1978)
- Generalized nested logit (GNL) model (Wen and Koppelman, 2001)
- Paired combinational logit (PCL) model (Koppelman and Wen, 2000)
- Cross-nested logit (CNL) model (Vovsha, 1997)
- Ordered GEV-nested logit (OGEV-NL) model (Whelan et al., 2002)
- Product differentiation logit (PDL) model (Bresnahan et al., 1997)
- Choice set generation logit (GenL) model (Swait, 2001)

Bhat (2002, 2007) and Hess (2005) give a detailed description of each of these model structures.
The major advantage of all GEV models is that they allow partial relaxations of IID assumption regarding the error term while still maintaining closed-form expressions for the choice probabilities, as opposed to MNP models. In spite of this, these models also have drawbacks, such as strict restrictions on the parameters to be applied in the utility maximisation framework, homoscedasticity, and inapplicability to situations involving panel data with a temporally correlated error term.

Models with non-identical but independent error terms belong to the heteroscedastic class of models. Specific model structures include:

- Negative exponential model (Daganzo, 1979),
- Heteroscedastic multinomial logit (HMNL) model (Swait and Stacey, 1996)
- Oddball alternative model (Recker, 1995)
- Heteroscedastic extreme-value (HEV) model (Bhat, 1995).

The heteroscedastic models accommodate more flexible cross-elasticity patterns amongst alternatives than many of the GEV models as discussed above. However, they may not have a closed form for deriving choice probabilities (such as HEV model).

Models with non-identical, non independent error components arise as either multinomial probit (MNP) models or the mixed logit (ML) class of models. In the ML models, the error term is decomposed into a non-IID component with some distribution and an IID component with Gumbel distribution (Train, 2003). Models having this structure are alternatively termed error component logit (ECL) models as referred to Section 6.1.4.2. MNP models represent the overall error components as jointly distributed with multivariate normal distributions without partitioning the error term. It should be pointed out that both structures do not have a closed-form of choice probability.

The ML models can also accommodate unobserved response heterogeneity, as well as mixed GEV (MGEV) class of models. In order to achieve this effect, ML models are represented as random coefficient logit (RCL) structure as referred to Section 6.1.4.2.
MGEV models are generated by superimposing random coefficients over the closed-form analytic GEV structures (Bhat, 1999; Bhat and Zhao, 2002; Bhat and Guo, 2004). Although ML structure is more general than the GEV structure, in some instances when the correlation across alternatives are extremely large, using MGEV models may achieve a higher computational efficiency than using ML models (Bhat, 2007).

So far, classification outlines of various discrete choice models and the associated assumptions regarding model structure have been provided. More comprehensive descriptions of each model category can be found in many studies (Ben-Akiva and Lerman, 1985; Bhat, 2002; Train, 2003; Hess, 2005; Bhat, 2007). In this thesis, we only discuss in details the MNL model (in Section 6.1.2) and ML models (in Section 6.1.4) which are used in our research.

6.1.4 Mixed Logit (ML) models

6.1.4.1 Choice probability

In recent years, with the advent of simulation methodologies (e.g. simulated maximum likelihood estimation), the ML models have been widely employed in travel behaviour analysis due to its high flexibility in approximating any random utility model (McFadden and Train, 2000). As described by Train (2003), an ML model is defined on the basis of the functional form of its choice probability. Although an ML model can be derived from various behavioural specifications based on different interpretations, any behavioural specification leading to the choice probability taking the particular form in Equation (6.6) is called an ML model. Stated formally, the choice probability of an ML model is expressed in the form:

$$P_{nj} = \int L_{nj}(\beta_{nj}) f\left(\beta_{nj}\right) d\beta_{nj} \quad (6.6)$$
Where $L_{nj}(\beta_{nj})$ is the choice probability of standard MNL model given the vector of parameters $\beta_{nj}$, namely, i.e. $L_{nj}(\beta_{nj}) = \text{Prob}(n, j \in C_n) = \frac{e^{\gamma_{nj}}}{\sum_{k \in C_n} e^{\gamma_{nk}}}$; $f(\beta_{nj})$ is the joint probability density function of $\beta_{nj}$. Equation (6.6) represents that the ML choice probability is the integral of the MNL choice probability over the density distribution of random parameters. From this point, the MNL model can be regarded as a special case of ML models when $\beta_{nj}$ are generated as fixed parameters (i.e. the density function $f(\beta_{nj}) = 1$ when $\beta_{nj}$ equal the fixed values and otherwise equal zero).

### 6.1.4.2 Model structures

As mentioned in Section 6.1.3, existing ML models are interpreted as two structures: error component logit (ECL) structure and random coefficient logit (RCL) structure, which are equivalent mathematically (Train, 2003). The two structures can also be combined to accommodate random taste heterogeneity, heteroscedasticity, and inter-alternative correlation.

Given generic form of coefficients, RCL structure specifies $\beta_n$ in Equation (6.1) as a vector of random coefficients that vary across individual $n$. Assuming linear-in-parameter specification, the utility function is expressed as:

$$U_{nj} = \beta_n \varepsilon_{nj} + \varepsilon_{nj} \quad (6.7)$$

Where $\beta_n$ is the vector of random coefficients for individual $n$ representing the individual response heterogeneity, $\varepsilon_{nj}$ is random error component with IID Gumbel distribution. The variation of coefficients across different individuals in the population constitutes the density function $f(\beta_n)$ with mean $\bar{\beta}_n$ and deviations $\sigma_{\beta_n}$. As $\beta_n$ is not observed by the researchers, the choice probability conditional on $\beta_n$ is represented
as a standard logit formula, i.e.

\[ L_{nj}(\beta_n) = \frac{e^{\beta_n z_{nj}}}{\sum_{i=1}^{J} e^{\beta_i z_{ni}}} \]  \hspace{1cm} (6.8) 

Therefore the unconditional choice probability is the integral of Equation (6.8) over all possible \( \beta_n \), which leads to the specification in Equation (6.6).

In the ECL structure, the utility function is specified as:

\[ U_{nj} = \alpha z_{nj}^f + \gamma_n z_{nj}^r + \epsilon_{nj} \]  \hspace{1cm} (6.9) 

Where \( z_{nj}^f \) and \( z_{nj}^r \) are vectors of variables relating to individual \( n \) from alternative \( j \); \( \alpha \) is a vector of fixed coefficients; \( \gamma_n \) is a vector of random coefficients with zero mean, whose distribution depends on the underlying assumptions on the parameters; \( \epsilon_{nj} \) is IID Gumbel distribution. The correlations among the utilities for different alternatives are created via the error component (i.e. \( \gamma_n z_{nj}^r + \epsilon_{nj} \)) rather than random coefficients.

As shown above, when \( z_{nj}^r \) are identically zero, Equation (6.9) collapses to the MNL model structure; when the random parameters \( \beta_n \) in Equation (6.7) are decomposed into distributions with mean \( \bar{\beta}_n = \alpha \) and standard deviation \( \sigma_{\beta_n} = \gamma_n \), the utility function is rewritten as:

\[ U_{nj} = \alpha z_{nj}^f + \gamma_n z_{nj}^r + \epsilon_{nj} \]  \hspace{1cm} (6.10) 

Equation (6.10) can be considered as ECL structure with \( z_{nj}^r = z_{nj}^r \) and the error component equals to \( \gamma_n z_{nj} + \epsilon_{nj} \). Therefore the RCL and ECL specifications are mathematically equivalent.
6.1.4.3 Empirical issues

There are several key empirical issues deserving our attention in specifying, estimating and applying an ML model (Hensher and Greene, 2003). The first is selecting which parameters to treat as random. Estimation of the models with many attributes of alternative as random parameters is time consuming even with contemporary computing resources. Various statistical tests can be conducted to accept or reject the preservation of certain random parameters (McFadden and Train, 2000; Brownstone, 2001).

The second issue is selecting the distributions of the random parameters. The distributions of random parameters are essentially researchers’ approximations to individuals’ real behavioural patterns. The influences of selecting different distributional assumptions of random parameters are significant, particularly when the sign of the parameters is empirically important. In practical modelling, the researcher specifies a distribution for the random coefficient and estimates the parameters (i.e. mean and variance) of that distribution. There are 4 popular predefined functional forms typically selected for the distribution of random parameters: normal, lognormal, triangle and uniform. In most cases, \( f(\beta_n) \) has been assumed as normal distribution (i.e. \( \beta_n \sim N(\beta_n, \sigma) \)) with mean \( \beta_n \) and standard deviation \( \sigma \) to be estimated. Lognormal distribution is appropriate when the sign of the parameter is same for each individual, such as if the parameter relating to travel cost is thought to be negative for all travellers.

The random coefficient \( \beta_n \) with lognormal distribution is expressed as \( \beta_n = e^x \) where \( x \) is a normally distributed variable. In both uniform and triangular distributions, the mean \( \bar{\beta}_n \) and spread \( s \) (i.e. the equal distance left and right to the mean) are to be estimated. In uniform distribution, \( f(\beta_n) \) is flat and \( \beta_n \) is uniformly distributed between \( \bar{\beta}_n - s \) and \( \bar{\beta}_n + s \). Stated explicitly, the density function is represented as:
\[ f(\beta_n) = \tilde{\beta}_n + s(2x - 1) \text{ for } \tilde{\beta}_n - s \leq \beta_n \leq \tilde{\beta}_n + s \] (6.11)

Where \( x \) is standard uniform distribution from 0 to 1. In the triangular distribution, the density \( f(\beta_n) \) increases from zero at \( \tilde{\beta}_n - s \), linearly rises to \( \tilde{\beta}_n \) and then linearly decreases to zero at \( \tilde{\beta}_n + s \). Stated mathematically, the density function is expressed as:

\[
f(\beta_n) = \begin{cases} 
\frac{(\beta_n - (\tilde{\beta}_n - s))}{s^2} & \text{for } \tilde{\beta}_n - s \leq \beta_n \leq \tilde{\beta}_n \\
\frac{(\tilde{\beta}_n + s) - \beta_n}{s^2} & \text{for } \tilde{\beta}_n \leq \beta_n \leq \tilde{\beta}_n + s
\end{cases}
\] (6.12)

In practice, all distributions have strengths and weakness. The weakness is often associated with the extreme values of the distributions, which may imply behaviourally illogical signs for the symmetrical distributions. For example, the lognormal distribution is quite useful in the sense that all parameter estimates are limited to the positive domain, but the unbounded right-hand tail may lead to unreasonably large estimated coefficients for some non-negligible portion of individuals. This unbounded problem also exists in the normal distribution in both sides. With regards to uniform and triangular distributions, this unbounded problem does not exist. However, when \( \tilde{\beta}_n - s \), both symmetrical distributions can potentially give the “wrong” sign to some areas. Hence truncated or constrained distributions are considered to be the most promising direction for future modelling applications.

The third issue is related to the number of draws taken from the distributions and the parameter stability. According to Hensher and Greene (2003), the number of draws required to secure stable estimation varies with the complexity of model specification. In general, greater complexity of the model specification (in terms of the random parameters, treatment of heterogeneity, and correlation between the attributes and alternatives) will
increase the number of draws required in the estimation process. Recently, a number of studies have introduced more intelligent ways to obtain an accurate estimation with relatively lower number of draws (as referred to Section 6.1.5.2).

6.1.4.4 Repeated observations - panel data

ML models can be applied when working with panel data in an SC choice experiment, in which each respondent is presented with several repeated choice scenarios. The simplest specification treats the coefficients as varying over the respondents rather than over choice scenarios for each respondent. Suppose each sampled individual respondent \( n (n = 1,2,\ldots,N) \) faces \( J \) choice alternatives in \( T \) choice scenarios. The utility that individual \( n \) obtains from choosing alternative \( j (j = 1,2,\ldots,J) \) in choice scenario \( t (t = 1,2,\ldots,T) \) is given by the utility function in a general linear form:

\[
U_{njt} = \beta_n z_{njt} + \eta_{njt} + \epsilon_{njt}
\]  

(6.13)

Where \( U_{njt} \) is utility of individual \( n \) from alternative \( j \) in choice scenario \( t \); \( z_{njt} \) is a vector of variables describing the individual \( n \) and alternative \( j \) in choice scenario \( t \); \( \beta_n \) is a vector of random coefficients for individual \( n \) with density function \( f(\beta_n) \); \( \epsilon_{njt} \) is random error component with Gumbel distribution, being IID over individual \( n \), alternative \( j \) and choice scenario \( t \); \( \eta_{njt} \) is an additional error term representing specific preference of individual \( n \) for alternative \( j \), \( \eta_{njt} \) is generally assumed to be normal distribution with zero mean and variance to be estimated.

Defining a sequence of alternatives \( i^n = \{i^n_1, i^n_2, \ldots, i^n_T\} \) as the sequence of \( T \) choice decisions made by individual \( n \), the probability that individual \( n \) makes the sequence of these choices conditional on \( \eta_{njt} \), is the product of logit formulas:

144
\begin{equation}
L_{nj}(\beta, \eta_{nj}) = \prod_{n=1}^{N} \frac{e^{\beta \cdot \eta_{nj}}}{\sum_{j=1}^{J} e^{\beta \cdot \eta_{nj}}} \tag{6.14}
\end{equation}

Since \( \varepsilon_{nj} \) is also IID Gumbel distribution, the unconditional choice probability is the integral of Equation (6.14) over all possible \( \eta_{nj} \), which generalises the same specification as in Equation (6.6). It should be noted that the only difference between ML model with repeated choices and one choice per respondent is that the conditional choice probability as calculated in Equation (6.14) involves a product of logit formulae, one for each choice scenario, as opposed to only one logit formula with one choice in Equation (6.8).

6.1.5 Model estimation

In this section, we introduce two procedures for the estimation of discrete choice models: traditional maximum-likelihood procedures and maximum simulated likelihood procedures.

6.1.5.1 Maximum-likelihood estimation (MLE)

When working with models having closed form of choice probability, such as MNL and GEV models, traditional maximum-likelihood procedures can be applied in model estimation (Train, 2003). Assuming that there is a sample of \( N \) choice observations and each choice observation is independent of others, the log-likelihood function is defined as:

\begin{equation}
\text{LL}(\beta) = \sum_{n=1}^{N} \sum_{j=J} y_{nj} \ln \left( \text{Prob}(n, j) \right) \tag{6.15}
\end{equation}

Where \( \text{Prob}(n, j) \) is the choice probability of individual \( n \) choosing alternative \( j \), and \( y_{nj} \) is a dummy variable with \( y_{nj} = 1 \) if individual \( n \) chooses alternative \( j \) and zero otherwise.
It has been shown that $LL(\beta_n)$ is globally concave for any MNL model with a linear-in-parameters utility specification, whereas for more complex GEV models, estimation code based on various numerical maximization algorithms, such as BHHH, Newton-Raphson, DFP, and BFGS and so on, must be applied (Train, 2003). In both these situations, MLE yields the value of the parameter $\beta$ that maximises the function in Equation (6.15), satisfying the first order condition:

$$\frac{dLL(\beta)}{d\beta} = 0$$

(6.16)

### 6.1.5.2 Maximum simulated likelihood estimation (MSLE)

For models with an unclosed form integral of the choice probability, such as ML models and probit models, simulation-based Monte-Carlo integration techniques are frequently employed, in which the choice probability is calculated numerically through simulation.

Returning to the ML models, the open form integral of the unconditional choice probability $P_{nj}$ in Equation (6.6) can be approximated by taking $R$ independent draws $\beta_n^r \ (r=1,2,\ldots,R)$ from density function $f(\beta_n|\theta)$ with $\theta$ representing the parameters, such as mean and variance, and calculating the logit formula probability $L_{nj}(\beta_n^r)$ for each draw. The simulated choice probability $SP_{nj}$ can be represented as the average of resulting $L_{nj}(\beta_n^r)$ over $R$ independent draws, namely that:

$$SP_{nj} = \frac{1}{R} \sum_{r=1}^{R} L_{nj}(\beta_n^r)$$

(6.17)

Correspondingly, the simulated log likelihood function ($SLL$) becomes:
\[ SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} y_{nj} \ln \left( SP_{nj} \right) \]  \hspace{1cm} (6.18)

Where \( y_{nj} \) is a dummy variable, which equals one when individual \( n \) choose alternative \( j \) and zero otherwise. Under the MLSE procedure, our aim is to find the values of \( \theta \) that maximise Equation (6.18).

This procedure can also be applied to panel data, in which the decisions of a number of repeated choice observations are made by the same individual \( n \). Assuming that the estimated parameters vary only across individuals rather than choice observations over the same individual, as described in Section 6.1.4.4, the logit formula probability \( L_{nj}(\beta_n) \) is replaced by the product of probabilities of a sequence of observed choice decisions \( i^n = \{i_{1n}, i_{2n}, \ldots, i_{Tn}\} \) made by same individual \( n \). Stated formally,

\[ L_n(\beta_n) = \prod_{t=1}^{T} L_{tn}(\beta_n) \]  \hspace{1cm} (6.19)

Hence the simulated choice probability and simulated log-likelihood function can be represented as:

\[ SP_n = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} L_{tn}(\beta_n^r) \]  \hspace{1cm} (6.20)

\[ SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} y_{nj} \ln \left( SP_{nj} \right) \]  \hspace{1cm} (6.21)

Where \( y_{nj} \) equals one when individual \( n \) chooses alternative \( i_{tn} \) in scenario \( t \) and zero otherwise.

The classical Monte Carlo integration is called Pseudo Monte-Carlo (PMC) integration, in which the draws are generated using a pseudo-random number generator. Hence the generated points tend to be unevenly distributed, which leads to imprecision in the simulated choice probabilities. An alternative to PMC integration is to use
quasi-Monte Carlo, which provides more evenly distributed random points over the domain of the integration, leading to a more accurate approximation of integrals with lower number of draws. In the context of discrete choice models, Halton sequences are widely used, principally due to model stability and reduction in computational time (Train, 2000; Bhat, 2001). However, Halton sequences have severe limitations when used in high-dimensional integral (Bhat, 2003b). A number of other alternatives, such as scrambled Halton sequence (Bhat, 2003b), shuffled Halton sequence (Hess and Polak, 2003a, b), the Modified Latin Hypercube Sampling (MLHS) (Hess et al., 2006) have been proposed to overcome these difficulties.

6.1.6 Model specification tests

In the remainder of this thesis, four statistical tests (i.e. t-test, likelihood ratio test, P-test, and C-test) are used to make inferences about various parameters and model specifications. In this section, we introduce each of them in turn.

6.1.6.1 T-test

T-test is used to examine if the value of an individual parameter $\beta$ is significantly different from 0 or other known value of $\beta^*$ (Ben-Akiva and Lerman, 1985). More formally, the following hypotheses are tested:

$$H_0 : \beta = \beta^*$$

$$H_1 : \beta \neq \beta^*$$

(6.22) (6.23)

Where $H_0$ represents the null hypothesis and $H_1$ represents the alternative hypothesis. The simplest form of this test is to assume $\beta$ to be normally distributed with known variance $\sigma^2_\beta$. In this case, the test statistics is calculated as:
\[ \frac{\beta - \beta^*}{\sigma_\beta} \]  \hspace{1cm} (6.24)

It follows standard normal distribution \( N(0,1) \). For certain level of significance \( \alpha \), the null hypothesis is accepted if Equation (6.24) satisfies:

\[ \text{Prob}\left( \Phi^{-1}\left(\frac{\alpha}{2}\right) < \frac{\beta - \beta^*}{\sigma_\beta} < \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \right) = 1 - \alpha \]  \hspace{1cm} (6.25)

Where \( \Phi^{-1}() \) is the inverse cumulative standard normal distribution function.

There is also a more complex form of this test, in which the actual variance of \( \beta \) is not known. In this case, we have only an estimate of mean and variance of \( \beta \). Under the null hypothesis, the test statistics is t-distributed. For more details, please see (Ben-Akiva and Lerman, 1985).

6.1.6.2 Likelihood ratio test

In modelling analysis, a set of restrictions can be imposed on parameters. Likelihood ratio (LR) test is used to test the specification of restricted model estimated by maximum likelihood procedure (Ben-Akiva and Lerman, 1985).

The null hypothesis assumes that the restricted model is more appropriate than unrestricted model. The value of the likelihood ratio test statistics equals:

\[ -2(LL_R - LL_{UR}) \]  \hspace{1cm} (6.26)

Where \( LL_R \) is the final log likelihood value of the restricted model and \( LL_{UR} \) is final log likelihood value of the unrestricted model. This statistic is \( \chi^2 \) distributed with \( K_U - K_R \) degree of freedom where \( K_U \) and \( K_R \) are the numbers of estimated coefficients in the unrestricted and restricted model respectively.

In discrete choice models, an important aspect of model specification is the
distinction between alternative specific attributes and generic attributes. The generic model is obtained by imposing the restriction of equal coefficient of relevant attributes on the alternative specific model. In this context, LR test can also be applied. Thus a null hypothesis states that the restricted generic model is correct. The likelihood ratio test statistic is calculated as:

\[-2(LL_G - LL_{AS})\]

(6.27)

Where \(LL_G\) is the final log likelihood value of the generic model and \(LL_{AS}\) is the final log likelihood value of the alternative specific model. Under the null hypothesis, the test statistic can be shown to be \(\chi^2\) distributed with \(K_{AS} - K_G\) degrees of freedom, where \(K_{AS}\) is the number of estimated coefficients in alternative specific model and \(K_G\) is the number of estimated coefficients in generic model.

6.1.6.3 Non-nested tests: P-test and C-test

The statistical tests that are discussed so far can only be applied to test nested hypothesis, in that that one model specification (i.e. restricted model) can be obtained by imposing parameter restrictions on the other (i.e. unrestricted model) (Ben-Akiva and Lerman, 1985). However, there are also instances when we need to make a comparison between two non-nested specifications, i.e. one cannot be obtained as a special case of the other. A number of tests have been proposed to examine these non-tested hypotheses (Cox, 1961, 1962; Pesaran and Deaton, 1978; Davidson and MacKinnon, 1981; Horowitz, 1982; Doran, 1993).

In this section, we mainly introduce the work by Davidson and MacKinnon (1981). Consider the following null hypotheses:

\[H_0: y_i = f_i(x_i, \beta) + \varepsilon_{0i}\]

(6.28)
Where $y_i$ is the $i$th observation of dependent variable, $x_i$ is a vector of exogenous variable, $\beta$ is a vector of coefficients, $f_i(\ )$ can be linear or nonlinear function, $\varepsilon_{0i}$ is independent normal distribution with zero mean. Suppose there is an alternative hypothesis on the specification of $y_i$:

$$H_1: \quad y_i = g_i(z_i, \gamma) + \varepsilon_{0i} \quad (6.29)$$

Where $z_i$ is an alternative vector of exogenous variables, $\gamma$ is a vector of coefficients, $g_i(\ )$ is an alternative function which can be linear or non-linear, $\varepsilon_{0i}$ is assumed to be normal distribution with zero mean.

Davidson and MacKinnon discussed three non-nested tests, i.e. a J-test, a C-test, and a P-test, to examine the truth of $H_0$. Consider the following three nonlinear regressions:

$$y_i = (1 - \alpha) f_i(x_i, \beta) + \alpha \hat{g}_i + \varepsilon_i \quad (6.30)$$

$$y_i = (1 - \alpha) \hat{f}_i + \alpha \hat{g}_i + \varepsilon_i \quad (6.31)$$

$$y_i = (1 - \alpha) \hat{f}_i + \alpha \hat{g}_i + b \hat{F}_i + \varepsilon_i \quad (6.32)$$

Where $\hat{g}_i = g_i(z_i, \gamma)$ and $\gamma$ is the maximum likelihood estimate of $\gamma$; $\hat{f}_i = f_i(x_i, \beta)$ and $\hat{\beta}$ is the maximum likelihood estimate of $\beta$; $\hat{F}_i$ is a row vector consist of the derivative of $f_i$ with respect to the parameters $\beta$ evaluated at $\hat{\beta}$.

They recommend the J-test based on Equation (6.30) when $H_0$ is linear in the parameters, the P-test based on Equation (6.31) when $H_0$ is not linear in the parameters, and the C-test based on Equation (6.32) as a simple preliminary test when $H_0$ is not linear in the parameters and the derivatives of specification under null hypothesis with respect to the parameters are not easy to evaluate. In all the tests, if $H_0$ is true, then the
true value of $\alpha$ is zero. Hence a t-test is further performed to examine the significance of estimation of $\alpha$.

6.2 Basic choice models based on activity production approach

At the first stage of model estimation, MNL models are adopted simply to identify the basic specifications of utilities having the best overall level of fit to the empirical data. As there are only two alternatives in our SC experiment, the estimation results will not be influenced by the limitations of MNL model induced by the IID assumption on the error term (i.e. IIA property). It should be noted that all the models in Section 6.2 and Section 6.3 were estimated using BIOGEME\(^V\) 1.5 (Bierlaire, 2003).

6.2.1 Basic utility models

The basic utility specifications take the vector $z_{nj}$ in Equation (6.1) consisting of the SC designed variables $X_{nj}$ alone. The systematic utilities $V_j$ of both mobile shopping and conventional shopping are formulated as the sum of the outcome utility and process utility components. In the interest of simplicity, the outcome utilities are represented as two dummy variables, characterising the superiority of the quality of flowers obtained through one shopping activity over another. For example, when flowers bought online are qualitatively superior to those bought from a shop, the dummy variable of mobile shopping equals to one, and otherwise it is zero. Correspondingly, when

\(^V\) BIOGEME (Bierlaire's Optimization Toolbox for GEV Model Estimation) is an open resource objected-oriented software package designed for the maximum likelihood estimation of various Generalized Extreme Value (GEV) models, including Multinomial Logit models (MNL), Probit models, Mixed Logit models and Nested Logit models. BIOGEME permits flexible forms of nonlinear utility functions, which are ideal for this research application (we employ version 1.5).
flowers bought from a physical shop are qualitatively superior to those bought online, the dummy variable of conventional shopping equals to one, and otherwise it is zero.

In terms of the process utility function, three plausible forms that were described in proceeding chapter (linear additive function, Cobb-Douglas function and CES function) are taken into account. Therefore, there exist a totally of \(3 \times 3 = 9\) possible combinations of process utility functions for mobile shopping and conventional shopping as illustrated in Table 6.2. The estimation results of these models will be provided in Section 6.2.1.1. These combinations are constructed based on the MNL model structure. As mentioned in Chapter 5, with an aim to investigate the simultaneous use of time while travelling, journey time is included as an additional attribute of mobile shopping. Hence the disutility of travel itself is also taken into account in specifying the overall utility of mobile shopping.

<table>
<thead>
<tr>
<th>(V_m): Linear additive</th>
<th>(V_m): Cobb-Douglas</th>
<th>(V_c): CES</th>
</tr>
</thead>
<tbody>
<tr>
<td>(V_m): Linear additive</td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>(V_m): Cobb-Douglas</td>
<td>Model 5</td>
<td>Model 8</td>
</tr>
<tr>
<td>(V_m): CES</td>
<td>Model 6</td>
<td>Model 7</td>
</tr>
</tbody>
</table>

Note: \(V_m\) is systematic utility of mobile shopping, \(V_c\) is systematic utility of conventional shopping

6.2.1.1 Estimation results of plausible basic models

In this section, the estimation results of these basic utility models are presented as follows.

**Model 1**

We start with the simple linear process utility functions of both mobile shopping and conventional shopping. Among all the SC designed variables, the attribute of the quality of the flowers is the only generic attribute shared by the two shopping alternatives. Hence both the generic and alternative specific forms of this attribute are estimated here.
The generic model is formulated as:

$$V_m = \beta_{m0} + \beta_{m1}T_{journey} + \beta_{m2}C_{online} + \beta_{m3}T_{online} + \beta_m Q^m_{flowers}$$  \hspace{1cm} (6.33)

$$V_c = \beta_{c1}TC + \beta_{c2}TT + \beta_{c3}T_{conventional} + \beta_c Q^c_{flowers}$$  \hspace{1cm} (6.34)

The alternative specific model is written as:

$$V_m = \beta_{m0} + \beta_{m1}T_{journey} + \beta_{m2}C_{online} + \beta_{m3}T_{online} + \beta_m Q^m_{flowers}$$  \hspace{1cm} (6.35)

$$V_c = \beta_{c1}TC + \beta_{c2}TT + \beta_{c3}T_{conventional} + \beta_c Q^c_{flowers}$$  \hspace{1cm} (6.36)

Where:

- $V_m$ = systematic utility of mobile shopping
- $T_{journey}$ = Journey time of mobile shopping
- $C_{online}$ = Online cost of mobile shopping
- $T_{online}$ = Online duration of mobile shopping
- $Q^m_{flowers}$ = dummy variable. It equals to 1 when the respondent faces the situations described by ‘I got the flowers that I preferred’ in mobile shopping and ‘I settled for an alternative’ in conventional shopping, and zero otherwise.
- $\beta_{m0}, \beta_{m1}, \beta_{m2}, \beta_{m3}, \beta_m$ = alternative specific parameters of mobile shopping
- $V_c$ = systematic utility of conventional shopping
- $TC$ = Extra travel cost of conventional shopping
- $TT$ = Extra travel time of conventional shopping
- $T_{conventional}$ = Shopping time of conventional shopping
- $Q^c_{flowers}$ = dummy variable. It equals to 1 when the respondent faces the situations described by ‘I got the flowers that I preferred’ in conventional shopping and ‘I settled for an alternative’ in mobile shopping, and zero otherwise.
\( \beta_{c1}, \beta_{c2}, \beta_{c3}, \beta_{c4} = \) alternative specific parameters of conventional shopping

\( \beta_{G} = \) generic coefficient to the attributes of quality of flowers

The estimation results of generic model in Equation (6.33) and (6.34) and alternative specific model in Equation (6.35) and (6.36) are presented in Table 6.3.

| Table 6.3 Estimation results for the generic and alternative specific models |
|-----------------------------|-----------------------------|-----------------------------|
|                             | Alternative specific        | Generic                     |
| Mobile shopping             |                             |                             |
| Constant (\( \beta_{m0} \)) | -1.41(-2.49)                | -1.41(-2.51)                |
| Journey time (\( \beta_{m1} \)) | 0.002(0.32*)               | 0.002(0.32*)               |
| Online cost (\( \beta_{m2} \)) | -0.41(-10.56)               | -0.41(-10.56)               |
| Online duration (\( \beta_{m3} \)) | -0.03(-2.11)               | -0.03(-2.11)               |
| Quality of the flowers (\( \beta_{m4} \)) | 1.85(7.38)                | ---                         |
| Conventional shopping       |                             |                             |
| Extra travel cost (\( \beta_{c1} \)) | -0.36(-7.77)               | -0.35(-7.76)               |
| Extra travel time (\( \beta_{c2} \)) | -0.08(-8.79)               | -0.08(-8.82)               |
| Shopping time (\( \beta_{c3} \)) | -0.09(-6.99)               | -0.09(-6.99)               |
| Quality of the flowers (\( \beta_{c4} \)) | 1.86(8.32)                | ---                         |
| Generic                     |                             |                             |
| Quality of the flowers (\( \beta_{G} \)) | ---                        | 1.85(11.87)                |
| Adjusted rho-square         | 0.335                      | 0.337                      |
| Initial log likelihood      | -636.309                   | -636.309                   |
| Final log likelihood        | -413.920                   | -413.920                   |

* indicate that the corresponding parameters was not significant at 5% level

With high similarity in general pattern of coefficients between the two specifications, a likelihood ratio test is further conducted to examine the significance of difference. According to the introduction in Section 6.1.6.2, the value of the likelihood ratio test statistic is effectively zero as the final log likelihood has the same value within rounding tolerances in both model specifications. In the case of our estimation as shown in Table 6.3, the number of parameters in the generic model is 8 and the number of parameters in the alternative specific model is 9. Given that the value of the Chi-square distribution with 1 degree of freedom at the significance level of 0.05 is \( \chi^2_{1,0.05} = 3.84 \), the null hypothesis is accepted. This implies that the generic model with relates to the attribute of quality of flowers is a more appropriate specification.

It is also of note that in Equation (6.34) and (6.36), the extra travel time and shopping time in conventional shopping activity are regarded as two separate attributes.
However, in the activity production approach proposed in Chapter 4, these two attributes are summed as the total input time of activity participation. This implies a restricted utility specification of conventional shopping by imposing a constraint on the corresponding parameters that $\beta_{c2}$ equals to $\beta_{c3}$. As opposed to the unrestricted generic model in Equation (6.34), the restricted model is expressed as:

$$V_m = \beta_{m0} + \beta_{m1}T_{journey} + \beta_{m2}C_{online} + \beta_{m3}T_{online} + \beta_GQ_{flowers}$$  (6.37)

$$V_c = \beta_{c1}TC + \beta_{c2,3}(TT + T_{conventional}) + \beta_GQ_{flowers}$$  (6.38)

A comparison is made in Table 6.4 between the restricted and unrestricted generic models.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Unrestricted form</th>
<th>Restricted form</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant($\beta_{m0}$)</td>
<td>-1.41(-2.51)</td>
<td>-1.34(-2.45)</td>
</tr>
<tr>
<td>Journey time($\beta_{m1}$)</td>
<td>0.002(0.32*)</td>
<td>0.002(0.30*)</td>
</tr>
<tr>
<td>Online cost($\beta_{m2}$)</td>
<td>-0.41(-10.56)</td>
<td>-0.41(-10.66)</td>
</tr>
<tr>
<td>Online duration($\beta_{m3}$)</td>
<td>-0.03(-2.11)</td>
<td>-0.03(-2.13)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extra travel cost($\beta_{c1}$)</td>
<td>-0.36(-7.77)</td>
<td>-0.36(-7.76)</td>
</tr>
<tr>
<td>Extra travel time($\beta_{c2}$)</td>
<td>-0.08(-8.79)</td>
<td>---</td>
</tr>
<tr>
<td>Shopping time($\beta_{c3}$)</td>
<td>-0.09(-6.99)</td>
<td>---</td>
</tr>
<tr>
<td>Total input time($\beta_{c2,3}$)</td>
<td>---</td>
<td>-0.08(-10.53)</td>
</tr>
<tr>
<td>Generic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quality of flowers($\beta_G$)</td>
<td>1.85(11.87)</td>
<td>1.85(11.86)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.337</td>
<td>0.338</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-636.309</td>
<td>-636.309</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-413.920</td>
<td>-414.068</td>
</tr>
</tbody>
</table>

* indicate that the corresponding parameters was not significant at 5% level

With the minor exception of a slight increase of the adjusted rho-square value in the restricted model, the results show a very similar pattern of coefficient estimates in both restricted formulation and unrestricted formulation. Therefore the likelihood ratio test is conducted to choose the more appropriate form. With the estimation results in Table 6.4, this test statistics equals $-2\left[\left(-414.068\right) - \left(-413.920\right)\right] = 0.296$. The difference between the number of parameters of unrestricted model and restricted model is 1. Given that the value of Chi-square distribution of 1 degree of freedom at the
significance level of 0.05 is $\chi^2_{0.05} = 3.84$, the null hypothesis is accepted, which supports our assumption. This demonstrates that SC respondents treated roughly equally the attributes of shopping time and extra travel time. It is the sum of these attributes that most influences their shopping choice decisions. Therefore in the following estimations, extra travel time and shopping time are consistently summed as the entire input time entering the process utility function for the conventional shopping alternatives.

It is also our interest to investigate the interrelationship between the online time of mobile shopping and the journey time. Two alternative ways are examined to allow for the interaction between them in a linear utility function, namely

$$V_m = \beta_{m0} + \beta_{m1}T_{\text{journey}} + \beta_{m2}C_{\text{online}} + \beta_{m3}T_{\text{online}} + \beta_{m4}Q_{\text{flowers}}$$  \hspace{1cm} (6.39)$$

$$V_m = \beta_{m0} + \beta_{m1}T_{\text{journey}} + \beta_{m2}C_{\text{online}} + \beta_{m3}T_{\text{online}}T_{\text{journey}} + \beta_{m4}Q_{\text{flowers}}$$  \hspace{1cm} (6.40)$$

It has been examined that neither of the above specifications performs better than the utility of mobile shopping in Equation (6.37). Therefore in the following estimation, when utility of mobile shopping is represented as a linear function, no interaction between $T_{\text{online}}$ and $T_{\text{journey}}$ is incorporated.

Overall, among all the linear utility specifications discussed above, the restricted model in Equation (6.37) and (6.38) with generic attribute of quality of flowers has the best level of fit to the SC data. As shown in Table 6.4, all the coefficients except journey time are significant. The negative sign of constant coefficient of mobile shopping indicates that in our hypothetical shopping scenario respondents prefer conventional shopping to mobile shopping. In both shopping activities, all the coefficients of input time and money are negative, which indicates that respondents derive an overall disutility from activity production process. The positive sign of the generic attribute of quality of flowers interprets that respondents obtain a utility from the outcome of consumption. The
insignificance of journey time implies that respondents are indifferent to the length of journey when undertaking mobile shopping activity.

**Model 2**

In Model 2, the process utility of mobile shopping is considered to be a linear additive function, whereas the process utility of conventional shopping is assumed to be of a Cobb-Douglas form. Stated explicitly,

\[ V_m = \beta_{m0} + \beta_{m1}T_{\text{journey}} + \beta_{m2}C_{\text{online}} + \beta_{m3}T_{\text{online}} + \beta_{G}Q_{\text{flowers}} \]  

(6.41)

\[ V_c = \beta_{c1}TC^\lambda_{c1} \left( TT + T_{\text{conventional}} \right)^\lambda_{c2} + \beta_{G}Q_{\text{flowers}} \]  

(6.42)

Given same notation for the explanatory variables as described in Model 1, \( \lambda_{c1}, \lambda_{c2} \) are parameters of the Cobb-Douglas process utility of conventional shopping. The estimation results of Model 2 are shown in Table 6.5.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient ( t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
</tr>
<tr>
<td>Constant (( \beta_{m0} ))</td>
<td>-44.0(-0.62*)</td>
</tr>
<tr>
<td>( \beta_{m1} )</td>
<td>0.0017(0.25*)</td>
</tr>
<tr>
<td>( \beta_{m2} )</td>
<td>-0.409(-10.65)</td>
</tr>
<tr>
<td>( \beta_{m3} )</td>
<td>-0.025(-2.13)</td>
</tr>
<tr>
<td>Conventional</td>
<td></td>
</tr>
<tr>
<td>shopping</td>
<td></td>
</tr>
<tr>
<td>( \beta_{c1} )</td>
<td>-36.8(-0.53*)</td>
</tr>
<tr>
<td>( \lambda_{c1} )</td>
<td>0.019(0.66*)</td>
</tr>
<tr>
<td>( \lambda_{c2} )</td>
<td>0.06(0.67*)</td>
</tr>
<tr>
<td>Generic</td>
<td></td>
</tr>
<tr>
<td>Quality of flowers (( \beta_{G} ))</td>
<td>1.83(11.83)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.332</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-636.309</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-417.030</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

In comparison with the estimation results of Model 1, the specification of Cobb-Douglas process utility of conventional shopping in Model 2, leads to an insignificance constant coefficient of mobile shopping. Despite that, a similar pattern of other coefficient values is observed in mobile shopping. With regards to the conventional shopping, all the coefficients of process utility are insignificant, which may be due to the
inappropriate specification. The coefficient of outcome utility remains to be significant and positive.

**Model 3**

In Model 3, the process utility of mobile shopping remains in a linear additive form, whereas the process utility of conventional shopping arises as a CES function, namely that:

\[
V_m = \beta_{m0} + \beta_{m1}T_{journey} + \beta_{m2}C_{online} + \beta_{m3}T_{online} + \beta_G Q^n_{flowers} \quad (6.43)
\]

\[
V_c = \beta_{c1} \left[ \beta_{c2} T C^\lambda_{\text{conventional}} + (1 - \beta_{c2}) (TT + T_{\text{conventional}})^\lambda_{\text{conventional}} \right]^{1/\lambda_{\text{conventional}}} + \beta_G Q^c_{flowers} \quad (6.44)
\]

Where \( \beta_{c1}, \beta_{c2}, \lambda_{\text{conventional}} \) are parameters of CES process utility of conventional shopping. Table 6.6 summarizes the estimation results of Model 3.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
</tr>
<tr>
<td>Constant (( \beta_{m0} ))</td>
<td>-1.68(-2.85)</td>
</tr>
<tr>
<td>( \beta_{m1} )</td>
<td>0.002(0.34*)</td>
</tr>
<tr>
<td>( \beta_{m2} )</td>
<td>-0.413(-10.66)</td>
</tr>
<tr>
<td>( \beta_{m3} )</td>
<td>-0.026(-2.18)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
</tr>
<tr>
<td>( \beta_{c1} )</td>
<td>-0.721(-4.82)</td>
</tr>
<tr>
<td>( \beta_{c2} )</td>
<td>0.978(31.97)</td>
</tr>
<tr>
<td>( \lambda_{\text{conventional}} )</td>
<td>1.92(3.37)</td>
</tr>
<tr>
<td>Generic</td>
<td></td>
</tr>
<tr>
<td>Quality of flowers (( \beta_G ))</td>
<td>1.86(11.89)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.339</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-1628.643</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-412.424</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

As compared with the estimation results of Model 1, the specification of CES process utility of conventional shopping in Model 3 does not result in any significant change in coefficients of outcome utility and linear utility of mobile shopping. In CES process utility of conventional shopping, all the coefficients are significant. The negative sign of scale parameter \( \beta_{c1} \) indicates that respondents derive a disutility from production process of conventional shopping.
Model 4

In Model 4, the process utility of mobile shopping exhibits a Cobb-Douglas form, while the process utility of conventional shopping exhibits a CES form, namely that:

\[ V_m = \beta_{m1} T_{journey} + \beta_{m2} T_{online} \lambda_{m1} C_{online} \lambda_{m2} + \beta G Q_{flowers} \]  

(6.45)

\[ V_c = \beta_{c1} \left( \beta_{c2} T C^{\lambda_{c1}} + (1 - \beta_{c2}) (TT + T_{conventional})^{\lambda_{c1}} \right)^{\frac{1}{\lambda_{c1}}} + \beta G Q_{flowers} \]  

(6.46)

Where \( \beta_{m2}, \lambda_{m1}, \lambda_{m2} \) are parameters of Cobb-Douglas process utility of mobile shopping.

Estimation results are summarised in Table 6.7

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient ( t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td>( \beta_{m1} ) 0.0016(0.23*)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{m2} ) -1.40(-3.16)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{m1} ) 0.116(2.20)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{m2} ) 0.49(7.00)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td>( \beta_{c1} ) -0.71(-4.71)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{c2} ) 0.977(29.73)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{c1} ) 1.89(3.33)</td>
</tr>
<tr>
<td>Generic Quality of flowers</td>
<td>( \beta G ) 1.86(11.89)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.340</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-491.880</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-412.087</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

Similarly, in Cobb-Douglas form of process utility of mobile shopping, the interrelationship between online time and journey time is also investigated. 4 alternative specifications are examined to allow for the interaction between them. Stated formally,

\[ V_m = \beta_{m1} T_{journey} + \beta_{m2} \left( T_{journey} - T_{online} \right) \lambda_{m1} C_{online} \lambda_{m2} + \beta G Q_{flowers} \]  

(6.47)

\[ V_m = \beta_{m1} T_{journey} + \beta_{m2} \left( T_{journey} + T_{online} \right) \lambda_{m1} C_{online} \lambda_{m2} + \beta G Q_{flowers} \]  

(6.48)

\[ V_m = \beta_{m1} T_{journey} + \beta_{m2} \left( \frac{T_{online}}{T_{journey}} \right) \lambda_{m1} C_{online} \lambda_{m2} + \beta G Q_{flowers} \]  

(6.49)
\[ V_m = \beta_{m1}T_{\text{journey}} + \beta_{m2}(T_{\text{online}}T_{\text{journey}})^{\lambda_{m2}} C_{\text{online}}^{\lambda_{c2}} + \beta_G Q_{\text{flowers}}^m \]  

(6.50)

Among all these specifications, the most successful one is presented in Equation (6.47), in which \( T_{\text{journey}} \) interacts with \( T_{\text{online}} \) in a difference form to enter the process utility of mobile shopping. The estimation results of modified version of Model 4 are listed in Table 6.8.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
</tr>
<tr>
<td>( \beta_{m1} )</td>
<td>-0.0187(-1.98)</td>
</tr>
<tr>
<td>( \beta_{m2} )</td>
<td>-1.98(-3.97)</td>
</tr>
<tr>
<td>( \lambda_{m1} )</td>
<td>-0.135(-2.45)</td>
</tr>
<tr>
<td>( \lambda_{m2} )</td>
<td>0.605(5.69)</td>
</tr>
<tr>
<td>Conventional</td>
<td></td>
</tr>
<tr>
<td>( \beta_{c1} )</td>
<td>-0.737(-4.94)</td>
</tr>
<tr>
<td>( \beta_{c2} )</td>
<td>0.980(35.1)</td>
</tr>
<tr>
<td>( \lambda_{c1} )</td>
<td>1.97(3.42)</td>
</tr>
<tr>
<td>Generic</td>
<td></td>
</tr>
<tr>
<td>Quality of flowers (( \beta_G ))</td>
<td>1.87(11.94)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.342</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-415.579</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-410.812</td>
</tr>
</tbody>
</table>

Considering first the results in Table 6.8, we note that all the coefficients are statistically significant. In comparison, the model in Table 6.7 has a slightly poorer overall level of fit and the estimated coefficients generally have lower significance than the model in Table 6.8. Particularly, the coefficient of journey time is not plausible in terms of both the positive sign and level of insignificance. Therefore it is reasonable to assume modified form of Model 4 has a better overall level of fit than Model 4. As shown in Table 6.8, the negative signs of scale parameters \( \beta_{m2} \) and \( \beta_{c1} \) which represent negative process utilities in both shopping activities, and the positive sign in generic coefficient of outcome utility, accords with our findings in previous specifications.

**Model 5**

In Model 5, the process utility of mobile shopping is of modified Cobb-Douglas form as described in Equation (6.47), while the process utility of conventional shopping
is a linear additive function, namely that:

\[
V_m = \beta_{m1} T_{\text{journey}} + \beta_{m2} \left( T_{\text{journey}} - T_{\text{online}} \right) + \lambda_{m1} C_{\text{online}} + \lambda_{m2} + \beta_G Q_{\text{flowers}}
\]

(6.51)

\[
V_c = \beta_{c1} TC + \beta_{c2,3} (TT + T_{\text{conventional}}) + \beta_G Q_{\text{flowers}}
\]

(6.52)

Table 6.9 summaries the estimation results of Model 5.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient ( t-statistics)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td>(\beta_{m1}) = -0.0175 (-1.91*)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(\beta_{m2}) = -1.64 (-3.76)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(\lambda_{m1}) = -0.139 (-2.37)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(\lambda_{m2}) = 0.666 (5.61)</td>
<td></td>
</tr>
<tr>
<td>Conventional shopping</td>
<td>(\beta_{c1}) = -0.358 (-7.75)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(\beta_{c2,3}) = -0.0863 (-10.65)</td>
<td></td>
</tr>
<tr>
<td>Generic</td>
<td>Quality of flowers ((\beta_G)) = 1.86 (11.91)</td>
<td></td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.341</td>
<td></td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-1744.390</td>
<td></td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-412.630</td>
<td></td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

In comparison with the modified Model 4, the specification of linear process utility of conventional shopping in Model 5, results in generally lower levels of significance in coefficients of mobile shopping, particularly in the attribute of journey time. With regards to outcome utility and process utility of conventional shopping, all the coefficients are significant and exhibit a similar pattern to Model 1 in Table 6.4. Besides, Model 5 has a similar overall level of fit to modified Model 4.

**Model 6**

In Model 6, the process utility of mobile shopping is assumed to be of a CES function, while the process utility of conventional shopping is a linear additive function, i.e.:

\[
V_m = \beta_{m1} T_{\text{journey}} + \beta_{m2} \left[ \beta_{m3} T_{\text{online}} + (1 - \beta_{m3}) C_{\text{online}} \right]^{\frac{1}{\lambda_{m1}}} + \lambda_{m1} + \beta_G Q_{\text{flowers}}
\]

(6.53)

\[
V_c = \beta_{c0} + \beta_{c1} TC + \beta_{c2,3} (TT + T_{\text{conventional}}) + \beta_G Q_{\text{flowers}}
\]

(6.54)
Where $\beta_m$, $\beta_n$ and $\lambda$ are parameters of the CES process utility function of mobile shopping. It should be noted that the interaction between the journey time and online time of mobile activities was also examined by modifying the CES functional form according to 4 alternative ways as shown in Model 4. However, in comparison with Equation (6.53), no better specification was found. Estimation results of Model 6 are listed in Table 6.10.

Table 6.10 Estimation results for Model 6

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
</tr>
<tr>
<td>$\beta_{m1}$</td>
<td>0.0015 (0.22*)</td>
</tr>
<tr>
<td>$\beta_{m2}$</td>
<td>-0.379 (-6.00)</td>
</tr>
<tr>
<td>$\beta_{m3}$</td>
<td>0.278 (1.13*)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>-0.464 (-0.39*)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
</tr>
<tr>
<td>Constant ($\beta_c$)</td>
<td>1.41 (2.59)</td>
</tr>
<tr>
<td>$\beta_{c1}$</td>
<td>-0.357 (-7.72)</td>
</tr>
<tr>
<td>$\beta_{c2,3}$</td>
<td>-0.0846 (-10.43)</td>
</tr>
<tr>
<td>Generic</td>
<td></td>
</tr>
<tr>
<td>Quality of flowers ($\beta_G$)</td>
<td>1.85 (11.83)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.338</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-435.071</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-413.071</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

The results show that all the estimated coefficients of CES process utility of mobile shopping are insignificant except the scale parameter $\beta_{m1}$. Similar to the linear specification of mobile shopping as represented in Model 1 to Model 3, the CES specification also leads to an insignificant and positive coefficient of journey time. The positive sign of linear constant coefficient of conventional shopping indicates that respondents prefer using conventional shopping to mobile shopping, which accords our previous findings. The negative signs in $\beta_{m2}$, $\beta_{c1}$ and $\beta_{c2,3}$, and the positive sign in $\beta_G$ represent negative process utilities and positive outcome utilities in both shopping activities.

**Model 7**

In Model 7, the process utility of mobile shopping is also assumed to be of a CES
form, while the process utility of conventional shopping is of Cobb-Douglas form, i.e.:

$$V_m = \beta_m T_{journey} + \beta_{m1} T_{journey}^{\lambda_{m1}} + (1 - \beta_{m2}) C_{online}^{\lambda_{m2}} + \beta_{G} Q_{flowers}^m$$  \hspace{1cm} (6.55)$$

$$V_c = \beta_c T C^{\lambda_c} (T_{journey} - T_{conventional})^{\lambda_c} + \beta_{G} Q_{flowers}^c$$  \hspace{1cm} (6.56)$$

Table 6.11 lists the estimation results.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient ( t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping β_{m1}</td>
<td>-0.003(-0.47*)</td>
</tr>
<tr>
<td>β_{m2}</td>
<td>-0.384(6.31)</td>
</tr>
<tr>
<td>β_{m3}</td>
<td>0.270(1.23*)</td>
</tr>
<tr>
<td>λ_{m1}</td>
<td>-0.304(-0.30*)</td>
</tr>
<tr>
<td>Conventional shopping β_{c1}</td>
<td>-0.088(-1.54*)</td>
</tr>
<tr>
<td>λ_{c1}</td>
<td>0.235(5.79)</td>
</tr>
<tr>
<td>λ_{c2}</td>
<td>0.932(6.55)</td>
</tr>
<tr>
<td>Generic Quality of flowers (β_{G})</td>
<td>1.80(11.77)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.327</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-444,859</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-419,972</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

As compared with Model 6, changing the specification of process utility of conventional shopping from linear function to Cobb-Douglas function, leads to a plausible sign in the coefficient of journey time. The other estimated coefficients in mobile shopping exhibit a similar pattern to those in Model 6. With regards to conventional shopping, the coefficients of Cobb-Douglas process utility have the same sign but rather different values as those in Model 2. Among all the models discussed so far, Model 7 has the lowest overall level of fit.

**Model 8**

In Model 8, both the process utility of mobile shopping and that of conventional shopping are represented as a Cobb-Douglas form, namely that:

$$V_m = \beta_m T_{journey} + \beta_{m2} (T_{journey} - T_{online})^{\lambda_{m1}} C_{online}^{\lambda_{m2}} + \beta_{G} Q_{flowers}^m$$  \hspace{1cm} (6.57)$$
\[
V_c = \beta_{c1} T_{c1} C^{\lambda_{c1}} (TT + T_{conventional})^{\lambda_{c2}} + \beta_G Q_{flowers}^{c}
\] (6.58)

Table 6.12 summaries the estimation results of Model 8.

Table 6.12 Estimation results for Model 8

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td>( \beta_{m1} ) = -0.0234(-2.07)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{m2} ) = -33.1(-0.51*)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{m1} ) = -0.0162(-0.52*)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{m2} ) = 0.06(0.53*)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td>( \beta_{c1} ) = -26.2(0.42*)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{c1} ) = 0.0243(0.55*)</td>
</tr>
<tr>
<td></td>
<td>( \lambda_{c2} ) = 0.06(0.53*)</td>
</tr>
<tr>
<td>Generic Quality of flowers (( \beta_G ))</td>
<td>1.84(11.83)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.335</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-58752.3</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-415.264</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

The results show that when using the Cobb-Douglas process utility in both shopping activities, all the coefficients are insignificant except \( \beta_G \) and the coefficient of journey time. This may be due to the reason that both shopping activities exhibit the same form of process utility function, which supports the assumption proposed in our modelling framework that the each technology is characterised by a unique process utility function.

**Model 9**

In model 9, both the process utility of mobile shopping and that of conventional shopping are formulated as CES functions, i.e.

\[
V_m = \beta_{m1} T_{m1}^{\lambda_{m1}} + \beta_{m2} \left[ \beta_{m3} T_{online}^{\lambda_{m3}} + (1 - \beta_{m3}) C_{online}^{\lambda_{m3}} \right]^{\lambda_{m4}} + \beta_G Q_{flowers}^m
\] (6.59)

\[
V_c = \beta_{c1} \left[ \beta_{c2} T_{c1}^{\lambda_{c1}} + (1 - \beta_{c2}) (TT + T_{conventional})^{\lambda_{c2}} \right]^{\lambda_{c4}} + \beta_G Q_{flowers}^c
\] (6.60)

Table 6.13 summaries the estimation results of Model 9.
Table 6.13 Estimation results for Model 9

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Coefficient (t-statistics)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
</tr>
<tr>
<td>$\beta_{m1}$</td>
<td>-0.016 (-1.89*)</td>
</tr>
<tr>
<td>$\beta_{m2}$</td>
<td>-0.429 (7.57)</td>
</tr>
<tr>
<td>$\beta_{m3}$</td>
<td>0.207 (1.38*)</td>
</tr>
<tr>
<td>$\lambda_{m1}$</td>
<td>0.211 (0.29*)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
</tr>
<tr>
<td>$\beta_{c1}$</td>
<td>-0.523 (-3.76)</td>
</tr>
<tr>
<td>$\beta_{c2}$</td>
<td>0.931 (11.32)</td>
</tr>
<tr>
<td>$\lambda_{c1}$</td>
<td>1.44 (2.86)</td>
</tr>
<tr>
<td>Generic</td>
<td></td>
</tr>
<tr>
<td>Quality of flowers ($\beta_{G}$)</td>
<td>1.83 (11.88)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.334</td>
</tr>
<tr>
<td>Initial log likelihood</td>
<td>-695.523</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-416.038</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

Similar to Model 8, although the process utilities of both shopping activities are specified as same function form, Model 9 has a higher level of significance in estimated coefficients than Model 8. For conventional shopping, all the coefficients are significant. For mobile shopping, only scale parameter $\beta_{m2}$ is significant.

6.2.1.2 Identification of best basic model

Comparing the estimation results in Table 6.4 - Table 6.13, for each shopping activity, the coefficients of given process utility function always have the same sign and comparable estimated value. Among all the models, the modified Model 4 in Table 6.8, in which process utility of mobile shopping arises as a modified Cobb-Douglas form and process utility of conventional shopping exhibits as a CES form, emerges as the best basic model at this stage based on raw goodness of fit consideration. This is mainly due to two reasons. Firstly, among the entire set of models discussed above, modified Model 4 is the only specification in which each of the estimated coefficients is found to be statistically significant and plausible, while in the remaining models, various coefficients are statistically insignificant. Using the insignificant estimation results to derive further findings and interpretation in this research is less desirable. Also with respect to the attribute of journey time of mobile shopping activity, Model 1,2,3, and 6 present positive estimation results and Model 5,7,8, and 9 present negative but insignificant results. All of
these are inconsistent with our prior expectation. Secondly, modified Model 4 displays the highest overall level of fit in terms of both the values of adjusted rho-square and final log likelihood among all the models. A comparison is made in Table 6.14 between different model specifications.

Table 6.14 Comparisons of the overall level of fit of various models

<table>
<thead>
<tr>
<th>Model specification</th>
<th>Adjusted rho-square</th>
<th>Final log likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modified V_m: Cobb-Douglas V_c: CES</td>
<td>0.342</td>
<td>-410.812</td>
</tr>
<tr>
<td>Model 4 V_m: Cobb-Douglas V_c: CES</td>
<td>0.340</td>
<td>-412.087</td>
</tr>
<tr>
<td>Model 4 V_m: Cobb-Douglas V_c: CES</td>
<td>0.338</td>
<td>-414.068</td>
</tr>
<tr>
<td>Model 1 V_m: Linear V_c: Linear</td>
<td>0.332</td>
<td>-417.030</td>
</tr>
<tr>
<td>Model 2 V_m: Linear V_c: Cobb-Douglas</td>
<td>0.339</td>
<td>-412.424</td>
</tr>
<tr>
<td>Model 3 V_m: Linear V_c: CES</td>
<td>0.341</td>
<td>-412.630</td>
</tr>
<tr>
<td>Model 5 V_m: Cobb-Douglas V_c: Linear</td>
<td>0.338</td>
<td>-413.071</td>
</tr>
<tr>
<td>Model 6 V_m: CES V_c: Linear</td>
<td>0.327</td>
<td>-419.972</td>
</tr>
<tr>
<td>Model 7 V_m: CES V_c: Cobb-Douglas</td>
<td>0.335</td>
<td>-415.264</td>
</tr>
<tr>
<td>Model 8 V_m: Cobb-Douglas V_c: Cobb-Douglas</td>
<td>0.334</td>
<td>-416.038</td>
</tr>
<tr>
<td>Model 9 V_m: CES V_c: CES</td>
<td>0.334</td>
<td>-416.038</td>
</tr>
</tbody>
</table>

The results show that both the values of adjusted rho-square and the final log likelihood function are quite close. Among the total 10 specifications, Model 7 incorporating CES process utility for mobile shopping and Cobb-Douglas process utility for conventional shopping (the opposite to the combination of modified Model 4) has the lowest level of fit. Model 8 and Model 9 consisting of the same functional form of process utility in both shopping alternatives have comparatively poorer but still acceptable results. The slight differences in empirical results among these models suggest the need to apply formal specification tests to determine the structure that is most consistent with the data. We proceed on the basis of selecting modified Model 4 as our preferred basic model.
According to the description in Section 6.1.6.3, modified Model 4 is non-nested with all the other models in Table 6.14, as illustrated in above equations. Therefore we apply two non-nested tests (i.e. P-test and C-test) to examine these competing hypotheses against modified Model 4.

Considering non-nested hypotheses of alternative specifications for the systematic utility of mobile shopping \( V_m \) and that of conventional shopping \( V_c \) in all the other models, as oppose to the specification in modified Model 4, we have:

\[
H_0 : \quad V_m = V_m^4 \quad V_c = V_c^4 \\
H_1 : \quad V_m = V_m^r \quad V_c = V_c^r
\]  
(6.61)

(6.62)

Where \( V_m^4 \) and \( V_c^4 \) represent the specification in modified Model 4, while \( V_m^r \) and \( V_c^r \) \((r = 1, 2, 3, 5..., 9)\) represent the alternative specifications in all the other models. Under the null hypothesis, modified Model 4 is correctly specified and other models have no power to improve on it. This testing strategy will indicate whether modified Model 4 is robust against the other models in Table 6.14. In the C-test, one considers a composite model of the form:

\[
V_m = (1 - \alpha)\hat{V}_m^4 + \alpha V_m^r \\
V_c = (1 - \alpha)\hat{V}_c^4 + \alpha V_c^r
\]  
(6.63)

(6.64)

Where \( \hat{V}_m^4 = V_m^4 \left( X_m, \hat{\beta}_m^4 \right) \), \( \hat{V}_c^4 \) is the predicted value of \( V_m \) in modified Model 4 based on the design variables of mobile shopping \( X_m \) and estimation \( \hat{\beta}_m^4 \) in Table 6.8; \( \hat{V}_c^4 = V_c^4 \left( X_c, \hat{\beta}_c^4 \right) \), \( \hat{\beta}_c^4 \) is the vector of parameter estimates of conventional shopping in...
modified Model 4, $\hat{V}_c^4$ is the predicted value of $V_c$ in modified Model 4 based on the
design variables of conventional shopping $X_c$ and estimation $\hat{\beta}_c^4$, and $\alpha$ is the parameter
to be estimated. Identically, in p-test, we devise a combination of the form:

$$V_m = (1-\alpha)\hat{V}_m^4 + \alpha V_m^r + F_m^4 B$$

(6.65)

$$V_c = (1-\alpha)\hat{V}_c^4 + \alpha V_c^r + F_c^4 B$$

(6.66)

Suppose $\beta_m^4$ and $\beta_c^4$ are vectors of coefficients of $V_m^4$ and $V_c^4$ in modified Model 4, $F_m^4$ is
a row vector containing the derivatives of function $V_m^4$ with respect to each parameter in $\beta_m^4$ evaluated at corresponding element in $\beta_m^4$; $F_c^4$ is a row vector containing the
derivatives of function $V_c^4$ with respect to each parameter in $\beta_c^4$ evaluated at
corresponding element in $\beta_c^4$; $\alpha$ is the parameter to be estimated; B is the column vector
of coefficients of $F_m^4$ and $F_c^4$. In both tests, if $H_0$ is true, then the true value of $\alpha$ is
zero. Hence a t-test is further performed to examine the significance of $\alpha$. A comparison
is made between modified Model 4 and each competing specification in the remaining
models. The results of the C-test and P-test are listed in Table 6.15 and Table 6.16,
respectively.

<table>
<thead>
<tr>
<th>Model</th>
<th>$\alpha$</th>
<th>t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>-0.09</td>
<td>0.33*</td>
</tr>
<tr>
<td>Model 2</td>
<td>-0.06</td>
<td>-0.45*</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.013</td>
<td>0.02*</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.184</td>
<td>0.35*</td>
</tr>
<tr>
<td>Model 5</td>
<td>0.025</td>
<td>0.05*</td>
</tr>
<tr>
<td>Model 6</td>
<td>0.225</td>
<td>0.63*</td>
</tr>
<tr>
<td>Model 7</td>
<td>0.086</td>
<td>0.40*</td>
</tr>
<tr>
<td>Model 8</td>
<td>-0.015</td>
<td>0.49*</td>
</tr>
<tr>
<td>Model 9</td>
<td>0.132</td>
<td>0.49*</td>
</tr>
</tbody>
</table>

* indicate that the corresponding parameters are insignificant at 5% level
The results indicate that none of the estimated values of $\alpha$ are significantly different from zero. This implies that the null hypothesis is accepted in each test. Therefore, it is advisable to regard the modified form of Model 4 as a basic specification for further analysis. It should be noted that in modified Model 4, mobile shopping and conventional shopping have different specifications of the process utility. This is consistent with our previously proposed assumption that each production technology is in principle characterized by a distinct process utility function.

### 6.2.2 Results analysis

In Section 6.2.1, the basic utility model best fitting the data is identified. The problem addressed in this section is how to interpret the results and derive further analysis from this specification. Substituting the coefficients in modified Model 4 with the estimated values in Table 6.8 leads to the following formulations of utilities:

$$V_m = \beta_{m1}T_{journey} + \beta_{m2}(T_{journey} - T_{online})^{\lambda_{m2}}C_{online}^{\lambda_{m2}} + \beta_{C}Q_{flowers}^{c}$$

$$= (-0.0187) T_{journey} + (-1.98)(T_{journey} - T_{online})^{-0.135} C_{online}^{0.605} + 1.87Q_{flowers}^{c}$$

$$V_c = \beta_{c1}[\beta_{c2}T_{C}^{\lambda_{c1}} + (1 - \beta_{c2})(T_{TT} + T_{conventional})^{\lambda_{c1}}]^{\frac{1}{\lambda_{c1}}} + \beta_{C}Q_{flowers}^{m}$$

$$= (-0.737)[0.98T_{C}^{1.97} + 0.02(T_{TT} + T_{conventional})^{1.97}]^{1/1.97} + 1.87Q_{flowers}^{m}$$

The process utilities of mobile shopping and conventional shopping are respectively represented as:
\[ V_m = \beta_{m2} \left( T_{journey} - T_{\text{online}} \right)^{\lambda_{m2}} C_{\text{online}} \lambda_{m2} = (-1.98) \left( T_{journey} - T_{\text{online}} \right)^{-0.135} C_{\text{online}}^{0.605} \quad (6.69) \]

\[ V_c = \beta_{c1} \left[ \beta_{c2} TC^{\lambda_1} + (1 - \beta_{c2}) (TT + T_{\text{conventional}})^{\lambda_1} \right]^{1/\lambda_1} \]

\[ = (-0.737) \left[ 0.98 TC^{1.97} + 0.02 (TT + T_{\text{conventional}})^{1.97} \right]^{1/1.97} \quad (6.70) \]

Where \( V_m \) = process utility of mobile shopping

\( V_c \) = process utility of conventional shopping

As \( \beta_{m2} < 0 \) and \( \beta_{c1} < 0 \), \( V_m \) and \( V_c \) are always negative. This indicates that in both shopping alternatives the production process is a source of disutility. Process utilities decrease with increasing combination of input time and money. In keeping with our hypotheses, increasing duration and increasing money expenditure during an activity participation lead to lower production efficiency for a given consumption output. Hence in this experiment, input time and money expenditure are more appropriate to be considered as ‘production costs’ rather than ‘allocated resource’ as assumed in existing activity-based duration models (Kitamura et al., 1996; Yamamoto et al., 2000). This is true in some maintenance activities (such as online shopping for groceries) or other non-leisure activities with a pure aim to obtain the outcome of desired ‘goods’ (e.g. flower shopping in this experiment). However, in leisure activities, such as mobile gaming or listening to music while mobile, individuals may inherently enjoy the process of activity participation, during which the consumption of time and money expenditure may generate positive process utility to the individuals.

With regards to the ‘scale of return’ of the production function in Equation (6.69), as \( \lambda_{m1} + \lambda_{m2} = -0.135 + 0.605 = 0.47 \) and \( 0.47 < 1 \), this indicate that \( V_m \) exhibits decreasing scale of return. This implies that when input time and money expenditure each increase by the same proportion, the process utility of mobile shopping will decrease less than
proportionally. In Equation (6.70), as the parameter \( \mu \) originally defined in Equation (4.15) equals to 1, the process utility of conventional shopping exhibits constant scale of return. This represents that when input time and money expenditure each increase by a certain proportion, \( V_p \) will correspondingly decrease by the same proportion.

Regarding the outcome utility, as \( \beta_G > 0 \), both shopping activities have positive values. As the quality of flowers is the only generic attribute in this experiment, both shopping alternatives bring out an equal value of outcome utility when the preferred flowers are obtained. Thus it can be interpreted that respondents are concerned only with their consumption outcome rather than how the outcome is achieved (i.e. whether by conventional shopping or mobile shopping).

In the following part of this chapter, in order to better understand the impact of technology, we shift out attention to the process utility of shopping activities. The impact of each design variable on the process utility function and the interrelationship between the design variables are examined.

6.2.2.1 Result analysis of process utility of mobile shopping

In this section, the effects of SC design variables (i.e. journey time, input time and input money expenditure) on the process utility of mobile shopping and the interrelationship between input time and input money expenditure, as well as online time and journey time, are examined. It is important that the empirical results presented here help us better understand individual’s technology usage in activity participation. However, as the SC experiment is proposed built on a specific shopping episode in a hyperthetical scenario, the magnitude of these empirical effects is required to be assessed.

**Relationship between process utility of mobile shopping \( V_m \) and journey time \( T_{\text{journey}} \)**

Given value of online time \( T_{\text{online}} \) and online cost \( C_{\text{online}} \), the relationship between
\( V_m^p \) and \( T_{\text{journey}} \) can be represented as:

\[
V_m^p = (-1.98) \left( T_{\text{journey}} - T_{\text{online}}^0 \right)^{-0.135} C_{\text{online}}^0 \right)^{0.605}
\]  

(6.71)

Using the attribute values and ranges proposed in our experiment, for example, \( T_{\text{online}}^0 = 10 \text{ min} \) \( C_{\text{online}}^0 = \£ 3 \) and \( T_{\text{journey}} \in (0, 60) \text{ min} \), the resulting graph of Equation (6.71) is plotted in Figure 6.1.

![Graph](image)

**Figure 6.1 Relationship between \( V_m^p \) and \( T_{\text{journey}} \)**

We make the assumption that mobile shopping is completed while travelling so that \( T_{\text{journey}} \) is no smaller than \( T_{\text{online}}^0 \). The figure shows a monotonically increasing trend of \( V_m^p \) and decreasing trend of slope among the entire range of \( T_{\text{journey}} \). An abrupt increase can be observed when \( T_{\text{journey}} \) is close to the initial value \( T_{\text{online}}^0 \).

The same conclusion can be reached by taking the first order and second order partial derivatives of Equation (6.69) with respect to \( T_{\text{journey}} \). Stated explicitly,
\[
\frac{\partial V^p_m}{\partial T_{\text{journey}}} = \beta_m^2 \lambda_m (T_{\text{journey}} - T_{\text{online}})^{\lambda_m-1} C_{\text{online}}^\lambda_m \\
= (-1.98) \times (-0.135) (T_{\text{journey}} - T_{\text{online}})^{-0.135-1} C_{\text{online}}^{0.605}
\]
\[
= 0.267 (T_{\text{journey}} - T_{\text{online}})^{-1.135} C_{\text{online}}^{0.605}
\]
\[
\frac{\partial^2 V^p_m}{\partial T_{\text{journey}}^2} = \beta_m^2 \lambda_m (\lambda_m - 1)(T_{\text{journey}} - T_{\text{online}})^{\lambda_m-2} C_{\text{online}}^{\lambda_m}
\]
\[
= (-0.3)(T_{\text{journey}} - T_{\text{online}})^{-2.135} C_{\text{online}}^{0.605}
\]

As in Equation (6.72) $\beta_m^2 \lambda_m > 0$ and in Equation (6.73) $\beta_m^2 \lambda_m (\lambda_m - 1) < 0$, thus we have $\frac{\partial V^p_m}{\partial T_{\text{journey}}} > 0$, $\frac{\partial^2 V^p_m}{\partial T_{\text{journey}}^2} < 0$. This indicates that for any value of $T_{\text{online}}$ and $C_{\text{online}}$, mobile shopping always has an increasing process utility and decreasing marginal process utility relating to the journey time $T_{\text{journey}}$.

In activity-based travel analysis, ‘activity duration’ is defined as the available time for activity participation according to one’s current schedule. Our interpretation of journey time as the maximum available time for the mobile shopping activity coincides with the classical definition of ‘activity duration’. From the perspective of activity-based travel analysis, longer journey time leads to longer ‘activity duration’ for mobile shopping. The result of $\frac{\partial V^p_m}{\partial T_{\text{journey}}} > 0$ and $\frac{\partial^2 V^p_m}{\partial T_{\text{journey}}^2} < 0$ accord with the ‘saturation effect’ between the utility of an activity and ‘activity duration’ under activity-based utility frameworks, in which utility of an activity increases and marginal utility decreases with changes in activity duration.

Relationship between process utility of mobile shopping $V^p_m$ and input variables

Given the values of $T_{\text{journey}} = T_{\text{journey}}^0$ and $C_{\text{online}} = C_{\text{online}}^0$, Equation (6.69) can be
rewritten as:

\[ V_m^p = (-1.98) (T_{\text{journey}}^0 - T_{\text{online}}^0)^{-0.135} C_{\text{online}}^{0.605} \]  

(6.74)

Setting \( T_{\text{journey}}^0 = 60 \text{min} \) and \( C_{\text{online}}^0 = £3 \), the relationship expressed in Equation (6.74) is shown graphically in Figure 6.2.

![Figure 6.2 Relationship between \( V_m^p \) and \( T_{\text{online}} \)](image)

The figure shows that \( V_m^p \) displays a concave pattern among the entire range of \( T_{\text{online}} \).

\( V_m^p \) decreases slightly when \( T_{\text{online}} \) is smaller than \( T_{\text{journey}} \) and a rapid decrease is observed when \( T_{\text{online}} \) approaches the limit \( T_{\text{journey}} \).

Similarly, given the value of \( T_{\text{journey}}^0 \) and \( T_{\text{online}}^0 \), the functional relationship between \( V_m^p \) and \( C_{\text{online}} \) is generalised as:

\[ V_m^p = (-1.98) (T_{\text{journey}}^0 - T_{\text{online}}^0)^{-0.135} C_{\text{online}}^{0.605} \]  

(6.75)

If we set \( T_{\text{journey}}^0 = 60 \text{min} \), \( T_{\text{online}}^0 = 10 \text{min} \) and \( C_{\text{online}} \in (0,8) \), Equation (6.75) is
represented graphically by the curves in Figure 6.3.

![Graph showing relationship between \( V_p \) and \( C_{online} \)](image)

**Figure 6.3 Relationship between \( V_p \) and \( C_{online} \)**

Compared with Figure 6.2, \( V_p \) exhibits a more abrupt convex pattern of decrease with changes in \( C_{online} \). This implies that online cost is an empirically more significant factor influencing the decision to take part in mobile shopping than online time.

Taking the first order partial derivative of Equation (6.69) on \( T_{online} \) and \( C_{online} \) lead to the following formulations:

\[
\frac{\partial V_p}{\partial T_{online}} = \left(-\beta_{m2} A_{m1}\right) \left(T_{journey} - T_{online}\right)^{\lambda_{m1}-1} C_{online}^{\lambda_{m2}} \quad (6.76)
\]

\[
= -(-1.98)(-0.135) \left(T_{journey} - T_{online}\right)^{-0.135-1} C_{online}^{0.605}
\]

\[
= (-0.27) \left(T_{journey} - T_{online}\right)^{-1.135} C_{online}^{0.605}
\]

\[
\frac{\partial V_p}{\partial C_{online}} = \beta_{m2} \lambda_{m2} \left(T_{journey} - T_{online}\right)^{\lambda_{m1}} C_{online}^{\lambda_{m2}-1} \quad (6.77)
\]

\[
= (-1.98)(0.605) \left(T_{journey} - T_{online}\right)^{-0.135} C_{online}^{-0.395}
\]

\[
= (-1.20) \left(T_{journey} - T_{online}\right)^{-0.135} C_{online}^{-0.395}
\]

As in Equation (6.76) \( -\beta_{m2} A_{m1} < 0 \) and in Equation (6.77) \( \beta_{m2} A_{m2} < 0 \), this indicates that for any value of \( T_{journey} \), \( C_{online} \) and \( T_{online} \), \( \frac{\partial V_p}{\partial T_{online}} \) and \( \frac{\partial V_p}{\partial C_{online}} \) are always
negative. This result is consistent with the observations in Figure 6.2 and Figure 6.3.

Considering the situation in which \( \frac{\partial V_m^p}{\partial T_{online}} = \frac{\partial V_m^p}{\partial C_{online}} \), we have:

\[
C_{online} = \left( -\frac{\lambda_{m2}}{\lambda_{m1}} \right) (T_{journey} - T_{online}) = 4.5(T_{journey} - T_{online}) 
\]  

This result represents that the change in process utility of mobile shopping per unit of online time equals the change per unit of online cost when Equation (6.78) is satisfied.

Correspondingly, when \( C_{online} > \left( -\frac{\lambda_{m2}}{\lambda_{m1}} \right) (T_{journey} - T_{online}) \), then \( \frac{\partial V_m^p}{\partial T_{online}} > \frac{\partial V_m^p}{\partial C_{online}} \) and

when \( C_{online} < \left( -\frac{\lambda_{m2}}{\lambda_{m1}} \right) (T_{journey} - T_{online}) \), \( \frac{\partial V_m^p}{\partial T_{online}} < \frac{\partial V_m^p}{\partial C_{online}} \).

Overall, an increase in either input variable will lower the production efficiency and correspondingly generates a lower process utility. However, the influence of these two input factors to the process utility function varies with the relationship between input money expenditure and the remaining journey time, as well as estimated coefficient determined by the underlying technology.

**Relationship between input time** \( T_{online} \) **and input money expenditure** \( C_{online} \)

To construct the indifference curve between the input time \( T_{online} \) and input money expenditure \( C_{online} \) of mobile shopping with Equation (6.69), we simply take a given value \( V_m^{p0} \) and \( T_{journey}^0 \), and solve for online cost \( C_{online} \) as a function of the online time \( T_{online} \), namely that:

\[
C_{online} = \left( V_m^{p0} \left( \frac{T_{journey}^0 - T_{online}}{T_{online}} \right)^{-\lambda_{m2}} \frac{1}{\beta_{m2}} \right) = \left( V_m^{p0} \left( \frac{T_{journey}^0 - T_{online}}{T_{online}} \right)^{0.135} \frac{1}{0.605} \right)^{-1.98} 
\]  

(6.79)
Consider the situations in which the indifference curves have different values of $V_m^{p0}$. For example, given $T_{\text{journey}}^0 = 60\text{ min}$, and $V_m^{p0}$ respectively equals to:

$$V_m^{p1} = (-1.98) \times (60 - 10)^{-0.135} \times 3^{0.605} = -2.27$$ when $T_{\text{online}} = 10\text{ min}$ $C_{\text{online}} = \£3$

$$V_m^{p2} = (-1.98) \times (60 - 10)^{-0.135} \times 8^{0.605} = -4.11$$ when $T_{\text{online}} = 10\text{ min}$ $C_{\text{online}} = \£8$

and $V_m^{p1} > V_m^{p2}$. The indifference curves when $V_m^{p0} = V_m^{p1}$ and $V_m^{p0} = V_m^{p2}$ are plotted in Figure 6.4.

![Indifference curves of mobile shopping](image)

**Figure 6.4** The indifference curves of mobile shopping

In Figure 6.4, the indifference curve of higher process utility will shift towards the origin, which implies individuals are found to empirically prefer the combination of both less time and less money in the process of activity production. This can also be explained by using Equation (6.79). As $V_m^{p0} < 0$, a higher value of $V_m^{p0}$ leads to a smaller absolute value of $|V_m^{p0}|$, which corresponds to a smaller value of $C_{\text{online}}$ among the entire range of $T_{\text{online}}$. Hence the corresponding indifference curve is closer to the origin.

It is also our interest to examine the marginal technical rate of substitution (MTS) between $T_{\text{online}}$ and $C_{\text{online}}$. According to the definition previously discussed in Chapter 4,
the $MTS$ of mobile shopping can be calculated as the ratio between Equation (6.77) and Equation (6.76), namely that:

$$MTS_m = \frac{\partial V_{m}^p}{\partial T_{\text{online}}} = \frac{(-\lambda_m) C_{\text{online}}}{\lambda_m^2 (T_{\text{journey}} - T_{\text{online}})} = 0.225 \left( \frac{C_{\text{online}}}{T_{\text{journey}} - T_{\text{online}}} \right)$$

This result indicates that $MTS_m$ not only depends on the estimated coefficient $\frac{\lambda_m}{\lambda_{m2}}$ determined by the presence of mobile technology, but also varies with the ratio between input money $C_{\text{online}}$ and remaining time on the journey $T_{\text{journey}} - T_{\text{online}}$. As $T_{\text{journey}} - T_{\text{online}}$ tends to be 0, $MTS_m$ approaches infinity, which can be interpreted to mean that when input time reaches its maximum, no extra amount of time can be replaced with money. Correspondingly, when no money expenditure is input to activity participation, $MTS_m$ is zero. Overall, the use of mobile technology characterised by the Cobb-Douglas form of process utility does not allow for a perfect substitution effect. Both input time and money are pre-requirements for mobile shopping activity. Without either of them, analysis of activity production may not in principle be tractable.

**The relationship between journey time $T_{\text{journey}}$ and online duration $T_{\text{online}}$**

Taking a given value of utility $V_{m}^{p0}$ and $C_{\text{online}}^{0}$ and solving for $T_{\text{online}}$ as a function of the $T_{\text{journey}}$, leads to:

$$T_{\text{online}} = T_{\text{journey}} - \left[ \frac{V_{m}^{p0}}{\beta m_2 C_{\text{online}}^0 \lambda_{m2}} \right]^{\frac{1}{\lambda_m}} = T_{\text{journey}} - \left[ \frac{V_{m}^{p0}}{(-1.98) C_{\text{online}}^0 \lambda_{m2}} \right]^{\frac{1}{0.135}}$$

From Equation (6.81), $T_{\text{online}} \geq 0$ only when $T_{\text{journey}} \geq \left[ \frac{V_{m}^{p0} \lambda_{m2}}{\beta m_2 C_{\text{online}}} \right]^{\frac{1}{\lambda_m}}$. Thus it can be
concluded that conducting a mobile activity has a minimum requirement for the journey’s
duration, namely that:

\[
T_{\text{min}} = \left[ \frac{V_{m}^{p0}}{\beta_{m2}^{0} C_{\text{online}}^{0}} \right]^{1} \lambda_{w1} = \left[ \frac{V_{m}^{p0}}{(-1.98) C_{\text{online}}^{0}} \right]^{1} \frac{0.605}{0.135}
\]

Equation (6.82) interprets that in order to achieve certain level of process utility \( V_{m}^{p0} \),
\( T_{\text{min}} \) is technological. As previously discussed, the description of journey time in our
activity production framework coincides with the definition of activity duration as used in
activity based travel analysis. From this perspective, the result in Equation (6.82)
accords with previous studies by De Serpa (1972), who first proposed a technical
constraint by introducing the minimum requirement of activity duration.

**Simultaneous use of time**

Although recent researchers argue that activities conducted while travelling may
lead to an overall positive utility of travelling, none have successfully disentangled the
intrinsic utility of travel itself and the utility of activities while on the move (Mokhtarian
and Salomon, 2001; Redmond and Mokhtarian, 2001). In Equation (6.67), the overall
utility of mobile shopping \( V_{m} \) is disaggregated as the sum of the two components: the
utility of travelling itself and the utility of mobile shopping while travelling. In order to
identify the impact of conducting mobile shopping on the utility of travel itself, we
consider two different situations. Firstly when mobile shopping is not performed while
travelling so that the relevant design variables equal to zero namely, \( T_{\text{online}} = 0 \),
\( C_{\text{online}} = 0 \) and \( Q_{\text{flowers}} = 0 \). Thus Equation (6.67) leads to the disutility of travelling itself,
vernacularly that:
\[ V_m = \beta_m T_{\text{journey}} = -0.0187T_{\text{journey}} \tag{6.83} \]

Within the range \( T_{\text{journey}} \in (0, 60) \text{ min} \), the graph of Equation (6.83) can be plotted in Figure 6.5.

![Figure 6.5 Disutility of travel itself](image)

We now consider the situation when mobile shopping is conducted, which generalises the exact formulation of Equation (6.67). Suppose \( C_{\text{online}} = £1 \), \( T_{\text{online}} = 10 \text{ min} \) and \( Q_{\text{flowers}} = 1 \) representing that the preferred flowers are obtained through mobile shopping, Equation (6.67), together with the disutility of travel in Equation (6.83), are plotted in Figure 6.6.
Figure 6.6 Overall utility of travel compared with disutility of travel

The result shows that the disutility of travelling is reduced significantly by simultaneously performing mobile shopping. The overall utility of travel displays a sharp increase when $T_{\text{journey}}$ is close to $T_{\text{online}} = 10$ min and then decreases gradually after reaching a maximum. This represents that there exists an optimal value of journey time for given attribute values of mobile activities. It is also our interest to find this optimal journey time $T_{\text{journey}}^{\text{opt}}$ when the maximum overall utility of travel is obtained. Let the first order differentiation of Equation (6.67) on $T_{\text{journey}}$ equal to zero, namely that:

$$\frac{\partial V_m}{\partial T_{\text{journey}}} = \beta_{m1} + \beta_{m2} \lambda_m (T_{\text{journey}} - T_{\text{online}})^{\lambda_m - 1} C_{\text{online}}^{\lambda_m}$$

$$= -0.0187 + 0.267 (T_{\text{journey}} - T_{\text{online}})^{1.135} C_{\text{online}}^{0.605} = 0$$

We have:

$$T_{\text{journey}}^{\text{opt}} = \left( -\frac{\beta_{m1} C_{\text{online}}^{-\lambda_m}}{\beta_{m2} \lambda_m^{\lambda_m - 1}} \right)^{\frac{1}{\lambda_m - 1}} + T_{\text{online}} = \left( 0.07 C_{\text{online}}^{-0.605} \right)^{0.88} + T_{\text{online}}$$

$$= 10.4 C_{\text{online}}^{0.53} + T_{\text{online}}$$

The result implies that optimal value of journey time relies on the input variables of
activity production as determined by the underlying technology. Also in Equation (6.84), as \( \lambda_{ml} - 1 = -1.135 \), when \( T_{journey} \gg T_{online} \), \( \left(T_{journey} - T_{online}\right)^{\lambda_{ml}-1} \) is close to zero, \( \frac{\partial V_m}{\partial T_{journey}} \) is asymptotic to \( \beta_{ml} \) which represents the slope of intrinsic disutility of travel itself. As observed in Figure 6.6, the curves are parallel when the difference between journey time and online time is large. This indicates that when remaining journey time is too long, the overall marginal utility of travel approximately equals to the marginal disutility of travel itself.

### 6.2.2.2 Result analysis of process utility of conventional shopping

In this section, the effects of input time and money expenditure on the process utility of conventional shopping and the trade-off between these input factors are examined.

**Relationship between process utility \( V_{cp} \) and input variables**

In Equation (6.70), given a value of input time \( TT^0 + T_{conventional} \), the functional relationship between process utility \( V_{cp} \) and input money expenditure \( TC \) is written as:

\[
V_{cp} = (-0.737) \left[ 0.98TC^{1.97} + 0.02 \left( TT^0 + T_{conventional} \right)^{1.97} \right]^{1/1.97}
\]  

(6.86)

If we set \( TT^0 + T_{conventional} = 20 \text{ min} \) and \( TC \in (0, 5) \), the curve of Equation (6.86) is plotted in Figure 6.7.
As can be seen, $V_c$ shows a decreasing trend among the entire range of $TC$.

Correspondingly, given a value of $TC = TC^0$, the functional relationship between

$V_c$ and input time $TT + T_{conventional}$ in Equation (6.70) is formulated as:

$$V_c = (-0.737) \left[ 0.98(TC^0)^{1.97} + 0.02( TT + T_{conventional} )^{1.97} \right]^{1/1.97}$$  \hspace{1cm} (6.87)

For example, assuming $TC^0 = 3\text{£}$ and $ TT + T_{conventional} \in (0, 60) \text{ min}$, the curve of Equation (6.87) is shown in Figure 6.8
In this result, a similar decreasing pattern of $V^p_c$ with respect to $TT + T_{conventional}$ is observed.

The same conclusions can be reached by taking the first order partial derivatives of Equation (6.70) on input time $TT + T_{conventional}$ and input money expenditure $TC$, which generalised as:

$$\frac{\partial V^p_c}{\partial TC} = \beta_{c1}\beta_{c2}\left[\beta_{c2}TC^\lambda_1 + (1 - \beta_{c2})(TT + T_{conventional})\right]^{\lambda_2 - 1}TC^{\lambda_1 - 1}$$

$$= -0.737 \times 0.98 \times \left[0.98TC^{1.97} + 0.02(TT + T_{conventional})^{1.97}\right]^{1 - 1.97}TC^{0.97}$$

$$= (-0.72)\left[0.98TC^{1.97} + 0.02(TT + T_{conventional})^{1.97}\right]^{-0.5}TC^{0.97}$$

$$\frac{\partial V^p_c}{\partial (TT + T_{conventional})} = \beta_{c1}(1 - \beta_{c2})\left[\beta_{c2}TC^\lambda_1 + (1 - \beta_{c2})(TT + T_{conventional})\right]^{\lambda_2 - 1}$$

$$\times (TT + T_{conventional})^{\lambda_1 - 1}$$

$$= (-0.01)\left[0.98TC^{1.97} + 0.02(TT + T_{conventional})^{1.97}\right]^{-0.5}$$

$$\times (TT + T_{conventional})^{0.97}$$

As $\beta_{c1}\beta_{c2} < 0$ and $\beta_{c1}(1 - \beta_{c2}) < 0$, both Equation (6.88) and Equation (6.89) represent...
negative marginal process utilities with respect to input time and money expenditure, namely, \( \frac{\partial V^p_c}{\partial TC} < 0 \) and \( \frac{\partial V^p_c}{\partial (TT + T_{conventional})} < 0 \). This result is consistent with the observations in Figure 6.7 and Figure 6.8, which implies that an increase in any input variable leads to a decrease in \( V^p_c \). As oppose to mobile shopping, in which online cost is the major factor that influence the shopping decisions, in conventional shopping activity, both input money expenditure and time have significant effects on respondents’ behaviour.

**Relationship between input time and input money**

In order to build the indifference curve between input money expenditure \( TC \) and input time \( TT + T_{conventional} \) with Equation (6.70), \( V^p_c \) is assumed to be given as \( V^{p0}_c \) and \( TC \) is solved as a function of \( TT + T_{conventional} \), i.e.:

\[
TC = \left[ \frac{\left( \frac{V^{p0}_c}{\beta c_1} \right)^{\lambda_1} - (1 - \beta c_2)(TT + T_{conventional})^{\lambda_1}}{\beta c_2} \right]^{\frac{1}{\lambda_1}}
\]

\[
= \left[ \frac{\left( \frac{V^{p0}_c}{-0.737} \right)^{1.97} - 0.02(TT + T_{conventional})^{1.97}}{0.98} \right]^{\frac{1}{1.97}}
\]

We consider the situations when the indifference curves have different values of \( V^{p0}_c \). For instance, assume \( V^{p0}_c \) respectively equals to:

\[
V^{p1}_c = (-0.737) \times \left[ 0.98 + 0.02 \times 30^{1.97} \right]^{\frac{1}{1.97}} = -3.13
\]

when \( TC = \£1 \) and \( TT + T_{conventional} = 30 \text{ min} \).
and \( \frac{V_c}{p_1} = (0.737) \times \left[ 0.98 \times 5^{1.97} + 0.02 \times 40^{1.97} \right]^{1.97} = -5.46 \)

when \( TC = 5 \)£ and \( TT + T_{\text{conventional}} = 40 \) min

Thus \( \frac{V_c}{p_1} > \frac{V_c}{p_2} \). The indifference curves when \( V_c^{p_0} = V_c^{p_1} \) and \( V_c^{p_0} = V_c^{p_2} \) are depicted in Figure 6.9

Figure 6.9 The indifference curves of conventional shopping

The general pattern of indifference curves in Figure 6.9 is similar to that of mobile shopping in Figure 6.4 in that higher process utility drives the indifference curve inward. This result can also be derived by using Equation (6.90). As \( \beta_1 < 0, 0 < \beta_2 < 1 \) and \( \lambda_1 > 1 \), a higher value of \( V_c^{p_0} \) leads to a smaller value of \( TC \) among the entire range of \( TT + T_{\text{conventional}} \). Hence the corresponding indifference curve shifts towards the origin, which we can interpret to mean that individuals empirically prefer the combination of both less time and less money in the conventional shopping context.

In terms of the marginal rate of substitution between input time and money expenditure for conventional shopping activity, it is calculated as the ratio between Equation (6.89) and (6.88):

\[ \text{MRS} = \frac{\frac{V_c}{p_1}}{\frac{V_c}{p_2}} = \frac{V_c^{p_1}}{V_c^{p_2}} \]
Equation (6.91) implies that $M_{TS_c}$ not only depends on the estimated coefficient that characterised the absence of mobile technology, but also rely on the ratio between input variables. As displayed in Equation (6.80) for mobile shopping activity, conventional shopping activity does not permit the perfect substitution effect between input time $TT + T_{conventional}$ and money expenditure $TC$ either. $M_{TS_c}$ tends to infinity when $TC$ approaches zero, implying that time cannot be replaced with money expenditure. Therefore, both input time and money are necessary to pursue conventional shopping activity. As can be imagined, the absence of technology in a conventional context results in the temporal and spatial constraints confronted by individuals, under which both time (e.g. travel time) and money (e.g. travel cost) have to be devoted to pursue activities.

It should be mentioned that for both mobile shopping in Equation (6.69) and conventional shopping in Equation (6.70), the ‘saturation effect’ of the duration models is not captured via the attribute of $T_{online}$ and $TT + T_{conventional}$. This effect arises as existing scheduling models regard ‘activity duration’ as the ‘available time allocated to activity according to the current schedule’; hence time is considered to be a ‘consumption resource’. The previously-discussed utility models in Chapter 3 merge the process utility component with the outcome utility component. Researchers have assumed that longer activity duration gives rise to better consumption outcomes. Thus individuals are considered to obtain higher utility (corresponding to the sum of process utility and outcome utility in our model) when more time is assigned to an activity. However in the model proposed above, the attributes $T_{online}$ and $TT + T_{conventional}$ are respectively defined
as the actual amount of time spent in a mobile shopping activity and a conventional shopping activity. The process utility and outcome utility are treated separately. Hence no 'saturation effect' is incorporated.

6.2.2.3 Comparison between conventional shopping and mobile shopping

The estimation results of the process utility functions in both shopping alternatives have been examined in depth in this chapter. Hence the problem addressed in this section is to compare these estimation results, through which the impact of mobile technology on people’s activity participation behaviour can be identified.

*Comparing the process utility with respect to input time*

It has been found previously that both the process utility of conventional shopping \( V_{c}^{p} \) and the process utility of mobile shopping \( V_{m}^{p} \) decrease with respect to the input time. In Equation (6.69) and Equation (6.70), suppose both shopping alternatives have the same input money expenditure, for example, \( T_{\text{journey}}^{0} = 60\text{min} \) \( C_{\text{online}}^{0} = £3 \) for mobile shopping and \( T_{C}^{0} = £3 \) for conventional shopping. The resulting diagraphs of Equation (6.69) and Equation (6.70) are drawn in Figure 6.10
Figure 6.10 Comparison of process utilities with respect to input time

As previously discussed, although both curves have decreasing trends with respect to the increase of input time, mobile shopping exhibits concave pattern as oppose to an approximately linear pattern of conventional shopping activity. This represents that respondents are more sensitive to the input time consumed in conventional shopping than that in mobile shopping, presumably due to the time use effect of engaging in mobile shopping while simultaneously travelling. As can be seen in Figure 6.10, given the same value of input money expenditure, the presence of mobile technology enables a higher process utility in mobile shopping among the entire range of input time. The curves of process utility in both shopping alternatives diverge when input time increases. This implies that when a larger amount of input time is required for the activity production process, it is more likely that respondents will choose mobile shopping given an unchanged consumption outcome.

Comparison between process utilities with relates to input money expenditure

It has also been observed in previous analysis that both the process utility of conventional shopping and the process utility of mobile shopping $V^p_m$ decrease with respect to the input money expenditure. To make a comparison of this effect, consider both shopping activities having the same input time. For mobile shopping activity, assume $T^0_{journey} = 60\text{min}$ and $T^0_{online} = 20\text{min}$. For conventional shopping activity, assume $TT^0 + T^0_{conventional} = 20\text{min}$. Hence the diagraphs of Equation (6.69) and Equation (6.70) can be plotted in Figure 6.11.
Figure 6.11 Comparison of process utilities with relates to input money expenditure

As shown in Figure 6.11, $V_m^p$ and $V_c^p$ exhibit a similar pattern of decrease. $V_m^p$ has a higher value than $V_c^p$ among the entire range of input money expenditure. This indicates that respondents’ decisions in both shopping activities are continuously influenced by the amount of input money. Given value of input time and consumption outcome, individuals may prefer to use mobile shopping in the presence of mobile technology.

**Comparison of indifference curves of input variables**

With an aim to construct the indifference curves in Equation (6.79) and Equation (6.90) in one graph, we set $T_{journey}^0 = 45$ min and $V_m^{p0} = V_c^{p0} = -5.5$. The resulting function curves of Equation (6.79) and (6.90) are plotted in Figure 6.12.
Compared with mobile shopping, the indifference curves for conventional shopping have lower slopes among the entire range of input time. This implies that the adoption of mobile technology in a shopping activity gives rise to a more significant substitution effect in mobile shopping than in conventional shopping. Given any value of input money expenditure, the use of mobile technology permits to consume a higher amount of time than conventional shopping, while achieving same level of disutility in production process.

6.2.2.4 Summary

Overall conclusions from the estimation results are summarised here. In general, the results are keeping with our priori expectations. In both the conventional shopping and mobile shopping contexts, individuals appear to derive overall disutility from the production process and positive utility from the outcome consumption. For both shopping alternatives, increasing input time and/or money is found empirically to lead to higher disutility of production process and hence lower overall utility for a given consumption output. In both shopping activities, input money expenditure continuously influences an individual’s choice decision, while input time appears to play a more significant role in
conventional shopping than in mobile shopping. In this experiment, for a mobile shopping activity, respondents seem to be indifferent regarding how much time is input to conduct activities while they are travelling. Also the disutility of travel is compensated by the utility of mobile shopping conducted simultaneously while travelling. Given the same process utility, the presence of mobile technology brings about a more significant substitution effect between input variables than in conventional shopping.

It should also be noted that the definition of activity input time departs from the classical convention in activity-based analysis and the utility of an activity is separated into two components in our model; hence the ‘saturation effects’ of duration models are not captured in our model.

### 6.3 Extended specifications accommodating taste heterogeneity

#### 6.3.1 Taste heterogeneity

The SC data used in model estimation are pooled together over not only hypothetical choice sets but also sampled respondents. However, the MNL model structure presented above imposes various implicit assumptions, including that of identical parameter estimations across different individuals. Hence we extend the above classical model specification to accommodate taste heterogeneity across sampled respondents.

A number of studies have accommodated taste heterogeneity in travel choice behaviour (Ben-Akiva et al., 1993; Bhat, 1998, 2000c; Train, 1998). In this context, taste heterogeneity refers to taste variation across different individuals in the intrinsic bias towards difference alternatives (i.e. termed as ‘preference heterogeneity’) and responsiveness to independent variables (i.e. termed as ‘response heterogeneity’). Seen from another perspective, taste heterogeneity can also be decomposed into observed
heterogeneity and unobserved heterogeneity. Observed heterogeneity corresponds to that
due to the individual’s observed characteristics. Unobserved heterogeneity is associated
with that due to the individual’s unobservable characteristics, thus allowing for
differential sensitivity to explanatory variables amongst different group of people. In
discrete choice modelling, both observed and unobserved heterogeneity are relevant. As
proposed by Bhat (1996), researchers should always first attempt to attribute the
heterogeneity to the observable component to the degree possible, and only then consider
imposing the unobserved heterogeneity to the best observed specification.

According to Bhat (1998), there are different ways to capture the observed and
unobserved components of preference heterogeneity and response heterogeneity.
Observed preference heterogeneity can be incorporated by introducing the individual’s
characteristics as explanatory variables directly. Unobserved preference heterogeneity is
accommodated by inserting an additive stochastic error term in the utility function of each
alternative. Observed response heterogeneity is commonly captured by relating
individual characteristics to the attributes of alternatives (e.g., travel time divided by cost,
out-of-vehicle time divided by distance, the price divided by income and so on) or by
using data segmentation or attribute segmentation techniques. These techniques rely on
appropriate segmentation criteria and normally only one or two individual characteristics
are considered for segmentation in order to keep estimation manageable. Unobserved
response heterogeneity can be accommodated by “pure” random parameters.
Alternatively, in order to capture both observed and unobserved response heterogeneity
comprehensively, the means and standard deviations of random parameters can be
re-parameterised as a function of relevant observable variables. For example, we can
represent the mean of random parameters as a linear additive function of socio economic
characteristic or the attributes of alternatives.
6.3.2 Extended model specifications and estimation results

The basic utility models in Equation (6.47) and (6.46) are extended here to accommodate taste heterogeneity across individuals based on the procedures described above. In recent years, the mixed logit (ML) model structure has been employed to accommodate various types of taste heterogeneity in a holistic manner (Bhat, 1998; Hensher and Green, 2001). Therefore in this thesis, we formulate ML based models of shopping choice that accommodate both response heterogeneity and unobserved preference heterogeneity. To allow for unobserved preference heterogeneity, an individual-invariant bias constant, which varies with respondents rather than choice observations, was linearly added to basic utility function. With regards to the response heterogeneity, two specifications are examined here. The first specification allows for observed response heterogeneity by representing the selected coefficients as a function of relevant observed individual characteristics. The second specification for the response coefficients superimpose a random term over the observed response heterogeneity of the first specification, which allows for both observed and unobserved response heterogeneity. The unobserved response heterogeneity represents random taste variations to certain attributes across individuals with the same observed characteristics.

Consider \( U_{mnt} \) as the utility that individual \( n \) associates with mobile shopping in choice scenario \( t \) (\( t = 1,2,...,18 \)) and \( U_{cnt} \) as the utility that individual \( n \) associates with conventional shopping in choice scenario \( t \) (\( t = 1,2,...,18 \)), we have:

\[
U_{mnt} = V_m(z_{mnt};B_m) + \eta_{mnt} + \epsilon_{mnt} \tag{6.92}
\]

\[
U_{cnt} = V_c(z_{cnt};B_c) + \eta_{cnt} + \epsilon_{cnt} \tag{6.93}
\]

Where \( V_m \) is basic utility function of mobile shopping as shown in Equation (6.47); \( V_c \) is basic utility function of conventional shopping as shown in Equation (6.46); \( z_{mnt} \) is the
vector of SC designed attributes of mobile shopping to individual \( n \) in choice scenario \( t \); 
\( z_{nc} \) is the vector of SC designed attributes of conventional shopping to individual \( n \) in choice scenario \( t \). \( \eta_m \) and \( \eta_c \) are pure random term representing individual bias associated with mobile shopping and conventional shopping respectively. Both of them follow normal distributions with zero mean and vary only across individuals. \( \epsilon_{nm} \) and \( \epsilon_{nc} \) are IID Gumbel distribution over all choice set, choice alternatives and individuals, which are used to capture all the other idiosyncratic effect. \( B_{nm} \) is the coefficient vector of attributes of mobile shopping to individual \( n \), while \( B_{cn} \) is the coefficient vector of attributes of conventional shopping to individual \( n \).

According to the basic utility functions in Equation (6.47) and (6.46), \( B_{nm} \) includes the 5 elements of coefficients, while \( B_{cn} \) includes 4 elements of coefficient. Both \( B_{nm} \) and \( B_{cn} \) vary across individuals but not vary across choice sets. Corresponding to the first specification for response coefficient, the \( k^{th} \) element (\( k = 1, 2, 3, 4, 5 \)) \( B_{nm}^k \) of coefficient vector \( B_{nm} \) and the \( k^{th} \) (\( k = 1, 2, 3, 4 \)) element \( B_{cn}^k \) of coefficient vector \( B_{cn} \) are respectively represented as:

\[
B_{nm}^k = \kappa_{m0}^k + \gamma_m^k x_n \quad (6.94)
\]

\[
B_{cn}^k = \kappa_{c0}^k + \gamma_c^k x_n \quad (6.95)
\]

In the second specification for response coefficients, \( B_{nm}^k \) and \( B_{cn}^k \) are represented as:

\[
B_{nm}^k = \kappa_m^k + \gamma_m^k x_n + \nu_{nm}^k \quad (6.96)
\]

\[
B_{cn}^k = \kappa_c^k + \gamma_c^k x_n + \nu_{cn}^k \quad (6.97)
\]
Where \( x_n \) is the vector of relevant observed characteristics of individual \( n \), \( \gamma^k_m \) and \( \gamma^k_c \) are respectively the corresponding vectors of coefficients of mobile shopping and conventional shopping, \( \kappa^k_m \) and \( \kappa^k_c \) are constant coefficients; \( \nu^k_m \) and \( \nu^k_c \) represent the random response heterogeneity that vary across individuals but are independent across response coefficients. Both \( \nu^k_m \) and \( \nu^k_c \) are assumed to be normal distribution with zero mean and variances to estimate. According to the description in Section 6.1.4.2, we refer to the first specification as ECL structure, while the second specification as mixed RCL and ECL structure.

It should also be noted that in discrete choice theory, only difference between utilities matters, thus \( \eta_m \) and \( \eta_c \) are not independently identifiable. Therefore, in order to obtain manageable estimation using BIOGEME 1.5, we maintain the conventional shopping as the base in accommodating the preference heterogeneity across individuals and normalize the variance of preference term to zero. Thus Equation (6.92) and (6.93) are rewritten as:

\[
U_{mnt} = V_m \left( z_{mnt}; B_m \right) + \eta_{mnt} + \epsilon_{mnt} \quad (6.98)
\]

\[
U_{cnt} = V_c \left( z_{cnt}; B_c \right) + \epsilon_{cnt} \quad (6.99)
\]

Where \( \eta_{mnt-c} \) is difference between the random term \( \eta_{mnt} \) and \( \eta_{mc} \) also following a normal distribution with zero mean and standard deviation \( \sigma_{\eta_{mnt-c}} \) to be estimated.

To derive the unconditional choice probability of individual \( n \) to choose mobile shopping \( \text{Prob}(n,m) \) and conventional shopping \( \text{Prob}(n,c) \), we should calculate the integral of logit formula with relates to all independent random variables, namely that:
\[
\text{Prob}(n,m) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{v_m(n_m) + \eta_{mn,c}} e^{v_c(n_c)} \\
\times f(v_{mm}) f(v_{mc}) f(v_{cm}) f(v_{cc}) d\eta_{mn,c} d\eta_{mn,c} \\
\text{Prob}(n,c) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{v_c(n_c)} \\
\times f(v_{mm}) f(v_{mc}) f(v_{cm}) f(v_{cc}) d\eta_{mn,c} d\eta_{mn,c}
\]

Where \( f(\ ) \) is the probability density function of normal distribution with zero mean and variances to be estimated. Given our small dataset and the nonlinearity of basic utility specification, the estimation of models with all response coefficients of alternatives being random are time consuming and unrealistic. Therefore, in each extended basic specification, only one response coefficient is selected to incorporate observed and unobserved response heterogeneity. Based on the result analysis in section 6.2.2, several coefficients that are of our interest, namely the coefficients relevant to MTS\(_m\) in Equation (6.80) and MTS\(_c\) in Equation (6.91) as well as the generic attribute \( \beta_G \), are examined in the following part of this section.

As introduced in Section 6.1.5.2, each extended model was estimated using 500 Maximum Likelihood Halton Sequences (MLHS) draws. The stability of parameter estimates has been tested. An overall discussion on the estimation results is provided at the end of this section.

**Response heterogeneity of \( \beta_G \)**

In this specification, the response heterogeneity is only applied to the generic coefficient of outcome utility in both shopping alternatives. The other elements of coefficients in the response vector \( B_{mn} \) and \( B_{mc} \) are maintained to be same across all the individuals. Stated formally, \( \beta_G \) in corresponding ECL model and mixed RCL and ECL model are represented as:
\[ \beta_{Gn} = \kappa_G + \gamma_G' x_n \]
\[ \beta_{Gn} = \kappa_G + \gamma_G' x_n + \nu_{Gn} \]

Where \( x_n \) is a vector of relevant observed characteristics of individual \( n \); \( \gamma_G \) is corresponding vector of coefficients; \( \kappa_G \) is constant coefficient, \( \nu_{Gn} \) is normal distribution with zero mean and variance \( \sigma^2_{\nu_{Gn}} \) to be estimated. In order to search the specification of vector \( x_n \), all the individual characteristics collected through the questions in part 3 were taken into account. Three dummy variables associated with individual general internet usage and socio-demographic characteristics were considered to constitute the most successful specification of \( x_n \). These variables are:

- Dummy variable for gender male
- Dummy variable for income lower than 15k
- Dummy variable for having internet access at home and work

The results from the most successful specification are summarized in Table 6.17.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>RCL</th>
<th>RCL and ECL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \beta_{m1} )</td>
<td>-0.0209(-1.95*)</td>
<td>-0.0192(-1.60*)</td>
</tr>
<tr>
<td>( \beta_{m2} )</td>
<td>-2.49(-4.26)</td>
<td>-2.90(-4.60)</td>
</tr>
<tr>
<td>( \lambda_{m1} )</td>
<td>-0.132(-2.61)</td>
<td>-0.113(-2.54)</td>
</tr>
<tr>
<td>( \lambda_{m2} )</td>
<td>0.593(6.18)</td>
<td>0.579(6.82)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \beta_{c1} )</td>
<td>-0.898(-5.15)</td>
<td>-1.00(-5.20)</td>
</tr>
<tr>
<td>( \beta_{c2} )</td>
<td>0.979(36.62)</td>
<td>0.975(32.73)</td>
</tr>
<tr>
<td>( \lambda_{c1} )</td>
<td>1.97(3.63)</td>
<td>1.90(3.79)</td>
</tr>
<tr>
<td>Response heterogeneity(( \beta_{Gn} ))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0079(-0.02*)</td>
<td>-0.0838(-0.09*)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.957(2.86)</td>
<td>1.09(1.79*)</td>
</tr>
<tr>
<td>Low income</td>
<td>0.546(1.67*)</td>
<td>0.6(1.03*)</td>
</tr>
<tr>
<td>Internet access</td>
<td>1.61(3.42)</td>
<td>2.04(2.35)</td>
</tr>
<tr>
<td>( \sigma_{Gn} )</td>
<td>---</td>
<td>1.56(4.68)</td>
</tr>
<tr>
<td>Preference heterogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \eta_{nm,c} )</td>
<td>-0.943(-6.04)</td>
<td>-1.07(-5.99)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.385</td>
<td>0.402</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-379.268</td>
<td>-367.212</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level
Response heterogeneity of $\lambda_{c1}$

In this specification, the response heterogeneity is only applied to the coefficient $\lambda_{c1}$ of conventional shopping. Stated formally, the specifications of $\lambda_{c1}$ in ECL model and mixed RCL and ECL model are represented as:

$$\lambda_{c1n} = \kappa_{c1} + \gamma_{c1} ' x_n$$  \hspace{1cm} (6.104)$$

$$\lambda_{c1n} = \kappa_{c1} + \gamma_{c1} ' x_n + \nu_{c1n}$$  \hspace{1cm} (6.105)$$

Where $x_n$ is vector of relevant observed characteristics of individual $n$; $\gamma_{c1}$ is corresponding vector of coefficients; $\kappa_{c1}$ is constant coefficient, $\nu_{c1n}$ is normal distribution with zero mean and variance $\sigma_{\nu_{c1n}}^2$ to be estimated. Various specification of vector $x_n$ are searched in all the individual characteristics collected through the questions in part 3. The most successful specification of $x_n$ includes the following individual characteristics:

- Dummy variable for income lower than 15k
- Dummy variable for having internet access at home and work
- Dummy variable for no mobile internet experience
- Dummy variable for no mobile shopping experience
- Dummy variable for online shopping experience
- Big-five personality score: openness, extraversion and agreeableness

The results from the most successful specification are summarized in Table 6.18.
Table 6.18 Estimation results for response heterogeneity for $\lambda_{c1}$

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ECL</th>
<th>ECL and RCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile</td>
<td>$\beta_{m1}$</td>
<td>-0.0192(-1.78*)</td>
</tr>
<tr>
<td>Shopping</td>
<td>$\beta_{m2}$</td>
<td>-2.37(-4.18)</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{m1}$</td>
<td>-0.129(-2.45)</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{m2}$</td>
<td>0.601(6.10)</td>
</tr>
<tr>
<td>Conventional Shopping</td>
<td>$\beta_{c1}$</td>
<td>-0.846(-4.85)</td>
</tr>
<tr>
<td>Response heterogeneity($\lambda_{c1n}$)</td>
<td>$\beta_{c2}$</td>
<td>0.977(30.79)</td>
</tr>
<tr>
<td>Generic</td>
<td>$\beta_{G}$</td>
<td>2.28(11.64)</td>
</tr>
<tr>
<td>Preference heterogeneity</td>
<td>$\eta_{mn,c}$</td>
<td>-0.794(-5.02)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.390</td>
<td>0.396</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-372.222</td>
<td>-367.201</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

Response heterogeneity of $\lambda_{m2}$

In this specification, the response heterogeneity is only applied to the coefficient $\lambda_{m2}$ of mobile shopping. Stated formally,

$$
\lambda_{m2n} = \kappa_{m2} + \gamma_{m2}^\top x_n
$$  (6.106)

$$
\lambda_{m2n} = \kappa_{m2} + \gamma_{m2}^\top x_n + \nu_{m2n}
$$  (6.107)

Where $x_n$ is vector of relevant observed characteristics of individual $n$; $\gamma_{m2}$ is corresponding vector of coefficients; $\kappa_{m2}$ is constant coefficient; $\nu_{m2n}$ is normal distribution with zero mean and variance $\sigma_{\nu_{m2}}^2$ to be estimated. The most successful specification of $x_n$ comes from the same individual characteristics listed in Table 6.18.

The estimation results are summarised in Table 6.19.
Table 6.19 Estimation results for response heterogeneity of $\lambda_{m2}$

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ECL</th>
<th>ECL and RCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile</td>
<td>$\beta_{m1}$</td>
<td>-0.0226(-2.21)</td>
</tr>
<tr>
<td>Shopping</td>
<td>$\beta_{m2}$</td>
<td>-2.28(4.00)</td>
</tr>
<tr>
<td>$\lambda_{m1}$</td>
<td></td>
<td>-0.147(-2.68)</td>
</tr>
<tr>
<td>Conventional</td>
<td>$\beta_{c1}$</td>
<td>-0.790(-4.36)</td>
</tr>
<tr>
<td>Shopping</td>
<td>$\beta_{c2}$</td>
<td>0.960(19.43)</td>
</tr>
<tr>
<td>$\lambda_{c1}$</td>
<td></td>
<td>1.69(3.26)</td>
</tr>
<tr>
<td>Generic</td>
<td>$\beta_{g}$</td>
<td>2.33(11.65)</td>
</tr>
<tr>
<td>Response heterogeneity($\lambda_{m2n}$)</td>
<td>Constant</td>
<td>1.36(5.30)</td>
</tr>
<tr>
<td>Low income</td>
<td></td>
<td>0.0586(1.67*)</td>
</tr>
<tr>
<td>Internet access</td>
<td></td>
<td>-0.225(-3.92)</td>
</tr>
<tr>
<td>Online shopping</td>
<td></td>
<td>-0.386(-3.13)</td>
</tr>
<tr>
<td>No m-internet</td>
<td></td>
<td>-0.134(-3.26)</td>
</tr>
<tr>
<td>No m-shopping</td>
<td></td>
<td>0.190(2.51)</td>
</tr>
<tr>
<td>Openness</td>
<td></td>
<td>-0.0127(0.68*)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td></td>
<td>-0.0127(0.68*)</td>
</tr>
<tr>
<td>Extraversion</td>
<td></td>
<td>-0.0577(-2.60)</td>
</tr>
<tr>
<td>$\sigma_{nm2n}$</td>
<td></td>
<td>---</td>
</tr>
<tr>
<td>Preference heterogeneity</td>
<td>$\eta_{nm,c}$</td>
<td>-0.791(-4.89)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td></td>
<td>0.394</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td></td>
<td>-369.770</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

**Response heterogeneity of $\lambda_{m1}$**

In this specification, the response heterogeneity is only applied to the coefficient $\lambda_{m1}$ of mobile shopping. Stated formally,

\[
\hat{\lambda}_{mln} = \kappa_{m1} + \gamma_{m1}'x_n
\]  \hspace{1cm} (6.108)

\[
\hat{\lambda}_{mln} = \kappa_{m1} + \gamma_{m1}'x_n + \nu_{mln}
\]  \hspace{1cm} (6.109)

Where $x_n$ is vector of relevant observed characteristics of individual $n$; $\gamma_{m1}$ is corresponding vector of coefficients; $\kappa_{m1}$ is constant coefficient, $\nu_{mln}$ is normal distribution with zero mean and variance $\sigma^2_{\nu_{mln}}$ to be estimated. The most successful specification of $x_n$ comes from the same individual characteristics in Table 6.18. The estimation results are summarised Table 6.20.

202
Table 6.20 Estimation results for response heterogeneity for $\lambda_m$

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ECL</th>
<th>ECL and RCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile</td>
<td>$\beta_{m1}$</td>
<td>-0.0313(-3.19)</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{m2}$</td>
<td>0.793(4.91)</td>
</tr>
<tr>
<td>Shopping</td>
<td>$\beta_{m2}$</td>
<td>-1.70(-2.90)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.790(4.88)</td>
</tr>
<tr>
<td>Conventional</td>
<td>$\beta_c$</td>
<td>-0.739(-4.01)</td>
</tr>
<tr>
<td>Shopping</td>
<td>$\lambda_c$</td>
<td>0.954(16.71)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.955(16.56)</td>
</tr>
<tr>
<td>Generic</td>
<td>$\beta_G$</td>
<td>2.30(11.62)</td>
</tr>
<tr>
<td>Response heterogeneity($\lambda_{m2n}$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>$\beta_{c2}$</td>
<td>0.251(1.61*)</td>
</tr>
<tr>
<td>Low income</td>
<td></td>
<td>0.0468(1.63*)</td>
</tr>
<tr>
<td>Online shopping</td>
<td></td>
<td>0.0477(1.69*)</td>
</tr>
<tr>
<td>No m-internet</td>
<td>$\lambda_{c1}$</td>
<td>1.64(3.10)</td>
</tr>
<tr>
<td>No m-shopping</td>
<td></td>
<td>1.65(3.10)</td>
</tr>
<tr>
<td>Openness</td>
<td>$\lambda_{c2}$</td>
<td>0.90952(-0.63*)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>$\lambda_{c3}$</td>
<td>-0.00952(-0.63*)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>$\lambda_{c4}$</td>
<td>-0.036(-2.03)</td>
</tr>
<tr>
<td></td>
<td>$\sigma_{v_{m1n}}$</td>
<td>-0.0217(-0.68*)</td>
</tr>
<tr>
<td>Preference heterogeneity</td>
<td>$\eta_{nm,c}$</td>
<td>-0.809(-4.80)</td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td></td>
<td>0.386</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td></td>
<td>-374,571</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

**Response heterogeneity of $\beta_{c2}$**

In this specification, the response heterogeneity is only applied to the coefficient $\beta_{c2}$ in mobile shopping. As in Equation (6.46), $\beta_{c2}$ represents the importance of input money to the process utility relative to input time. $\beta_{c2}$ is larger than 0 and smaller than 1. Therefore a transformation is applied to the linear specification of $x_n$ to ensure $\beta_{c2n} \in [0,1]$. Stated formally,

$$
\beta_{c2n} = \frac{1}{1 + e^{\kappa_{c2}^{n} \gamma_{c2}^{n} x_n}}
$$

(6.110)

$$
\beta_{c2n} = \frac{1}{1 + e^{\kappa_{c2}^{n} \gamma_{c2}^{n} x_n + \nu_{c2n}}}
$$

(6.111)

Where $\gamma_{c2}$ is corresponding vector of linear coefficients; $\kappa_{c2}$ is constant coefficient, $\nu_{c2n}$ is normal distribution with zero mean and variance $\sigma_{v_{c2n}}^2$ to be estimated. In order to search the specification of vector $x_n$, all the individual characteristics collected through the questions in part 3 were taken into account. The results from the most successful
specification are summarized in Table 6.21.

Table 6.21 Estimation results for response heterogeneity of $\beta_{c2}$

<table>
<thead>
<tr>
<th>Attributes</th>
<th>ECL</th>
<th>ECL and RCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile Shopping</td>
<td>$\beta_{m1}$</td>
<td>-0.0141(-1.40*)</td>
</tr>
<tr>
<td></td>
<td>$\beta_{m2}$</td>
<td>-2.25(-4.34)</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{m1}$</td>
<td>-0.110(-2.18)</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{m2}$</td>
<td>0.570(6.15)</td>
</tr>
<tr>
<td>Conventional Shopping</td>
<td>$\beta_{c1}$</td>
<td>-0.818(-5.69)</td>
</tr>
<tr>
<td></td>
<td>$\lambda_{c1}$</td>
<td>2.15(3.53)</td>
</tr>
<tr>
<td>Generic</td>
<td>$\beta_{G}$</td>
<td>2.04(11.93)</td>
</tr>
<tr>
<td>Response heterogeneity($\lambda_{m2n}$)</td>
<td>Constant</td>
<td>-8.66(-3.00)</td>
</tr>
<tr>
<td></td>
<td>Low income</td>
<td>-0.282(-2.26)</td>
</tr>
<tr>
<td></td>
<td>Internet access</td>
<td>0.885(2.45)</td>
</tr>
<tr>
<td></td>
<td>Online shopping</td>
<td>2.19(2.03)</td>
</tr>
<tr>
<td></td>
<td>No m-internet</td>
<td>0.251(1.95*)</td>
</tr>
<tr>
<td></td>
<td>No m-shopping</td>
<td>-0.438(-2.07)</td>
</tr>
<tr>
<td></td>
<td>Openness</td>
<td>0.175(2.52)</td>
</tr>
<tr>
<td></td>
<td>Agreeableness</td>
<td>0.175(2.52)</td>
</tr>
<tr>
<td></td>
<td>Extraversion</td>
<td>0.210(2.49)</td>
</tr>
<tr>
<td></td>
<td>$\sigma_{uc2n}$</td>
<td>---</td>
</tr>
<tr>
<td>Preference heterogeneity</td>
<td>$\eta_{nm_{c}}$</td>
<td>-0.0824(-4.38)</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

Discussions

The results in Table 6.17 - Table 6.21 show that the extended models incorporating taste heterogeneity significantly outperform the basic model in Table 6.8 in terms of both the values of adjusted rho-square and final log likelihood. In general, the estimated coefficients in ECL models are similar to that of mixed ECL and RCL models. However, there are some differences. The standard deviations of the preference heterogeneity terms are significant in all ECL models. This implies a significant variation in preference for mobile shopping over conventional shopping when only observed response heterogeneity is incorporated. However, the terms of preference heterogeneity become relatively insignificant in Table 6.18 and Table 6.21 when the unobserved response heterogeneity is taken into account. This suggests that the `significant' preference heterogeneities in ECL model are actually a reflection of random response
heterogeneity to corresponding coefficients. Additionally, in Table 6.17, Table 6.18, Table 6.19 and Table 6.21, mixed ECL and RCL models have a higher overall level of fit than the corresponding ECL models. The estimated standard deviations of the response coefficients are highly significant indicating that there is random variation in tastes with respect to corresponding attributes even after accounting for observed sensitivity differences.

Additionally, in order to explain the influence of relevant individual characteristics on the response coefficients explicitly, we need to know the signs of these coefficients across different individuals. Based on the linear specifications in ECL model, the response coefficients are calculated using the estimated linear coefficients and the corresponding individual variables in our SC data. It turns out that by this calculation the response coefficients of each individual have the same sign as that in basic model. Hence for a positive response coefficient (e.g. $\lambda_{m2n}$, $\beta_{Gn}$, $\lambda_{cIn}$) of activity attributes, a negative sign on the coefficient of relevant individual characteristic implies lower response sensitivity and a positive sign indicates higher response sensitivity. On the contrary, for a negative response coefficient (e.g. $\lambda_{m1n}$) of activity attribute, a negative sign on the coefficient of individual characteristics implies higher response sensitivity and a positive sign indicates lower response sensitivity.

The results in Table 6.17 corresponding to the observed heterogeneity to the outcome utility show that male, individuals with low income and frequent internet access are more sensitive to outcome utility than female, individuals with high income and infrequent internet access, respectively. Individuals with low income may be concerned about whether their money has been spent appropriately and male may be concerned about the quality of a present to a female friends, such as flowers. To individuals with frequent internet access, online shopping may become a part of their daily life such that the quality of obtained goods raises their attention. The results in Table 6.19
corresponding to the observed heterogeneity to the online cost of mobile shopping show that individuals with low income and no mobile shopping experience are more sensitive to the online cost than individuals with high income and mobile shopping experience. Also individuals with frequent internet access, online shopping experience and without mobile internet access are less sensitive to the online cost than individuals without infrequent internet access, online shopping experience and with regular mobile internet access respectively. With regards to the results corresponding to the online time of mobile shopping in Table 6.20, individuals with low income and no mobile shopping experience are less sensitive to individuals with high income and regular mobile shopping experience. Also individuals with frequent internet access and online shopping experience are more sensitive than individuals without internet access and online shopping experience. Personal traits, such as extraversion, openness and agreeableness, also influence the response sensitivity of attributes of mobile shopping. Referring to the Equation (6.80), marginal substitution rate (MTS_m) between input time and money of mobile shopping relies on both the values of \( \lambda_{m2} \) and \( \lambda_{m1} \). It can be concluded that individuals with high income, frequent internet access, online shopping experience and high scores in personal traits have a higher value of MTS_m than individuals with low income, without frequent internet access and no online experience, and with low scores in personal traits.

With regards to the results of conventional shopping, similar conclusions could be reached. For example, as \( \beta_{c2} \) represents the importance attached to the input money expenditure by individuals in making conventional shopping choice decision while \( 1 - \beta_{c2} \) represents the importance attached to the input time when making conventional shopping choice decision. Hence based on the specification in Equation (6.110), in Table 6.21, a positive sign of coefficients of individual characteristics implies a lower response sensitivity to input money expenditure than that to input time, while a negative coefficients of individual characteristics implies a higher response sensitivity to input.
money than that to input time. It can be concluded that individuals with low income and no mobile shopping experience have a higher sensitivity to input money relative to input time than individuals with high income and mobile shopping experience. Referring to equation (6.91), marginal rate of substitution between input variables of conventional shopping (MTSc) relies on the values of βc2 and λc1. Higher value of λc1 and lower value of βc2 leads to larger value of MTSc. Hence individuals with high income, frequent internet access, online shopping experience obtain a higher value of MTSc than individuals with lower income, without frequent internet access and online shopping experience.

Finally, at the end of our model estimation, the issue of sequencing effect touched on Section 5.4.2. is re-examined using the extended ML model structure that incorporates the taste heterogeneity. With the best overall level of fit in terms of both the values of adjusted rho-square and model log likelihood, the specification that accommodates both preference heterogeneity and response heterogeneity of outcome utility is selected as our reference model. In this context, we apply the specification of addressing the sequencing effect described in Section 5.4.2. to our analysis, in which a specific error of replication is superimposed over the extended utility function. Stated explicitly, the extended specification addressing the sequencing effect based on our reference model is written as:

\[
U_{mnt} = V_m(z_{mnt}; \beta_{Gm}) + \eta_{mnt} + \phi_{mnt} + \varepsilon_{mnt} \quad (6.112)
\]

\[
U_{cnt} = V_c(z_{cnt}; \beta_{Gn}) + \varepsilon_{cnt} \quad (6.113)
\]

Where \( \beta_{Gn} \) is represented as the form in Equation (6.103). \( \phi_{mnt} \) (t = 1,2,...18) is the specific error of replication t following normal distribution with zero mean and variance to be estimated. The error variance of replication t is normalised as:

\[
\text{var}(\phi_{mnt}) = (\alpha(t-1)^2 + \beta(t-1) + 1)\sigma^2 \quad (6.114)
\]

Where \( \sigma \) is the standard deviation of reference base (i.e. first replication) and \( t \) is the
replication sequence ($t=1,2,\ldots,18$). The estimation results are summarised in Table 6.22.

The results show that the addition of specific error term of replication through the polynomial in Equation (6.114) has made only a small difference to the estimated coefficients. Comparing the overall performance of these two models, there is only a small improvement in the model likelihood while the adjusted rho-square declines slight. And finally, as the coefficients of polynomial in Equation (6.114) are all insignificant, there is no evidence of systematic change in the magnitude of errors through polynomial that moves through the sequence of replications. Overall, the results from this analysis is consistent with the previous results in Table 5.15 suggesting that there were no strong sequencing effect in the responses of shopping choices to the SC experiment.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Extended model</th>
<th>Extended model with sequencing effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{m1}$</td>
<td>-0.0192(-1.60*)</td>
<td>-0.0215(-1.51*)</td>
</tr>
<tr>
<td>$\lambda_{m1}$</td>
<td>-0.113(-2.54)</td>
<td>-0.113(-2.54)</td>
</tr>
<tr>
<td>$\lambda_{m2}$</td>
<td>0.579(6.82)</td>
<td>0.583(6.80)</td>
</tr>
<tr>
<td>Conventional shopping</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{c1}$</td>
<td>-1.00(-5.20)</td>
<td>-1.16(-4.11)</td>
</tr>
<tr>
<td>$\beta_{c2}$</td>
<td>0.975(32.73)</td>
<td>0.977(35.29)</td>
</tr>
<tr>
<td>$\lambda_{c1}$</td>
<td>1.90(3.79)</td>
<td>1.93(3.79)</td>
</tr>
<tr>
<td>Response heterogeneity($\beta_{Gn}$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0838(-0.09*)</td>
<td>-0.0907(-0.08*)</td>
</tr>
<tr>
<td>Gender</td>
<td>1.09(1.79*)</td>
<td>1.38(1.80*)</td>
</tr>
<tr>
<td>Low income</td>
<td>0.6(1.03*)</td>
<td>0.364(0.53*)</td>
</tr>
<tr>
<td>Internet access</td>
<td>2.04(2.35)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{Gn}$</td>
<td>1.56(4.68)</td>
<td>1.78(3.75)</td>
</tr>
<tr>
<td>Preference heterogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta_{num,c}$</td>
<td>-1.07(-5.99)</td>
<td>-1.25(-4.24)</td>
</tr>
<tr>
<td>Polynomials parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>-1.61(-1.25*)</td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>-0.118(-1.35*)</td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.00604(1.11*)</td>
<td></td>
</tr>
<tr>
<td>Adjusted rho-square</td>
<td>0.402</td>
<td>0.400</td>
</tr>
<tr>
<td>Final log likelihood</td>
<td>-367.212</td>
<td>-365.977</td>
</tr>
</tbody>
</table>

*indicate that the corresponding parameters are insignificant at 5% level

6.4 Conclusions

This chapter presented the estimation results of the utility model of shopping
choice based on the activity production approach previously discussed in Chapter 4. Although the SC data set used in this research is relatively small, the model provides us a number of significant and meaningful results. In general, these empirical results not only support the proposition previously made in our modelling framework, but also is in line with some basic assumptions in existing literatures. These empirical results are summarised here.

First of all, it was found that the best basic model arises as a modified Cobb-Douglas form of process utility of mobile shopping and a CES form of process utility of conventional shopping, which supports the proposition that each production technology is characterized by a unique process utility function. Additionally, the basic model allows for the interaction between the journey time and online time of mobile shopping as a difference form entering the process utility function. This is consistent with our intuition that journey time influences the decision of mobile shopping of individual travellers.

Secondly, the theoretical and empirical implications derived from the basic model suggest that in both shopping context, individuals obtain disutility from production process and utility from consumption outcome. To our SC respondents, input money expenditure plays a more significant role in mobile shopping than input time, while input time has a more significant effect in conventional shopping than in mobile shopping. The intrinsic disutility of travel itself is decreased by conducting simultaneous activity of mobile shopping. Given the same process utility, substitution effect between input variables differs between the two shopping contexts due to the presence of mobile technology.

Finally, ML based models were formulated to accommodate various taste heterogeneity. Strong evidence of variations in both response coefficients and alternative preference were found. Some deviations from our expectations are found, which are
likely to be the result of small data set and the commonality in socio-demographics among our respondents.
7 Conclusions and recommendations for further work

The research in this thesis allows us to draw a number of conclusions. This chapter starts by presenting them according to the research objectives described in Chapter 1. Potential directions for further research are then provided.

7.1 Summary of this research

In this section, we revisit the research objectives enunciated in Chapter 1 and summarise and the relevant findings and conclusions.

Specify a novel approach to formulate a theoretical framework which accurately represents the behavioural pattern associated with m-commerce.

1) Based on both microeconomic literature and activity-based travel demand literature, activity production approach is proposed to measure the utility of an activity involving the use of various technologies. Activity production approach regards activity as a ‘small firm’. Individual transforms the input time, money into the output of goods through activity production process. Travel is considered as a part of overall input to activity participation in the absence of technology. Both production process and consumption of outcome are sources of (dis)utility.

2) Based on this paradigm and existing goods/leisure framework, a unified activity utility model is formulated to deal with activities in the presence of various substituting technologies, e.g. mobile technology. Given fixed working hours, an individual aims to maximize the utility of whole activity pattern, which derived directly from the trade-off between consumption of goods and the ‘leisure time’. The goods are obtained through non-work activity participation. The leisure time is complementary to the work time and input time to the
activity participation.

Motivate a more operational specification dealing with utility of an activity involving the use of substituting mobile technology;

3) Combining the constraints with the direct utility function, an indirect utility model is derived to model the technology choice behaviour in activity participation. According to the concept of activity production, this indirect utility function is explicitly separated into a process utility component, which is empirically specified as a production function with relates to input time and money under certain technological context, and an outcome utility component. In this representation, the substitution effect between input time and money to activity participation using different technologies can be better identified.

Presents model estimation results and discusses the implications for behavioural pattern associated with mobile commerce

5) Data collection: Based on the empirical specification of indirect utility function, a stated choice survey was designed and undertaken to obtain the data necessary to estimate the models. A hypothetical shopping choice scenario and a D-efficient design were chosen in this survey. Respondents were recruited among staff and students at Imperial College London. A program written in VB was installed on the laptop to conduct computer-based personal interview. Each respondent was presented with 18 choices scenario between undertaking a shopping activity either conventionally or via a mobile service while travelling and asked to state their preferred choice of shopping method in each scenario. 67 interviews were carried out and totally 67×18=1206 choice observations were collected.

6) Diagnostic analysis: Generally speaking, the internal validity of raw dataset is high. It has been proved in Chapter 5 that both lexicographic response and sequencing effect of SC data did not influence the estimation results significantly. This was
also shown in Chapter 6 by tested the extended utility specification identified having the best fit to data. Hence only the responses of the non-traders (i.e. 5 out of 67) were excluded from the raw dataset.

7) Model estimations: Using the cleaned SC data, shopping choice models are specified based on the proposition in Chapter 4. Estimation results of 9 plausible forms of utility functions were provided and non-nested statistical tests were conducted to examine these competing hypotheses. The specification having the best overall level of fit is determined, in which the process utility of mobile shopping has a Cobb-Douglas functional form whereas the process utility of conventional shopping exhibits a CES form. It accords with our assumption that each technology is characterised by a unique production function. The basic model was also extended as ML structure to accommodate both preference heterogeneity and response heterogeneity.

8) Result analysis: The results analysis suggested online cost was the major factor that influenced mobile shopping decisions of respondents, while in conventional shopping, both time and money had significant effects in making shopping decisions. The substitution effects between input variables are different in the presence/absence of mobile technology. Travel time had both a minimum requirement and an optimal value for pursing simultaneous mobile activity with certain attributes. It was also interesting to observe that undertaking virtual activity while travelling significantly decreased the disutility of travel itself. Strong evidence of taste heterogeneity in both activity attributes and shopping alternatives were found.
7.2 Limitations of current work and recommendations for further work

This research demonstrates the capability of using a utility-based activity production framework to characterise the virtual activity participation while on the move. A number of directions on future research effort are also founded.

Characterising modification behaviour of conventional activity participation involving the use of m-commerce

As indicated in Chapter two, the other of the two characteristic behaviour patterns involving the use of mobile technology, namely modification behaviour of conventional activity participation, was not further investigated in this thesis. This was due to the reason that few contemporary dataset were available to estimate the integrated modelling framework, which incorporates the underlying key behavioural elements of information acquisition, perception updating, and (re)scheduling choice. As recently, a number of researches have been proposed to examine the impact of mobile technology on travel behaviour, it is worthwhile to search the relevant literatures for the available dataset.

The utility-based activity production framework

In chapter 4, a unified utility model built on the activity production approach was introduced. Some strong and intuitive assumptions were made. For example, leisure time and goods consumption are the main source of utility; wage and working hours are assumed to be fixed; working hours do not enter the utility function, etc. These assumptions are highly relevant to the specification of direct utility function and derivation of indirect utility function. The derived indirect utility function constitutes the theoretical foundation of our basic model of shopping choice in SC experiment. Hence it is also worth to examine the context in which these assumptions are not sustained and
attempt to derive other plausible specifications built on the same paradigm of activity production approach. For example, how an assumption of flexible working hours will affect the specification of direct utility and derived indirect utility. Also if working hours enter the utility directly, how the indirect utility will be specified.

**SC experiment**

The SC survey described in chapter 5 focused on a specific scenario of flower shopping embedded in a work related pattern. This data collection programme can be further improved from several perspectives. For example, it would be interesting to present respondents with different types of goods, such as grocery shopping, electronic shopping, and book shopping etc., to examine the impact of different type of goods on individual decisions of mobile shopping. It would also be reasonable to give other choice options to the respondents, for example by using electronic shopping at home or work place. As opposed to a typical work-related pattern, a variety of other scenarios can also be described and presented to the respondents, for example whether watch movie online at home or go to the cinema in a non work day pattern. These improvements in the SC survey can provide us well-rounded information to better understand the behavioural impact of mobile services.

**Sampling strategy**

In this research, all the respondents were recruited from the research staff and students at Imperial College. Only 67 of them successfully completed the survey. This sampling strategy brought about some insignificant empirical results as presented in Chapter 6, particularly the estimation of observed taste heterogeneity relating to the socio-demographic characteristics. Thus with allowable resource of time and money, it is worthwhile to collect a wider variety of sample to obtain more useful empirical results.

**Model estimations**

In chapter 6, modified Model 4 is identified as best basic model among all the 9
specifications through a series of formal statistical test. The later result analysis is completely referred to the specification of modified Model 4. However, the slight differences in empirical results among these basic models suggest that it is desirable to examine other specifications which have similar level of fit to our reference model.

Also in chapter 6, with our limited computing resources, the response heterogeneity is only applied to one selected coefficient in each extended mixed logit model. Hence in order to examine the taste heterogeneity in response variables more comprehensively, the access to high performance computing resources is required.
Reference


Arnott, R., De Palma, A. & Lindsey, R. (1988), Schedule delay and departure time decisions with heterogeneous commuters, *Transportation Research Record* 1197, 56-76.


Bates, J. & Roberts, M. (1986), *Value of time research: summary of methodology and findings*, paper presented at 14th PTRC Summer annual meeting, University of Sussex,
UK, 14-18 July.


interviews, *Transportation* 25, 147-167.


Daganzo, C. (1979), *Multinomial Probit: The Theory and its Application to Demand*
Forecasting, New York, Academic Press.


Levijoki, S. (2000), Privacy vs location awareness, Department of Computer Science, Helsinki University of Technology.

Ling, R. & Haddon, L. (2001), Mobile telephony, mobility and the coordination of everyday life, paper presented at the conference of the Machines that become us, Rutgers University, 18-19 April.


Supernak, J. (1992), Temporal utility profiles of activities and travel: uncertainty and


Townsend, A. M. (2003), *Research agenda: mobile communications and sustainable transportation*, Follow-up statement from the STELLA FG2 meeting, Newcastle, 8-10 May.


Appendix A: A comprehensive modelling framework of conventional activity modification

In Chapter 2, two characteristic behavioural patterns involving the use of mobile commerce are summarised, i.e. conventional activity modification behaviour and virtual activity participation behaviour. We now propose a discrete-choice based framework to model the conventional activity modification behaviour with use of mobile information services. This framework is built on earlier study on the information use in travel choice behaviour (Hato et al., 1999; Chorus et al., 2006) and the activity scheduling and rescheduling behaviour (Doherty and Miller, 2000; Doherty et al., 2002). It simultaneously incorporates the mobile information acquisition and/or reference process and its subsequent impact on individual perception updating as well as activity modification decisions.

A.1 Modelling assumptions

In this analysis, mobile information is distinguished between push information and pull information (D’Roza and Bilchey, 2003). Our classification here is due to the fact that modelling the impact of push information requires only information reference process, whereas modelling the impact of pull information requires both information acquisition process and information reference process (Hato et al., 1999). In this framework, we mainly focus on two types of mobile information (Chorus et al., 2006):

- Information that provides a fully reliable estimate regarding the related attributes of a known activity alternative (such as travel choice, activity duration, location).

We denote this type of information as type $E$ for estimate
• Information that generates a new activity alternative with assessment on the related attributes. We denote this type of information as type $G$ for generation.

With regards to the conventional activity modification behaviour, we assume that activity modification process is a dynamic process, including preplanning, adaptation and final execution (Doherty, 2000). Some activity attributes (such as travel time, activity location, and travel party) are not all necessarily decided at the preplan stage. Mobile information helps travellers to make these decisions close to the execution. An individual is assumed to face a pre planned schedule which consists of fixed activities and open activities. Fixed activities are the ones that people are committed to perform at fixed location with fixed time. Open activities are the ones that people have choice decisions regarding the activity attributes (such as timing, location, travel mode). Correspondingly, the time periods can be divided into blocks of fixed periods and open periods. During the modification process, individuals ask for the information and then make their decisions built on their updated perception through the information reference. At this stage, we assume that the information acquired is fully reliable, which implies that the individual perception will be fully updated by the information without uncertainty.

A.2 An overview of proposed framework

Based on the above assumptions, a comprehensive modelling framework is outlined in Figure A.1. This framework consists of two components: the component of knowledge updating through information and the component of activity reschedule choice. The component of knowledge updating through information is further divided into two subcomponents: information acquisition and/or reference process and the knowledge updating process.
Figure A.1 Proposed framework of conventional activity modification

At the pre-plan stage, an individual $i$ has a schedule $S_i^0 = (F_1, ..., F_n; O_1, ..., O_m)$ which consists of $n$ fixed activities (e.g. work, school) and $m$ open activities. All the attributes of fixed activities, such as timing and location, are predefined, while for open activities, some attributes are not decided at the pre-plan stage due to limited initial knowledge $R_i^0$ of individual $i$. This individual knowledge serves as a dynamic data base to store the individual complete perception regarding the attributes of the fixed activities and incomplete perception regarding the open activities $\Phi_i^0 = \{\phi^0_1, \phi^0_2, ..., \phi^0_m\}$, as well as that of travel environment. $\phi^0_j$ $(j=1...m)$ is a vector of individual’s initial perception regarding the attributes of open activity $j$, which includes a bundle of attributes such as activity duration, timing, location and associated travel choice.

In adaptation stage, it is assumed that only open activities are rescheduled. The individual $i$ updates the initial perception $\Phi_i^0$ via mobile information $I$ and
reschedules the above open activities. As referred to Section A.1, two types of information, namely $E$ type and $G$ type of information, are taken into account. In this framework, information is assumed to be completely reliable such that the individual’s initial perception is fully updated as $\Phi_i$. For example, when open activity $j$ is rescheduled with use of $E$ type of mobile information, initial perception vector $\phi_i^0$ is updated as $\phi_i$, whereas when using $G$ type of mobile information, an additional activity episode $m+1$ is inserted into preplanned schedule $S_i^0$ with $\phi_{m+1}^G$ being the vector of activity attributes provided by the assessment of $G$ type of information. As the (re)scheduling decisions has a sequential nature, previous scheduling decisions influence the latter scheduling decisions. With provision of both $E$ type and $G$ type of information, an updated schedule $S_i'$ consisting of $(O_1', O_{m'}, O_{m+1}')$ open activities is observed. The open activities labelled as $O_j'$ ($j=1\ldots m+1$) implies that the individual has updated perception $\Phi_i' = \{\phi_1', \phi_{m+1}'\}$ regarding the activity attributes. Thus the probability of observing activity schedule $S_i'$ can be written as a series of conditional probabilities.

$$\Pr(S_i'|S_i^0) = \Pr(O_1'|S_i^0)\Pr(O_2'|S_i^0, O_1')\ldots\Pr(O_{m+1}'|S_i^0, O_1',\ldots, O_{m'})$$  \hspace{1cm} (A.1)$$

In order to estimate this model, we need to know each conditional probability and represent it in terms of the utility function.

**A.2.1 Component of knowledge updating through information**

In this section, we discuss the subcomponent of information acquisition and/or reference process and subcomponent of perception updating respectively.
A.2.1.1 Subcomponent of information acquisition and/or reference

For pull information service, the information acquisition and information reference models are based on an early study by Hato et al. (1999). It is assumed that an individual decides to acquire the information to make rescheduling decision when the utility of information acquisition exceeds some threshold value, and refer to the acquired information if the utility of information reference is larger than some threshold value. This decision process is represented as a two-level tree structure as illustrated in Figure A.2, with information acquisition at the top level and information reference at the bottom level.

![Decision tree with use of pull information](image)

Where \( a \) and \( r \) are binary variables to specify whether individual \( i \) acquires and refers to the information or not. In modelling term, information acquisition and reference process is expressed as:

\[
a = 1, \text{ if } U_i^{a} \geq S_i^{a}; \quad a = 0, \text{ otherwise} \tag{A.2}
\]

\[
r = 1, \text{ if } U_i^{r} \geq S_i^{r}; \quad r = 0, \text{ otherwise} \tag{A.3}
\]

Where \( U_i^{a} \), \( U_i^{r} \) are the information acquisition utility and information reference utility of individual \( i \) respectively; \( S_i^{a} \) and \( S_i^{r} \) are the correspondent threshold values. More explicitly, \( U_i^{a} \) and \( U_i^{r} \), \( S_i^{a} \) and \( S_i^{r} \) can be represented as:
\[ U_{i}^{l_{u}} = \alpha \eta_{i} + \lambda v_{i}^{l_{u}} + \varepsilon_{u}^{l_{u}} \quad \text{(A.4)} \]

\[ S_{i}^{l_{u}} = \theta_{i}^{l_{u}} + \varepsilon_{s}^{l_{u}} \quad \text{(A.5)} \]

\[ U_{i}^{l_{v}} = \beta \kappa_{i} + \gamma I + \varepsilon_{u}^{l_{v}} \quad \text{(A.6)} \]

\[ S_{i}^{l_{v}} = \theta_{i}^{l_{v}} + \varepsilon_{s}^{l_{v}} \quad \text{(A.7)} \]

\[ \nu^{l_{v}} = \ln \left( \exp \left( V_{i}^{l_{v}} \right) + \exp \left( \theta_{i}^{l_{v}} \right) \right) \quad \text{(A.8)} \]

Where \( \eta_{i} \) is the vector of individual socio-demographic characteristics (e.g., gender, age, occupation, income) and internet knowledge (e.g., frequency of using online services); \( \kappa_{i} \) is a vector consisting of the characteristics of activity rescheduling conditions, such as the purpose of the activity, characteristic of activity provided by the information service, and the degree of scheduling confliction; \( I \) is the vector of information characteristics, including the cost, accuracy, scope; \( \alpha, \lambda, \beta, \gamma \) are vectors of parameters. \( \theta_{i}^{l_{u}} \) and \( \theta_{i}^{l_{v}} \) are deterministic parts of the threshold values. \( \varepsilon_{u}^{l_{u}}, \varepsilon_{s}^{l_{u}}, \varepsilon_{u}^{l_{v}}, \varepsilon_{s}^{l_{v}} \) are respective error components with IID Gumbel distribution; \( V_{i}^{l_{v}} \) is the deterministic term of information reference utility \( U_{i}^{l_{v}} \). Thus the probability that individual \( i \) will acquire and refer to the information service can be represented as a NL model:

\[
\Pr(a=1,r=1) = \frac{\exp(\alpha \eta_{i} + \lambda v_{i}^{l_{u}})}{\exp(\alpha \eta_{i} + \lambda v_{i}^{l_{u}}) + \exp(\theta_{i}^{l_{u}})} \cdot \frac{\exp(V_{i}^{l_{v}})}{\exp(V_{i}^{l_{v}}) + \exp(\theta_{i}^{l_{v}})} \quad \text{(A.9)}
\]

Simultaneously, we have

\[
\Pr(a=1,r=0) = \frac{\exp(\alpha \eta_{i} + \lambda v_{i}^{l_{u}})}{\exp(\alpha \eta_{i} + \lambda v_{i}^{l_{u}}) + \exp(\theta_{i}^{l_{u}})} \cdot \frac{\exp(\theta_{i}^{l_{v}})}{\exp(V_{i}^{l_{v}}) + \exp(\theta_{i}^{l_{v}})} \quad \text{(A.10)}
\]
\[
\Pr(a = 0) = \frac{\exp(\theta^0_i)}{\exp(\alpha \eta_i + \lambda \nu^c_i) + \exp(\theta^0_i)} \tag{A.11}
\]

Hence, each conditional probability in Equation A.1 can be represented as follow. For example, the conditional probability \( \Pr(O_i|S_i^0) \) of rescheduling activity \( O_i \) with use of pull information is expressed as:

\[
\Pr(O_i|S_i^0) = \Pr(O_i|S_i^0, a_i = 1, r_i = 1) \Pr(a_i = 1, r_i = 1) + \Pr(O_i|S_i^0, a_i = 1, r_i = 0) \Pr(a_i = 1, r_i = 0) + \Pr(O_i|S_i^0, a_i = 0) \Pr(a_i = 0) \tag{A.12}
\]

With regards to the push information, there is \( \Pr(a_i^0) = 0 \). Thus the decision tree in Figure A.2 is simplified as:

![Decision Tree](image)

Figure A.3 Decision tree with use of push information

Thus the probability of individual \( i \) referring or not referring to the push information is respectively represented as:

\[
\Pr(r = 1) = \frac{\exp(V_i^r)}{\exp(V_i^p) + \exp(\theta_i^r)} \tag{A.13}
\]

\[
\Pr(r = 0) = \frac{\exp(\theta_i^r)}{\exp(V_i^p) + \exp(\theta_i^r)} \tag{A.14}
\]

Hence the probability of rescheduling activity \( O_i \) with use of push information is written as:
\[
\Pr(O_i | S_i^0) = P(O_i | S_i^0, r_i^* = 1) \Pr(r_i^* = 1) \\
+ \Pr(O_i | S_i^0, r_i^* = 0) \Pr(r_i^* = 0)
\]  
(A.15)

A.2.1.2 Subcomponent of perception updating

Once individual decides to refer the acquired information to reschedule activity, the perception is assumed to be updated. The information provided is assumed to be fully reliable. For both \(E\) and \(G\) types of information, the perception updating process relies on the following two ways (Chorus et al., 2006).

The first is the perception updating regarding the decision choice set. The updated perception of constitution of the alternative choice sets perceived by individual \(i\) conditional on the information \(I\) is \(C_i(I) = C_i(I^0) \cup C_i(R_i^0)\), which includes the choice set within his existing knowledge \(C_i(R_i^0)\) and the choice set purely provided through information \(C_i(I^0)\).

The second is the perception updating regarding the activity attributes. In the previous section, we have defined the individual perception regarding the bundles of activities attributes as \(\Phi_i^0 = \{\phi^0_1, \ldots, \phi^0_m\}\). \(\phi^0_j\) \((j = 1, 2, \ldots, m)\) is attributes vector of open activity \(m\). When individual refers to the acquired information, the perception regarding the bundles of attributes of open activity is replaced by the value provided by the information which is represented as \(\phi_i^0\) in above choice set \(C_i(I)\). Later, when making activity choices, utility of activity relies on the updated perception \(\phi_i^0 = \phi_i^0\).

A.2.2 Component of activity rescheduling choice

In this subsection a discrete-choice based behavioural framework is presented to derive the probability of activity rescheduling decision with or without use of mobile
information. In Equation (A.12), we need to calculate \( \Pr(O_i^a | S_i^a, a_i^{\alpha_1} = 1, r_i^{\alpha_1} = 1) \),
\( \Pr(O_i^a | S_i^a, a_i^{\alpha_1} = 1, r_i^{\alpha_1} = 0) \) and \( \Pr(O_i^a | S_i^a, a_i^{\alpha_1} = 0) \). In equation (A.13), we need to
calculate \( P(O_i^a | S_i^a, r_i^{\alpha_1} = 1) \) and \( \Pr(O_i^a | S_i^a, r_i^{\alpha_1} = 0) \). According to discrete choice theory,
these probabilities are represented in terms of utility of activities either with or without
referring to mobile information. In terms of simplicity, MNL model structure is applied.

A.2.2.1 Utility of an activity

There are quite a lot of investigations on utility of an activity in existing
scheduling models (as referred to Chapter 2), which mainly depends on the temporal
attributes (activity timing and activity duration). In our discussion, we give a more
general activity utility function.

Utility of an activity without referring to mobile information

In this case, utility of an activity is determined by the individual’s initial
perception regarding the attributes of an activity, namely that:

\[
U_i^j = V_j(\phi_j^0; c_i; \theta) + \epsilon_j
\]

(A.16)

Where \( U_i^j \) is the utility of activity \( j \) perceived by individual \( i \); \( V_j(\theta) \) is the deterministic
part of \( U_i^j \); \( \phi_j^0 \) is perception of individual \( i \) regarding the attributes of activity \( j \); \( c_i \) is
the vector of characteristics of individual \( i \); \( \theta \) is the parameter vector. \( \epsilon_j \) follows IID
Gumbel distribution.

Utility of an activity with information reference

The utility of an activity with information reference relies on the individual
updated perception regarding the activities attributes and the constitution of the decision
choice sets. We assume that information is fully reliable and give the following notation.
\[ U_{i,j} = V_j (\phi_j^i; c_i; \theta^i) + \varepsilon_j \]  \hspace{1cm} (A.17)

Where \( U_{i,j} \) is the utility of activity \( j \) perceived by individual \( i \) with information reference; \( \phi_j^i \) is a vector of assessment of activity attributes provided by information, which equals the updated perception \( \phi_j \); the updated choice set through information reference is \( \overline{C_j(I)} = C_j(I) \cup C_j(R^i) \); \( \theta^i \) is the parameter vector with information reference.

A.2.2.2 Probability of an activity rescheduling choice

In this part, we will calculate the probability mentioned at the beginning of Section A.2.1 in term of the utility provided above. It is assumed that open activity is only rescheduled under the condition that provided mobile information is referred.

In equation (A.12), we can measure the following probability as:

\[ \Pr \left( O_i \mid S_{i}^{0}, a_i^{\alpha_i} = 1, r_i^{\alpha_i} = 1 \right) = \frac{e^{V_i(\phi_j^i)}}{e^{V_i(\phi_j^i)} + e^{V_i(\phi_j)}} \]  \hspace{1cm} (A.18)

\[ \Pr \left( O_i \mid S_{i}^{0}, a_i^{\alpha_i} = 1, r_i^{\alpha_i} = 0 \right) = \frac{e^{V_i(\phi_j^i)}}{e^{V_i(\phi_j^i)} + e^{V_i(\phi_j)}} \]  \hspace{1cm} (A.19)

\[ \Pr \left( O_i^\emptyset \mid S_{i}^{0}, a_i^{\alpha_i} = 0 \right) = 1 \]  \hspace{1cm} (A.20)

In equation (A.13), we can represent them as:

\[ \Pr \left( O_i \mid S_{i}^{0}, r_i^{\alpha_i} = 1 \right) = \frac{e^{V_i(\phi_j)}}{e^{V_i(\phi_j)} + e^{V_i(\phi_j^i)}} \]  \hspace{1cm} (A.21)

\[ \Pr \left( O_i^\emptyset \mid S_{i}^{0}, r_i^{\alpha_i} = 0 \right) = 1 \]  \hspace{1cm} (A.22)
A.3 Data requirement

As described above, the estimation of above modelling framework requires the activity scheduling and rescheduling data in the presence of mobile information services. Few of the existing data set is available to estimate this model. Considering collecting new dataset is time consuming and cost prohibitive, model estimation is not further conducted.
Appendix B: VB source code of interview program

Public Class Start
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form34.Show()
    End Sub
    Private Sub Start_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        End Sub
    End Class

Public Class Form34
    Private Sub Form34_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        End Sub
    Private Sub RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
        End Sub
    Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
        End Sub
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form36.Show()
    End Sub
    Private Sub RichTextBox3_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox3.TextChanged
        End Sub
    Private Sub RichTextBox4_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox4.TextChanged
        End Sub
    End Class

Public Class Form36
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form37.Show()
    End Sub
    Private Sub RichTextBox4_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox4.TextChanged
        End Sub
    Private Sub RichTextBox3_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox3.TextChanged
        End Sub
    Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
        End Sub
    Private Sub RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
        End Sub
    End Class

Public Class Form37
    Private Sub Form37_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        End Sub
    End Class
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form38.Show()
End Sub
End Class

Public Class Form38
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form39.Show()
    End Sub
    Private Sub TextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox2.TextChanged
        MyBase.Load
    End Sub
End Class

Public Class Form39
    Private Sub RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
        MyBase.Load
    End Sub
    Private Sub Form39_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        Button2.Click
        Form40.Show()
    End Sub
End Class

Public Class Form40
    Private Sub Form40_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        Button1.Click
        Form43.Show()
    End Sub
End Class

Public Class Form43
    Private Sub MenuStrip1_ItemClicked(ByVal sender As System.Object, ByVal e As System.Windows.Forms.ToolStripItemClickedEventArgs)
        MyBase.Load
    End Sub
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form44.Show()
    End Sub
    Private Sub PictureBox1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
        End Sub
    End Sub
End Class

Public Class Form44
    Private Sub Form44_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        Button1.Click
        Form45.Show()
    End Sub
End Class
Handles PictureBox1.Click
    End Sub
Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label1.Click
    End Sub
End Class

Public Class Form44
    Private Sub TextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox1.TextChanged
    End Sub
End Class

Public Class Form45
    Private Sub Label3_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label3.Click
    End Sub
    Private Sub Label2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label2.Click
    End Sub
    Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label1.Click
    End Sub
    Private Sub PictureBox4_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox4.Click
    End Sub
    Private Sub PictureBox3_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox3.Click
    End Sub
    Private Sub PictureBox2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox2.Click
        Form45.Show()
    End Sub
    Private Sub Label4_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label4.Click
    End Sub
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form46.Show()
    End Sub
    Private Sub PictureBox1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox1.Click
    End Sub
Private Sub Label5_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label5.Click
    End Sub
Private Sub Form45_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class
End Sub
End Class

Public Class Form46
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form47.Show()
End Sub
Private Sub TextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox2.TextChanged
End Sub
Private Sub Form46_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class

Public Class Form47
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form48.Show()
End Sub
Private Sub RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
End Sub
Private Sub Form47_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class

Public Class Form48
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form32.Show()
End Sub
Private Sub Form48_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class

Public Class Form32
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form33.Show()
End Sub
Private Sub PictureBox1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox1.Click
End Sub
End Class

Public Class Form33
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form32.Show()
End Sub
Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label1.Click
End Sub
End Class
Private Sub Form32_Load(sender As System.Object, e As System.EventArgs) Handles MyBase.Load
    End Sub
End Class

Public Class Form33
    Private Sub Button1_Click(sender As System.Object, e As System.EventArgs) Handles Button1.Click
        Form35.Show()
    End Sub
    Private Sub RichTextBox1_TextChanged(sender As System.Object, e As System.EventArgs) Handles RichTextBox1.TextChanged
        Handles RichTextBox1.TextChanged
        RichTextBox3.TextChanged
    End Sub
    Private Sub RichTextBox4_TextChanged(sender As System.Object, e As System.EventArgs) Handles RichTextBox4.TextChanged
        Handles RichTextBox4.TextChanged
        Private Sub PictureBox1_Click(sender As System.Object, e As System.EventArgs) Handles PictureBox1.Click
            Form33_Load(sender As System.Object, e As System.EventArgs) Handles MyBase.Load
        End Sub
        End Class

Public Class Form35
    Private Sub Form35_Load(sender As System.Object, e As System.EventArgs) Handles MyBase.Load
        Button1.Click
        Form69.Show()
    End Sub
    Private Sub Button1_Click(sender As System.Object, e As System.EventArgs) Handles Button1.Click
        PictureBox1_Click(sender As System.Object, e As System.EventArgs) Handles PictureBox1.Click
    End Sub
    Private Sub Label1_Click(sender As System.Object, e As System.EventArgs) Handles Label1.Click
        PictureBox1_Click(sender As System.Object, e As System.EventArgs) Handles PictureBox1.Click
    End Sub
End Class

Public Class Form69
    Private Sub Button1_Click(sender As System.Object, e As System.EventArgs) Handles Button1.Click
        Form70.Show()
    End Sub
    Private Sub Label1_Click(sender As System.Object, e As System.EventArgs) Handles Label1.Click
        PictureBox1_Click(sender As System.Object, e As System.EventArgs) Handles PictureBox1.Click
    End Sub
End Class
Private Sub Form69_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class

Public Class Form70
  Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label1.Click
    Form71.Show()
  End Sub
  Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form70_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
  End Sub
End Class

Public Class Form71
  Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label1.Click
    Form51.Show()
  End Sub
  Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form71_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
  End Sub
End Class

Public Class Form51
  Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
    Form2.Show()
  End Sub
  Private Sub PictureBox1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox1.Click
    RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
  End Sub
  Private Sub RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
  End Sub
  Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
  End Sub
  Private Sub RichTextBox3_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox3.TextChanged
  End Sub
  Private Sub RichTextBox4_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox4.TextChanged
  End Sub
End Sub

System.EventArgs) Handles RichTextBox4.TextChanged
End Sub
Private Sub Form51_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class

Public Class Form2
Dim choice
Dim con As New OleDb.OleDbConnection
Dim ds As New DataSet
Dim da As OleDb.OleDbDataAdapter
Dim sql As String
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Button1.Click
If RadioButton1.Checked = False And RadioButton2.Checked = False Then
    MsgBox("Please answer the question!")
End If
Randomize()
Dim randomformat
randomformat = Rnd()
If RadioButton1.Checked = True Then
    choice = 1
    Dim FILE_NAME As String = "C:\test2.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.WriteLine(choice)
        objWriter.Close()
    End If
    con.Close()
    If randomformat < 0.5 Then
        Form3.Show()
    Else
        Form52.Show()
    End If
End If
End If
End Sub
If RadioButton2.Checked = True Then
    choice = 2
    Dim FILE_NAME As String = "C:\test2.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.WriteLine(choice)
        objWriter.Close()
    End If
    con.Close()
    If randomformat < 0.5 Then
        Form3.Show()
    Else
        Form52.Show()
    End If
End If
End Sub
Private Sub Form2_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
    con.ConnectionString = "PROVIDER=Microsoft.Jet.OLEDB.4.0;Data Source = C:\data.mdb"
End Sub
Randomize()

Dim randomRow

randomRow = Int(Rnd() * 600) + 1

con.Open()

sql = "SELECT * FROM survey where id =" & randomRow

da = New OleDb.OleDbDataAdapter(sql, con)

da.Fill(ds, "survey")

Me.Journey_time.Text = ds.Tables("survey").Rows(0).Item(1)

Me.txtMcost.Text = ds.Tables("survey").Rows(0).Item(2)

Me.txtMduration.Text = ds.Tables("survey").Rows(0).Item(3)

Me.txtMpresent.Text = ds.Tables("survey").Rows(0).Item(4)

Me.txttc.Text = ds.Tables("survey").Rows(0).Item(5)

Me.txttt.Text = ds.Tables("survey").Rows(0).Item(6)

Me.txtduration.Text = ds.Tables("survey").Rows(0).Item(7)

Me.txtrpresent.Text = ds.Tables("survey").Rows(0).Item(8)

Dim FILE_NAME As String = "C:\test2.txt"

Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)

If System.IO.File.Exists(FILE_NAME) = True Then

objWriter.Write(randomRow)

objWriter.Write("   ")

objWriter.Write(Me.Journey_time.Text)

objWriter.Write("   ")

objWriter.Write(Me.txtMcost.Text)

objWriter.Write("   ")

objWriter.Write(Me.txtMduration.Text)

objWriter.Write("   ")

objWriter.Write(Me.txtMpresent.Text)

objWriter.Write("   ")

objWriter.Write(Me.txttc.Text)

objWriter.Write("   ")

objWriter.Write(Me.txttt.Text)

objWriter.Write("   ")

objWriter.Write(Me.txtduration.Text)

objWriter.Write("   ")

objWriter.Write(Me.txtrpresent.Text)

objWriter.Write("   ")

objWriter.Close()

Else

MsgBox("File Does Not Exist")

End If

con.Close()

End Sub

Private Sub Form2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Click

End Sub

Private Sub Label4_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Me.Label4.Click

End Sub

Private Sub Label8_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Me.Label8.Click

End Sub

Private Sub txtMcost_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Me.txtMcost.TextChanged

End Sub

Private Sub Label11_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Me.Label11.Click

End Sub

Private Sub Label10_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Me.Label10.Click

End Sub

Private Sub Label9_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Me.Label9.Click

End Sub

Private Sub Label8_Click_1(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label7_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label6_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label6.Click
End Sub
Private Sub Label5_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label5.Click
End Sub
End Sub
Private Sub Label3_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label2.Click
End Sub
Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub
Private Sub txtrpresent_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txtrpresent.TextChanged
End Sub
Private Sub txtrduration_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txtrduration.TextChanged
End Sub
Private Sub txtMpresent_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txtMpresent.TextChanged
End Sub
Private Sub txtMduration_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txtMduration.TextChanged
End Sub
Private Sub Journey_time_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Journey_time.TextChanged
End Sub
Private Sub txttt_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txttt.TextChanged
End Sub
Private Sub TextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label3_Click_1(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
End Class

Public Class Form3
    Dim choice As New OleDb.OleDbConnection
    Dim ds As New DataSet
    Dim da As OleDb.OleDbDataAdapter
    Dim sql As String
    Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Class

251
End Sub
Private Sub Panel1_Paint(ByVal sender As System.Object, ByVal e As System.Windows.Forms.PaintEventArgs)
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Button1.Click
If RadioButton1.Checked = False And RadioButton2.Checked = False Then
MsgBox("Please answer the question!")
End If
Randomize()
Dim randomformat
randomformat = Rnd()
If RadioButton1.Checked = True Then
choice = 1
Dim FILE_NAME As String = "C:\test2.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.WriteLine(choice)
  objWriter.Close()
End If
If randomformat < 0.5 Then
  Form5.Show()
Else
  Form53.Show()
End If
End If
End If
If RadioButton2.Checked = True Then
choice = 2
Dim FILE_NAME As String = "C:\test2.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.WriteLine(choice)
  objWriter.Close()
End If
If randomformat < 0.5 Then
  Form5.Show()
Else
  Form53.Show()
End If
End If
End Sub
Private Sub Panel2_Paint(ByVal sender As System.Object, ByVal e As System.Windows.Forms.PaintEventArgs)
End Sub
Private Sub PictureBox2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub PictureBox1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txtMcost_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txtMduration_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label3_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
End Sub
Private Sub Label2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txtrpresent_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txtduration_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txttc_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label7_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label6_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label5_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label8_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label11_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label10_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub arrive_minute_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub TextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label4_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label9_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txtMpresent_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Form3_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
con.ConnectionString = "PROVIDER=Microsoft.Jet.OLEDB.4.0;Data Source = C:\data.mdb"
Randomize()
randomRow3 = Int(Rnd() * 600) + 1
randomRow52 = 0
con.Open()
sql = "SELECT * FROM survey where id =" & randomRow3
da = New OleDb.OleDbDataAdapter(sql, con)
da.Fill(ds, "survey")
Me.Journey_time.Text = ds.Tables("survey").Rows(0).Item(1)
Me.txtMcost.Text = ds.Tables("survey").Rows(0).Item(2)
Me.txttduration.Text = ds.Tables("survey").Rows(0).Item(3)
Me.txtMpresent.Text = ds.Tables("survey").Rows(0).Item(4)
Me.txttc.Text = ds.Tables("survey").Rows(0).Item(5)
Me.txtt.Text = ds.Tables("survey").Rows(0).Item(6)
Me.txtduration.Text = ds.Tables("survey").Rows(0).Item(7)
Me.txtpresent.Text = ds.Tables("survey").Rows(0).Item(8)
Dim FILE_NAME As String = "C:\test2.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(randomRow3)
    objWriter.Write("   ")
    objWriter.Write(Me.Journey_time.Text)
    objWriter.Write("   ")
End If
objWriter.Write(Me.txtMcost.Text)
objWriter.Write("   ")
objWriter.Write(Me.txtMduration.Text)
objWriter.Write("   ")
objWriter.Write(Me.txtMpresent.Text)
objWriter.Write("   ")
objWriter.Write(Me.txttc.Text)
objWriter.Write("   ")
objWriter.Write(Me.txttt.Text)
objWriter.Write("   ")
objWriter.Write(Me.txtrduration.Text)
objWriter.Write("   ")
objWriter.Write(Me.txttpresent.Text)
objWriter.Write("   ")
objWriter.Close()

Else
   MsgBox("File Does Not Exist")
End If
con.Close()
End Sub
Private Sub Journey_time_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub txttt_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label10_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles RadioButton1.CheckedChanged
End Sub
Private Sub txtrpresent_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles txtrpresent.TextChanged
End Sub
Private Sub Panel2_Paint(ByVal sender As System.Object, ByVal e As System.Windows.Forms.PaintEventArgs)
Handles Panel2.Paint
End Sub
Private Sub PictureBox2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles PictureBox2.Click
End Sub
Private Sub Label6_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Label6.Click
End Sub
Private Sub Label5_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Label5.Click
End Sub
Private Sub txttt_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub Label8_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Label8.Click
End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles RadioButton2.CheckedChanged
End Sub
Private Sub txtMcost_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles txtMcostTextChanged
End Sub
Private Sub Label2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Label2.Click
End Sub

254
Public Class Form52
    Dim choice
    Dim con As New OleDb.OleDbConnection
    Dim ds As New DataSet
    Dim da As OleDb.OleDbDataAdapter
    Dim sql As String
    Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
        Dim randomformat
        randomformat = Rnd()
        If RadioButton1.Checked = True Then
            Dim FILE_NAME As String = "C:\test2.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                If RadioButton1.Checked = False And RadioButton2.Checked = False Then
                    MsgBox("Please answer the question!")
                End If
            End If
        End If
    End Sub
End Class
objWriter.WriteLine(choice)
objWriter.Close()
End If
If randomformat < 0.5 Then
Form5.Show()
Else
Form53.Show()
End If
End If
End If
If RadioButton2.Checked = True Then
choice = 2
Dim FILE_NAME As String = "C:\test2.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
objWriter.WriteLine(choice)
objWriter.Close()
End If
If randomformat < 0.5 Then
Form5.Show()
Else
Form53.Show()
End If
End If
End If
End Sub
End Sub
Private Sub PictureBox2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox2.Click
End Sub
Private Sub PictureBox1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles PictureBox1.Click
End Sub
Private Sub Label1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label1.Click
End Sub
Private Sub txtMcost_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txtMcost.TextChanged
End Sub
Private Sub txtrduration_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txtrduration.TextChanged
End Sub
Private Sub Label5_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label5.Click
End Sub
Private Sub Label6_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label6.Click
End Sub
Private Sub Label8_Click(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub Label11_Click(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub Label10_Click(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub Label10_Click(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub arrive_minute_TextChanged(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub TextBox2_TextChanged(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub Label4_Click(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub Label9_Click(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles e
End Sub
Private Sub txtMpresent_TextChanged(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles sender.TextChanged
End Sub
Private Sub Form52_Load(_ ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
Me.Journey_time.Text = ds.Tables("survey").Rows(0).Item(1)
Me.txtMcost.Text = ds.Tables("survey").Rows(0).Item(2)
Me.txtMduration.Text = ds.Tables("survey").Rows(0).Item(3)
Me.txtMpresent.Text = ds.Tables("survey").Rows(0).Item(4)
Me.txttc.Text = ds.Tables("survey").Rows(0).Item(5)
Me.txttt.Text = ds.Tables("survey").Rows(0).Item(6)
Me.txttrduration.Text = ds.Tables("survey").Rows(0).Item(7)
Me.textrpresent.Text = ds.Tables("survey").Rows(0).Item(8)
Dim FILE_NAME As String = "C:\test2.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(randomRow52)"
    objWriter.Write("   ")
    objWriter.Write(Me.Journey_time.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.txtMcost.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.txtMduration.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.txtMpresent.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.txttc.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.txttt.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.txttrduration.Text)"
    objWriter.Write("   ")
    objWriter.Write(Me.textrpresent.Text)"
    objWriter.Write("   ")
    objWriter.Close()
Else
    MsgBox("File Does Not Exist")
End If
con.Close()
End Sub
Private Sub Journey_time_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Journey_time.TextChanged
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(gender)
        objWriter.Write("  ")
        objWriter.Close()
    End If
End Sub
Private Sub txttt_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles txttt.TextChanged
End Sub
Private Sub Label10_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Label10.Click
End Sub
Public Class Form10
    Private Sub Form10_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        Dim FILE_NAME As String = "C:\\test1.txt"
        Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
        If System.IO.File.Exists(FILE_NAME) = True Then
            objWriter.Write(gender)
            objWriter.Write("  ")
            objWriter.Close()
        End If
        Form19.Show()
    End Sub
End Class
Public Class Form27
    Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button1.Click
        Form18.Show()
    End Sub
    Private Sub Form27_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
        Dim FILE_NAME As String = "C:\\test1.txt"
        Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
        If System.IO.File.Exists(FILE_NAME) = True Then
            objWriter.Write(gender)
            objWriter.Write("  ")
            objWriter.Close()
        End If
        Form19.Show()
    End Sub
End Class
Public Class Form18
    Dim gender
    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
        If RadioButton3.Checked = False And RadioButton2.Checked = False Then
            MsgBox("Please answer the question!")
        End If
        If RadioButton3.Checked = True Then
            gender = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(gender)
                objWriter.Write("  ")
                objWriter.Close()
            End If
            Form19.Show()
        End If
        If RadioButton2.Checked = True Then
            gender = 0
            Dim FILE_NAME As String = "C:\test1.txt"
        End If
    End Sub
End Class
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(gender)
    objWriter.Write("  ")
    objWriter.Close()
End If
Form19.Show()
End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles RadioButton3.CheckedChanged
End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles RadioButton2.CheckedChanged
End Sub
Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles RichTextBox2.TextChanged
End Sub
Private Form18_Load(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles MyBase.Load
End Sub
End Class

Public Class Form19
Dim age
Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles Button2.Click
    age = 2007 - ComboBox1.SelectedItem
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(age)
        objWriter.Write("  ")
        objWriter.Close()
    End If
Form20.Show()
End Sub
Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles RichTextBox2.TextChanged
End Sub
Private Sub ComboBox1_SelectedIndexChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles ComboBox1.SelectedIndexChanged
End Sub
Private Form19_Load(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles MyBase.Load
End Sub
End Class

Public Class Form20
Dim PhD = 0
Dim master = 0
Dim bachelor = 0
Dim a_level = 0
Dim o_level = 0
Dim other = 0
Dim no_qualification = 0
Dim input_other

Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
        MsgBox("Please answer the question!")
    End If
    If RadioButton7.Checked = True Then
        PhD = 1
        Dim FILE_NAME As String = "C:\test1.txt"
        Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
        If System.IO.File.Exists(FILE_NAME) = True Then
            objWriter.Write(PhD)
            objWriter.Write("  ")
            objWriter.Write(master)
            objWriter.Write("  ")
            objWriter.Write(bachelor)
            objWriter.Write("  ")
            objWriter.Write(a_level)
            objWriter.Write("  ")
            objWriter.Write(o_level)
            objWriter.Write("  ")
            objWriter.Write(other)
            objWriter.Write(input_other)
            objWriter.Write("  ")
            objWriter.Write(no_qualification)
            objWriter.Write("  ")
            objWriter.Close()
        End If
        Form21.Show()
    End If
    If RadioButton1.Checked = True Then
        master = 1
        Dim FILE_NAME As String = "C:\test1.txt"
        Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
        If System.IO.File.Exists(FILE_NAME) = True Then
            objWriter.Write(PhD)
            objWriter.Write("  ")
            objWriter.Write(master)
            objWriter.Write("  ")
            objWriter.Write(bachelor)
            objWriter.Write("  ")
            objWriter.Write(a_level)
            objWriter.Write("  ")
            objWriter.Write(o_level)
            objWriter.Write("  ")
            objWriter.Write(other)
            objWriter.Write(input_other)
            objWriter.Write("  ")
            objWriter.Write(no_qualification)
            objWriter.Write("  ")
            objWriter.Close()
        End If
        Form21.Show()
    End If
    If RadioButton2.Checked = True Then
        bachelor = 1
        Dim FILE_NAME As String = "C:\test1.txt"

Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(PhD)
    objWriter.Write(" ")
    objWriter.Write(master)
    objWriter.Write(" ")
    objWriter.Write(bachelor)
    objWriter.Write(" ")
    objWriter.Write(a_level)
    objWriter.Write(" ")
    objWriter.Write(o_level)
    objWriter.Write(" ")
    objWriter.Write(other)
    objWriter.Write(input_other)
    objWriter.Write(" ")
    objWriter.Write(no_qualification)
    objWriter.Write(" ")
    objWriter.Close()
End If
Form21.Show()
End If
If RadioButton3.Checked = True Then
    a_level = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(PhD)
        objWriter.Write(" ")
        objWriter.Write(master)
        objWriter.Write(" ")
        objWriter.Write(bachelor)
        objWriter.Write(" ")
        objWriter.Write(a_level)
        objWriter.Write(" ")
        objWriter.Write(o_level)
        objWriter.Write(" ")
        objWriter.Write(other)
        objWriter.Write(input_other)
        objWriter.Write(" ")
        objWriter.Write(no_qualification)
        objWriter.Write(" ")
        objWriter.Close()
    End If
End If
Form21.Show()
End If
If RadioButton4.Checked = True Then
    o_level = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(PhD)
        objWriter.Write(" ")
        objWriter.Write(master)
        objWriter.Write(" ")
        objWriter.Write(bachelor)
        objWriter.Write(" ")
        objWriter.Write(a_level)
        objWriter.Write(" ")
        objWriter.Write(o_level)
        objWriter.Write(" ")
        objWriter.Write(other)
        objWriter.Write(input_other)
        objWriter.Write(" ")
        objWriter.Write(no_qualification)
        objWriter.Write(" ")
        objWriter.Write(no_qualification)
        objWriter.Write(" ")
        objWriter.Close()
objWriter.Write("  ")
objWriter.Write(other)
objWriter.Write(input_other)
objWriter.Write("  ")
objWriter.Write(no_qualification)
objWriter.Write("  ")
objWriter.Close()

End If
Form21.Show()
End If
If RadioButton5.Checked = True Then
other = 1
input_other = TextBox1.Text
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(PhD)
  objWriter.Write("  ")
  objWriter.Write(master)
  objWriter.Write("  ")
  objWriter.Write(bachelor)
  objWriter.Write("  ")
  objWriter.Write(a_level)
  objWriter.Write("  ")
  objWriter.Write(o_level)
  objWriter.Write("  ")
  objWriter.Write(other)
  objWriter.Write(input_other)
  objWriter.Write("  ")
  objWriter.Write(no_qualification)
  objWriter.Write("  ")
  objWriter.Write("  ")
  objWriter.Close()
End If
Form21.Show()
End If
If RadioButton6.Checked = True Then
no_qualification = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(PhD)
  objWriter.Write("  ")
  objWriter.Write(master)
  objWriter.Write("  ")
  objWriter.Write(bachelor)
  objWriter.Write("  ")
  objWriter.Write(a_level)
  objWriter.Write("  ")
  objWriter.Write(o_level)
  objWriter.Write("  ")
  objWriter.Write(other)
  objWriter.Write(input_other)
  objWriter.Write("  ")
  objWriter.Write(no_qualification)
  objWriter.Write("  ")
  objWriter.Write("  ")
  objWriter.Close()
End If
Form21.Show()
End If
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub

Private Sub TextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox1.TextChanged
End Sub

Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
End Sub

Private Sub RadioButton5_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton5.CheckedChanged
End Sub

Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub

Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
End Sub

Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub

Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
End Sub

Private Sub Form20_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub

Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
End Sub

End Class

Public Class Form21
    Dim full_paid = 0
    Dim part_paid = 0
    Dim full_self = 0
    Dim part_self = 0
    Dim student = 0
    Dim no_employed = 0

    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
            MsgBox("Please answer the question!")
        End If

        If RadioButton1.Checked = True Then
            full_paid = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.WriteLine(full_paid)
                objWriter.WriteLine(" ")
                objWriter.WriteLine(part_paid)
                objWriter.WriteLine(" ")
                objWriter.WriteLine(full_self)
                objWriter.WriteLine(" ")
            End If
        End If
    End Sub
End Class
objWriter.Write(part_self)
objWriter.Write(" ")
objWriter.Write(student)
objWriter.Write(" ")
objWriter.Write(no_employed)
objWriter.Write(" ")
objWriter.Close()

End If
Form28.Show()

End If
If RadioButton2.Checked = True Then
part_paid = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
objWriter.Write(full_paid)
objWriter.Write(" ")
objWriter.Write(part_paid)
objWriter.Write(" ")
objWriter.Write(full_self)
objWriter.Write(" ")
objWriter.Write(part_self)
objWriter.Write(" ")
objWriter.Write(student)
objWriter.Write(" ")
objWriter.Write(no_employed)
objWriter.Write(" ")
objWriter.Close()
End If
Form28.Show()

End If
If RadioButton3.Checked = True Then
full_self = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
objWriter.Write(full_paid)
objWriter.Write(" ")
objWriter.Write(part_paid)
objWriter.Write(" ")
objWriter.Write(full_self)
objWriter.Write(" ")
objWriter.Write(part_self)
objWriter.Write(" ")
objWriter.Write(student)
objWriter.Write(" ")
objWriter.Write(no_employed)
objWriter.Write(" ")
objWriter.Close()
End If
Form28.Show()

End If
If RadioButton4.Checked = True Then
part_self = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
objWriter.Write(full_paid)
objWriter.Write(" ")
objWriter.Write(part_paid)
objWriter.Write(" ")
objWriter.Write(full_self)
objWriter.Write(" ")
objWriter.Write(part_self)
objWriter.Write(" ")
objWriter.Write(student)
objWriter.Write(" ")
objWriter.Write(no_employed)
objWriter.Write(" ")
objWriter.Close()

End If
Form28.Show()
End If
If RadioButton5.Checked = True Then
    student = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(full_paid)
        objWriter.Write(" ")
        objWriter.Write(part_paid)
        objWriter.Write(" ")
        objWriter.Write(full_self)
        objWriter.Write(" ")
        objWriter.Write(part_self)
        objWriter.Write(" ")
        objWriter.Write(student)
        objWriter.Write(" ")
        objWriter.Write(no_employed)
        objWriter.Write(" ")
        objWriter.Close()
    End If
    Form28.Show()
End If
If RadioButton6.Checked = True Then
    no_employed = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(full_paid)
        objWriter.Write(" ")
        objWriter.Write(part_paid)
        objWriter.Write(" ")
        objWriter.Write(full_self)
        objWriter.Write(" ")
        objWriter.Write(part_self)
        objWriter.Write(" ")
        objWriter.Write(student)
        objWriter.Write(" ")
        objWriter.Write(no_employed)
        objWriter.Write(" ")
        objWriter.Close()
    End If
    Form28.Show()
End If
End If
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
End Sub
Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub
Private Sub RadioButton5_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton5.CheckedChanged
End Sub
Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
End Sub
Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
End Sub
Private Sub Form21_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
End Sub
Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
    MsgBox("Please answer the question!")
End If
End Sub
Public Class Form28
    Dim income_5 = 1
    Dim income_7 = 0
    Dim income_6 = 0
    Dim income_4 = 0
    Dim income_3 = 0
    Dim income_2 = 0
    Dim income_1 = 0
    Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
End Sub
Private Sub Form28_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
End Sub
Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
    MsgBox("Please answer the question!")
End If
End Sub
Public Class Form28
    Dim income_5 = 1
    Dim income_7 = 0
    Dim income_6 = 0
    Dim income_4 = 0
    Dim income_3 = 0
    Dim income_2 = 0
    Dim income_1 = 0
    Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
End Sub
Private Sub Form28_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
End Sub
Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
    MsgBox("Please answer the question!")
End If
End Sub

End If
If RadioButton1.Checked = True Then
    income_1 = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(income_1)
        objWriter.Write("  ")
        objWriter.Write(income_2)
        objWriter.Write("  ")
        objWriter.Write(income_3)
        objWriter.Write("  ")
        objWriter.Write(income_4)
        objWriter.Write("  ")
        objWriter.Write(income_5)
        objWriter.Write("  ")
        objWriter.Write(income_6)
        objWriter.Write("  ")
        objWriter.Write(income_7)
        objWriter.Write("  ")
    End If
    Form50.Show()
End If
If RadioButton2.Checked = True Then
    income_2 = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(income_1)
        objWriter.Write("  ")
        objWriter.Write(income_2)
        objWriter.Write("  ")
        objWriter.Write(income_3)
        objWriter.Write("  ")
        objWriter.Write(income_4)
        objWriter.Write("  ")
        objWriter.Write(income_5)
        objWriter.Write("  ")
        objWriter.Write(income_6)
        objWriter.Write("  ")
        objWriter.Write(income_7)
        objWriter.Write("  ")
    End If
    Form50.Show()
End If
If RadioButton3.Checked = True Then
    income_3 = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(income_1)
        objWriter.Write("  ")
        objWriter.Write(income_2)
        objWriter.Write("  ")
        objWriter.Write(income_3)
        objWriter.Write("  ")
        objWriter.Write(income_4)
        objWriter.Write("  ")
        objWriter.Write(income_5)
        objWriter.Write("  ")
        objWriter.Write(income_6)
        objWriter.Write("  ")
        objWriter.Write(income_7)
        objWriter.Write("  ")
    End If
    Form50.Show()
End If
objWriter.Write("  ")
objWriter.Write(income_6)
objWriter.Write("  ")
objWriter.Write(income_7)
objWriter.Write("  ")
End If
Form50.Show()
End If
If RadioButton4.Checked = True Then
income_4 = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(income_1)
  objWriter.Write("  ")
  objWriter.Write(income_2)
  objWriter.Write("  ")
  objWriter.Write(income_3)
  objWriter.Write("  ")
  objWriter.Write(income_4)
  objWriter.Write("  ")
  objWriter.Write(income_5)
  objWriter.Write("  ")
  objWriter.Write(income_6)
  objWriter.Write("  ")
  objWriter.Write(income_7)
  objWriter.Write("  ")
End If
Form50.Show()
End If
If RadioButton5.Checked = True Then
income_5 = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(income_1)
  objWriter.Write("  ")
  objWriter.Write(income_2)
  objWriter.Write("  ")
  objWriter.Write(income_3)
  objWriter.Write("  ")
  objWriter.Write(income_4)
  objWriter.Write("  ")
  objWriter.Write(income_5)
  objWriter.Write("  ")
  objWriter.Write(income_6)
  objWriter.Write("  ")
  objWriter.Write(income_7)
  objWriter.Write("  ")
End If
Form50.Show()
End If
If RadioButton6.Checked = True Then
income_6 = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(income_1)
  objWriter.Write("  ")
  objWriter.Write(income_2)
  objWriter.Write("  ")
  objWriter.Write(income_3)
  objWriter.Write("  ")
  objWriter.Write(income_4)
  objWriter.Write("  ")
  objWriter.Write(income_5)
  objWriter.Write("  ")
  objWriter.Write(income_6)
  objWriter.Write("  ")
  objWriter.Write(income_7)
  objWriter.Write("  ")
End If
Form50.Show()
objWriter.Write(income_2)
objWriter.Write(" ")
objWriter.Write(income_3)
objWriter.Write(" ")
objWriter.Write(income_4)
objWriter.Write(" ")
objWriter.Write(income_5)
objWriter.Write(" ")
objWriter.Write(income_6)
objWriter.Write(" ")
objWriter.Write(income_7)
objWriter.Write(" ")
End If
Form50.Show()
End If
If RadioButton7.Checked = True Then
income_7 = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
objWriter.Write(income_1)
objWriter.Write(" ")
objWriter.Write(income_2)
objWriter.Write(" ")
objWriter.Write(income_3)
objWriter.Write(" ")
objWriter.Write(income_4)
objWriter.Write(" ")
objWriter.Write(income_5)
objWriter.Write(" ")
objWriter.Write(income_6)
objWriter.Write(" ")
objWriter.Write(income_7)
objWriter.Write(" ")
End If
Form50.Show()
End If
End Sub
Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
End Sub
Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
End Sub
Private Sub RadioButton5_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton5.CheckedChanged
End Sub
End Sub
End Class
Public Class Form50
    Private Sub Form50_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
Private Sub RichTextBox3_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox3.TextChanged
End Sub
Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
Public Class Form22
    Dim access_5 = 0
    Dim access_4 = 0
    Dim access_3 = 0
    Dim access_2 = 0
    Dim access_1 = 0

    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
            MsgBox("Please answer the question!")
        End If
        If RadioButton1.Checked = True Then
            access_5 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(access_5)
                objWriter.Write(" ")
                objWriter.Write(access_4)
                objWriter.Write(" ")
                objWriter.Write(access_3)
                objWriter.Write(" ")
                objWriter.Write(access_2)
                objWriter.Write(" ")
                objWriter.Write(access_1)
                objWriter.Write(" ")
            End If
            objWriter.Close()
        End If
    End Sub
End Class
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(access_5)
    objWriter.Write(" ")
    objWriter.Write(access_4)
    objWriter.Write(" ")
    objWriter.Write(access_3)
    objWriter.Write(" ")
    objWriter.Write(access_2)
    objWriter.Write(" ")
    objWriter.Write(access_1)
    objWriter.Write(" ")
    objWriter.Close()
End If
Form23.Show()
End If
If RadioButton4.Checked = True Then
    access_2 = 1
Dim FILE_NAME As String = C:\test1.txt
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(access_5)
    objWriter.Write(" ")
    objWriter.Write(access_4)
    objWriter.Write(" ")
    objWriter.Write(access_3)
    objWriter.Write(" ")
    objWriter.Write(access_2)
    objWriter.Write(" ")
    objWriter.Write(access_1)
    objWriter.Write(" ")
    objWriter.Close()
End If
Form23.Show()
End If
If RadioButton5.Checked = True Then
    access_1 = 1
Dim FILE_NAME As String = C:\test1.txt
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(access_5)
    objWriter.Write(" ")
    objWriter.Write(access_4)
    objWriter.Write(" ")
    objWriter.Write(access_3)
    objWriter.Write(" ")
    objWriter.Write(access_2)
    objWriter.Write(" ")
    objWriter.Write(access_1)
    objWriter.Write(" ")
    objWriter.Close()
End If
Form23.Show()
End If
End Sub
Private Sub RadioButton5_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton5.CheckedChanged
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
Public Class Form23
    Dim internet_4 As Integer = 0
    Dim internet_3 As Integer = 0
    Dim internet_2 As Integer = 0
    Dim internet_1 As Integer = 0
    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
            MsgBox("Please answer the question!")
            If RadioButton1.Checked = True Then
                Dim FILE_NAME As String = "C:\test1.txt"
                Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
                If System.IO.File.Exists(FILE_NAME) = True Then
                    objWriter.Write(internet_4) objWriter.WriteString(" ")
                    objWriter.Write(internet_3) objWriter.WriteString(" ")
                    objWriter.Write(internet_2) objWriter.WriteString(" ")
                    objWriter.Write(internet_1) objWriter.WriteString(" ")
                    objWriter.Close()
                End If
            End If
        End If
        If RadioButton2.Checked = True Then
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(internet_4) objWriter.WriteString(" ")
                objWriter.Write(internet_3) objWriter.WriteString(" ")
                objWriter.Write(internet_2) objWriter.WriteString(" ")
                objWriter.Write(internet_1) objWriter.WriteString(" ")
                objWriter.Close()
            End If
            Form25.Show()
        End If
        If RadioButton3.Checked = True Then
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(internet_4) objWriter.WriteString(" ")
                objWriter.Write(internet_3) objWriter.WriteString(" ")
                objWriter.Write(internet_2) objWriter.WriteString(" ")
                objWriter.Write(internet_1) objWriter.WriteString(" ")
                objWriter.Close()
            End If
        End If
    End Sub
End Class
objWriter.Write(internet_1)
objWriter.Write(" ")
objWriter.Close()  
End If
End If
Form25.Show()  
End If
If RadioButton3.Checked = True Then
internet_2 = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(internet_4)
  objWriter.Write(" ")
  objWriter.Write(internet_3)
  objWriter.Write(" ")
  objWriter.Write(internet_2)
  objWriter.Write(" ")
  objWriter.Write(internet_1)
  objWriter.Write(" ")
  objWriter.Close()
End If
Form25.Show()  
End If
End If
If RadioButton4.Checked = True Then
internet_1 = 1
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
  objWriter.Write(internet_4)
  objWriter.Write(" ")
  objWriter.Write(internet_3)
  objWriter.Write(" ")
  objWriter.Write(internet_2)
  objWriter.Write(" ")
  objWriter.Write(internet_1)
  objWriter.Write(" ")
  objWriter.Close()
End If
Form25.Show()  
End If
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub

Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub

Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
End Sub

Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub

Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
End Sub

Private Sub Form23_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
Public Class Form25
    Dim online_shopping_3 = 0
    Dim online_shopping_2 = 0
    Dim online_shopping_1 = 0
    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
            MsgBox("Please answer the question!")
        End If
        If RadioButton1.Checked = True Then
            online_shopping_3 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(online_shopping_3)
                objWriter.Write("   ")
                objWriter.Write(online_shopping_2)
                objWriter.Write("   ")
                objWriter.WriteLine(online_shopping_1)
                objWriter.Close()
            End If
            Form24.Show()
        End If
        If RadioButton2.Checked = True Then
            online_shopping_2 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(online_shopping_3)
                objWriter.Write("   ")
                objWriter.Write(online_shopping_2)
                objWriter.Write("   ")
                objWriter.WriteLine(online_shopping_1)
                objWriter.Close()
            End If
            Form24.Show()
        End If
        If RadioButton3.Checked = True Then
            online_shopping_1 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.Write(online_shopping_3)
                objWriter.Write("   ")
                objWriter.Write(online_shopping_2)
                objWriter.Write("   ")
                objWriter.WriteLine(online_shopping_1)
                objWriter.Close()
            End If
            Form24.Show()
        End If
    End Sub
End Class
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
    End Sub

Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
    End Sub

Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
    End Sub

Private Sub Form25_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
    End Sub
End Class

Public Class Form24
    Dim mobile_4 = 0
    Dim mobile_3 = 0
    Dim mobile_2 = 0
    Dim mobile_1 = 0

    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
            MsgBox("Please answer the question!")
        End If
        If RadioButton1.Checked = True Then
            mobile_4 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.WriteLine(mobile_4) ' mobile_4
                objWriter.WriteLine(mobile_3) ' mobile_3
                objWriter.WriteLine(mobile_2) ' mobile_2
                objWriter.WriteLine(mobile_1) ' mobile_1
                objWriter.Close()
            End If
            Form41.Show()
        End If
        If RadioButton2.Checked = True Then
            mobile_3 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.WriteLine(mobile_4) ' mobile_4
                objWriter.WriteLine(mobile_3) ' mobile_3
                objWriter.WriteLine(mobile_2) ' mobile_2
                objWriter.WriteLine(mobile_1) ' mobile_1
                objWriter.Close()
            End If
        End If
        If RadioButton1.Checked = True Then
            mobile_4 = 1
            Dim FILE_NAME As String = "C:\test1.txt"
            Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
            If System.IO.File.Exists(FILE_NAME) = True Then
                objWriter.WriteLine(mobile_4) ' mobile_4
                objWriter.WriteLine(mobile_3) ' mobile_3
                objWriter.WriteLine(mobile_2) ' mobile_2
                objWriter.WriteLine(mobile_1) ' mobile_1
                objWriter.Close()
            End If
            Form41.Show()
        End If
    End Sub
Form41.Show()
End If
If RadioButton3.Checked = True Then
    mobile_2 = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(mobile_4)
        objWriter.Write(" ")
        objWriter.Write(mobile_3)
        objWriter.Write(" ")
        objWriter.Write(mobile_2)
        objWriter.Write(" ")
        objWriter.Write(mobile_1)
        objWriter.Write(" ")
        objWriter.Close()
    End If
End If
Form41.Show()
End If
If RadioButton4.Checked = True Then
    mobile_1 = 1
    Dim FILE_NAME As String = "C:\test1.txt"
    Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
    If System.IO.File.Exists(FILE_NAME) = True Then
        objWriter.Write(mobile_4)
        objWriter.Write(" ")
        objWriter.Write(mobile_3)
        objWriter.Write(" ")
        objWriter.Write(mobile_2)
        objWriter.Write(" ")
        objWriter.Write(mobile_1)
        objWriter.Write(" ")
        objWriter.Close()
    End If
End If
Form41.Show()
End If
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
End Sub
Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub
Private Sub RichTextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox2.TextChanged
End Sub
Private Sub Form24_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
Public Class Form41
    Private Sub Form41_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
End Class

Public Class Form11
    Dim useful_N = 0
    Dim useful_S = 0
    Dim useful_M = 0
    Dim useful_Q = 0
    Dim useful_E = 0
    Dim practical_N = 0
    Dim practical_S = 0
    Dim practical_M = 0
    Dim practical_Q = 0
    Dim practical_E = 0
    Dim functional_N = 0
    Dim functional_S = 0
    Dim functional_M = 0
    Dim functional_Q = 0
    Dim functional_E = 0
    Dim helpful_N = 0
    Dim helpful_S = 0
    Dim helpful_M = 0
    Dim helpful_Q = 0
    Dim helpful_E = 0
    Dim efficient_N = 0
    Dim efficient_S = 0
    Dim efficient_M = 0
    Dim efficient_Q = 0
    Dim efficient_E = 0
    Private Sub Form11_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
End Sub
    Private Sub TextBox17_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox17.TextChanged
End Sub
    Private Sub TextBox8_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox8.TextChanged
End Sub
    Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
        If RadioButton1.Checked = True Then
            useful_N = 1
        End If
        If RadioButton2.Checked = True Then
            useful_S = 1
        End If
        If RadioButton3.Checked = True Then
            useful_M = 1
        End If
        If RadioButton4.Checked = True Then
            useful_Q = 1
        End If
        If RadioButton5.Checked = True Then
            useful_E = 1
        End If
        If RadioButton14.Checked = True Then
End Sub
practical_N = 1
End If
If RadioButton13.Checked = True Then
    practical_S = 1
End If
If RadioButton12.Checked = True Then
    practical_M = 1
End If
If RadioButton11.Checked = True Then
    practical_Q = 1
End If
If RadioButton10.Checked = True Then
    practical_E = 1
End If
If RadioButton20.Checked = True Then
    functional_N = 1
End If
If RadioButton19.Checked = True Then
    functional_S = 1
End If
If RadioButton18.Checked = True Then
    functional_M = 1
End If
If RadioButton17.Checked = True Then
    functional_Q = 1
End If
If RadioButton16.Checked = True Then
    functional_E = 1
End If
If RadioButton9.Checked = True Then
    helpful_N = 1
End If
If RadioButton8.Checked = True Then
    helpful_M = 1
End If
If RadioButton7.Checked = True Then
    helpful_Q = 1
End If
If RadioButton6.Checked = True Then
    helpful_E = 1
End If
If RadioButton25.Checked = True Then
    efficient_N = 1
End If
If RadioButton24.Checked = True Then
    efficient_S = 1
End If
If RadioButton23.Checked = True Then
    efficient_M = 1
End If
If RadioButton22.Checked = True Then
    efficient_Q = 1
End If
If RadioButton21.Checked = True Then
    efficient_E = 1
End If
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.WriteLine(useful_N)
    objWriter.Write(" ")
    objWriter.WriteLine(useful_S)
    objWriter.Write(" ")
    objWriter.WriteLine(useful_M)
    objWriter.Write(" ")
    objWriter.WriteLine(useful_Q)
    objWriter.Write(" ")
    objWriter.WriteLine(useful_E)
    objWriter.Write(" ")
    objWriter.WriteLine(practical_N)
    objWriter.Write(" ")
    objWriter.WriteLine(practical_S)
    objWriter.Write(" ")
    objWriter.WriteLine(practical_M)
    objWriter.Write(" ")
    objWriter.WriteLine(practical_Q)
    objWriter.Write(" ")
    objWriter.WriteLine(practical_E)
    objWriter.Write(" ")
    objWriter.WriteLine(functional_N)
    objWriter.Write(" ")
    objWriter.WriteLine(functional_S)
    objWriter.Write(" ")
    objWriter.WriteLine(functional_M)
    objWriter.Write(" ")
    objWriter.WriteLine(functional_Q)
    objWriter.Write(" ")
    objWriter.WriteLine(functional_E)
    objWriter.Write(" ")
    objWriter.WriteLine(helpful_N)
    objWriter.Write(" ")
    objWriter.WriteLine(helpful_S)
    objWriter.Write(" ")
    objWriter.WriteLine(helpful_M)
    objWriter.Write(" ")
    objWriter.WriteLine(helpful_Q)
    objWriter.Write(" ")
    objWriter.WriteLine(helpful_E)
    objWriter.Write(" ")
    objWriter.WriteLine(efficient_N)
    objWriter.Write(" ")
    objWriter.WriteLine(efficient_S)
    objWriter.Write(" ")
    objWriter.WriteLine(efficient_M)
    objWriter.Write(" ")
    objWriter.WriteLine(efficient_Q)
    objWriter.Write(" ")
    objWriter.WriteLine(efficient_E)
    objWriter.Write(" ")
    objWriter.Close()
End If
Form12.Show()
End Sub
Private Sub Button1_Click(ByVal sender As System.Object, ByVal e As System.EventArgs)
End Sub
Private Sub TextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox1.TextChanged
End Sub
Private Sub TextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox2.TextChanged
End Sub
Private Sub TextBox3_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox3.TextChanged
End Sub
Private Sub TextBox9_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox9.TextChanged
End Sub
Private Sub TextBox4_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox4.TextChanged
End Sub
Private Sub TextBox5_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox5.TextChanged
End Sub
Private Sub TextBox26_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox26.TextChanged
End Sub
Private Sub TextBox6_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox6.TextChanged
End Sub
End Sub
End Sub
Private Sub TextBox7_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox7.TextChanged
End Sub
Private Sub RadioButton25_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton25.CheckedChanged
End Sub
End Sub
Private Sub RadioButton23_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton23.CheckedChanged
End Sub
Private Sub RadioButton22_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton22.CheckedChanged
End Sub
End Sub
End Sub
Private Sub TextBox8_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox8.TextChanged
End Sub
Private Sub TextBox7_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox7.TextChanged
End Sub
Private Sub RadioButton20_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton20.CheckedChanged
End Sub
End Sub
End Sub
    End Sub
Private Sub RadioButton18_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton18.CheckedChanged
    End Sub
Private Sub RadioButton17_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton17.CheckedChanged
    End Sub
Private Sub RadioButton16_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton16.CheckedChanged
    End Sub
    End Sub
Private Sub RadioButton15_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton15.CheckedChanged
    End Sub
Private Sub RadioButton9_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton9.CheckedChanged
    End Sub
Private Sub RadioButton8_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton8.CheckedChanged
    End Sub
Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
    End Sub
Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
    End Sub
    End Sub
Private Sub TextBox4_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox4.TextChanged
    End Sub
    End Sub
Private Sub RadioButton13_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton13.CheckedChanged
    End Sub
Private Sub RadioButton12_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton12.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
    End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
    End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton9_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton9.CheckedChanged
    End Sub
Private Sub RadioButton8_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton8.CheckedChanged
    End Sub
Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
    End Sub
Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
    End Sub
    End Sub
Private Sub TextBox4_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox4.TextChanged
    End Sub
    End Sub
Private Sub RadioButton13_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton13.CheckedChanged
    End Sub
Private Sub RadioButton12_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton12.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
    End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
    End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton9_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton9.CheckedChanged
    End Sub
Private Sub RadioButton8_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton8.CheckedChanged
    End Sub
Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
    End Sub
Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
    End Sub
    End Sub
Private Sub TextBox4_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox4.TextChanged
    End Sub
    End Sub
Private Sub RadioButton13_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton13.CheckedChanged
    End Sub
Private Sub RadioButton12_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton12.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
    End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
    End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton9_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton9.CheckedChanged
    End Sub
Private Sub RadioButton8_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton8.CheckedChanged
    End Sub
Private Sub RadioButton7_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton7.CheckedChanged
    End Sub
Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
    End Sub
    End Sub
Private Sub TextBox4_TextChanged_1(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox4.TextChanged
    End Sub
    End Sub
Private Sub RadioButton13_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton13.CheckedChanged
    End Sub
Private Sub RadioButton12_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton12.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
    End Sub
Private Sub RadioButton2_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton2.CheckedChanged
    End Sub
Private Sub RadioButton3_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton3.CheckedChanged
    End Sub
Private Sub RadioButton11_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton11.CheckedChanged
    End Sub
Private Sub RadioButton10_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton10.CheckedChanged
    End Sub
Private Sub RadioButton9_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton9.CheckedChanged
    End Sub
Private Sub RadioButton8_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handler
Private Sub RadioButton4_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton4.CheckedChanged
End Sub
Private Sub RadioButton5_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton5.CheckedChanged
End Sub
Private Sub RichTextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RichTextBox1.TextChanged
End Sub
End Class

Public Class Form12
  Dim exciting_N = 0
  Dim exciting_S = 0
  Dim exciting_M = 0
  Dim exciting_Q = 0
  Dim exciting_E = 0
  Dim fun_N = 0
  Dim fun_S = 0
  Dim fun_M = 0
  Dim fun_Q = 0
  Dim fun_E = 0
  Dim amusing_N = 0
  Dim amusing_S = 0
  Dim amusing_M = 0
  Dim amusing_Q = 0
  Dim amusing_E = 0
  Dim thrilling_N = 0
  Dim thrilling_S = 0
  Dim thrilling_M = 0
  Dim thrilling_Q = 0
  Dim thrilling_E = 0
  Dim cheerful_N = 0
  Dim cheerful_s = 0
  Dim cheerful_M = 0
  Dim cheerful_Q = 0
  Dim cheerful_E = 0
End Sub
  Private Sub TextBox9_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox9.TextChanged
End Sub
  Private Sub TextBox4_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox4.TextChanged
End Sub
End Sub
End Sub
  Private Sub TextBox8_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox8.TextChanged
End Sub
  Private Sub TextBox2_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox2.TextChanged
End Sub
End Class
Private Sub TextBox3_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles TextBox3.TextChanged
End Sub
Private Sub TextBox5_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles TextBox5.TextChanged
End Sub
Private Sub TextBox6_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles TextBox6.TextChanged
End Sub
Private Sub TextBox17_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs)
Handles TextBox17.TextChanged
End Sub
Private Sub Button2_Click(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles Button2.Click
    If RadioButton1.Checked = True Then
        exciting_N = 1
    End If
    If RadioButton2.Checked = True Then
        exciting_S = 1
    End If
    If RadioButton3.Checked = True Then
        exciting_M = 1
    End If
    If RadioButton4.Checked = True Then
        exciting_Q = 1
    End If
    If RadioButton5.Checked = True Then
        exciting_E = 1
    End If
    If RadioButton14.Checked = True Then
        fun_N = 1
    End If
    If RadioButton13.Checked = True Then
        fun_S = 1
    End If
    If RadioButton12.Checked = True Then
        fun_M = 1
    End If
    If RadioButton11.Checked = True Then
        fun_Q = 1
    End If
    If RadioButton10.Checked = True Then
        fun_E = 1
    End If
    If RadioButton20.Checked = True Then
        amusing_N = 1
    End If
    If RadioButton19.Checked = True Then
        amusing_S = 1
    End If
    If RadioButton18.Checked = True Then
        amusing_M = 1
    End If
    If RadioButton17.Checked = True Then
        amusing_Q = 1
    End If
    If RadioButton16.Checked = True Then
        amusing_E = 1
    End If
If RadioButton15.Checked = True Then
    thrilling_N = 1
End If
If RadioButton9.Checked = True Then
    thrilling_S = 1
End If
If RadioButton8.Checked = True Then
    thrilling_M = 1
End If
If RadioButton7.Checked = True Then
    thrilling_Q = 1
End If
If RadioButton6.Checked = True Then
    thrilling_E = 1
End If
If RadioButton25.Checked = True Then
    cheerful_N = 1
End If
If RadioButton24.Checked = True Then
    cheerful_s = 1
End If
If RadioButton23.Checked = True Then
    cheerful_M = 1
End If
If RadioButton22.Checked = True Then
    cheerful_Q = 1
End If
If RadioButton21.Checked = True Then
    cheerful_E = 1
End If
Dim FILE_NAME As String = "C:\test1.txt"
Dim objWriter As New System.IO.StreamWriter(FILE_NAME, True)
If System.IO.File.Exists(FILE_NAME) = True Then
    objWriter.Write(exciting_N)
    objWriter.Write(" ")
    objWriter.Write(exciting_S)
    objWriter.Write(" ")
    objWriter.Write(exciting_M)
    objWriter.Write(" ")
    objWriter.Write(exciting_Q)
    objWriter.Write(" ")
    objWriter.Write(exciting_E)
    objWriter.Write(" ")
    objWriter.Write(fun_N)
    objWriter.Write(" ")
    objWriter.Write(fun_S)
    objWriter.Write(" ")
    objWriter.Write(fun_M)
    objWriter.Write(" ")
    objWriter.Write(fun_Q)
    objWriter.Write(" ")
    objWriter.Write(fun_E)
    objWriter.Write(" ")
    objWriter.Write(amusing_N)
    objWriter.Write(" ")
    objWriter.Write(amusing_S)
    objWriter.Write(" ")
    objWriter.Write(amusing_M)
    objWriter.Write(" ")
objWriter.Write("amusing _Q")
objWriter.Write("  ")
objWriter.Write("amusing _E")
objWriter.Write("  ")
objWriter.Write("thrilling _N")
objWriter.Write("  ")
objWriter.Write("thrilling _S")
objWriter.Write("  ")
objWriter.Write("thrilling _M")
objWriter.Write("  ")
objWriter.Write("thrilling _Q")
objWriter.Write("  ")
objWriter.Write("thrilling _E")
objWriter.Write("  ")
objWriter.Write("cheerful _N")
objWriter.Write("  ")
objWriter.Write("cheerful _s")
objWriter.Write("  ")
objWriter.Write("cheerful _M")
objWriter.Write("  ")
objWriter.Write("cheerful _Q")
objWriter.Write("  ")
objWriter.Write("cheerful _E")
objWriter.Write("  ")
objWriter.Close()

End If
If Form26.Show() End Sub
End Sub
Private Sub TextBox7_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox7.TextChanged
End Sub
End Sub
Private Sub TextBox1_TextChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles TextBox1.TextChanged
End Sub
Private Sub RadioButton1_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton1.CheckedChanged
End Sub
End Sub
Private Sub RadioButton20_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton20.CheckedChanged
End Sub
Private Sub RadioButton15_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton15.CheckedChanged
End Sub
Private Sub RadioButton9_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton9.CheckedChanged
End Sub
Private Sub RadioButton25_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton25.CheckedChanged
End Sub
End Sub

    Private Sub RadioButton6_CheckedChanged(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles RadioButton6.CheckedChanged
    End Sub

Public Class Form26
    Private Sub Form26_Load(ByVal sender As System.Object, ByVal e As System.EventArgs) Handles MyBase.Load
    End Sub
End Class
Appendix C: Screenshots of SC questionnaire

Online shopping choice exercise

Start

Thank you for agreeing to take part in this exercise.

The purpose of this exercise is to better understand how people make choices between conventional shopping and online shopping using mobile devices.

During the exercise we will describe what is involved in shopping online using mobile devices and ask you to choose between ways of conventional shopping and online shopping.

Next
This experiment is divided into three parts.

The first part gives you some background information about shopping using mobile devices.

The second part presents a number of hypothetical situations in which you have the choice of either shopping in the conventional way or shopping online using mobile device.

The final part asks some general questions regarding you and your use of mobile technology.

Your response to this exercise will assist us greatly in this research.

All the information will be treated as confidential and will only be used for the purpose of this research, and not disclosed to others.
Part One

Background information

In this exercise, you will be asked to consider using mobile devices to conduct online shopping and to compare this way of shopping to conventional shopping.

In this part, we will introduce each type of shopping activity in detail.
Online shopping using a mobile device

We would like you to consider a situation in which you can purchase the goods or services you want over the internet while you are travelling, using a mobile device such as a laptop or a PDA or a smart phone.

The goods you order will be delivered at a time of your choosing and to a destination you specify.

Process of online shopping using a mobile device

Connect to the website  Browse and select  Checkout
The conventional shopping process

Travel to the shop

Pick up a trolley

Browse and select

Pay at the cashier

Part Two

Shopping choice scenarios
In this part, we describe a hypothetical shopping scenario and ask you to choose between different versions of conventional shopping and online shopping during travel.

Assuming that you are not allowed to undertake online shopping during work time, you have two ways of buying flowers - either conventional shopping after work or online shopping using mobile device on the train.
Extra travel cost: The extra money required by you in travelling from your office to the extra shop to buy flowers.

Extra travel time: The extra time required by you in travelling from your office to the extra shop to buy flowers.

Shopping time: The time required in browsing, selecting the flowers, queuing and paying at cashier.

The flowers bought in the shop: We describe this as "I got flowers I wanted" or "I had to settle for a less satisfactory alternative."
Online shopping using a mobile device

1. Start from station at 7:30am

Arrive at office later

2. Online shopping using a mobile

3. Work during day time

Next
Online shopping using a mobile device

1. Work during day time
2. Work during day time
3. Work during day time
4. Flowers delivery from shop
5. Carry the flowers and arrive at party after work

Next
Journey time: The duration of the journey from station to your office.

Online cost: The money required to pay in order to access the internet for the whole journey via mobile plus the cost of delivery.

Online time: The time required connecting the internet instantly, browsing, searching, comparing flowers, placing the order, booking the delivery time and paying online during journey on the train.

The flowers bought online: We describe this as "I received my preferred flowers" or "I received a less satisfactory alternative."

Example

<table>
<thead>
<tr>
<th>Journey time: 35 min</th>
<th>Extra travel cost: GBP 1.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online cost: GBP 8.00</td>
<td>Extra travel time: 10 min</td>
</tr>
<tr>
<td>Online time: 10 min</td>
<td>Shopping time: 15 min</td>
</tr>
<tr>
<td>I received a less satisfactory alternative.</td>
<td>I settled for a less satisfactory alternative.</td>
</tr>
</tbody>
</table>

- Online shopping with mobile
- Conventional shopping
Part Three

General Questions

First, we would like to ask you a few questions about yourself.
What is your gender?

- Female
- Male

When were you born?

1980 -
What is your highest educational qualification?

- PhD
- Master’s Degree
- Bachelor’s Degree
- A/AS levels or equivalent
- O levels/CSE/GCSE or equivalent
- Other qualifications (Please specify)
- No formal qualifications

What is your current employment?

- Full time paid employment
- Part time paid employment
- Full time self employment
- Part time self employment
- Full time student
- Part time student
- Not currently employed

Next
What is your annual individual income?

- Less than £4,000
- £4,000 - £8,000
- £8,000 - £15,000
- £15,000 - £30,000
- £30,000 - £75,000
- More than £75,000
- Decline to answer

Next, we would like to ask you some questions about your use of the internet.
How would you describe your current access to the internet?

- I always have access at home and work and when I am travelling.
- I always have access at home and at work.
- I only have access at work.
- I only have access at home.
- I don't have access to the internet at all.

Next

How would you describe your use of the internet?

- I regularly use the internet several hours per day.
- I regularly use the internet several hours per week.
- I only use the internet occasionally
- I never use internet.

Next
How would you describe your experience of online shopping?

- I regularly use online shopping services
- I occasionally use online shopping services
- I never use online shopping services.

How would you describe your use of the mobile internet?

- I regularly use the mobile internet several hours per day.
- I regularly use the mobile internet several hours per week.
- I only use mobile internet occasionally.
- I never use mobile internet.
How would you describe your experience of online shopping using the mobile internet?

- I regularly use online shopping services with mobile internet
- I occasionally use online shopping services with mobile internet
- I never use online shopping services with mobile internet.

Finally, we would like to ask a few broader questions about how you see yourself.
How well do the following statements describe your personality?

<table>
<thead>
<tr>
<th>I see myself a person who...</th>
<th>Disagree strongly</th>
<th>Disagree a little</th>
<th>Neutral</th>
<th>Agree a little</th>
<th>Agree strongly</th>
</tr>
</thead>
<tbody>
<tr>
<td>is reserved</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>is generally trusting</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>tends to be lazy</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>handles stress well</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>has few artistic interests</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

How well do the following statements describe your personality?

<table>
<thead>
<tr>
<th>I see myself a person who...</th>
<th>Disagree strongly</th>
<th>Disagree a little</th>
<th>Neutral</th>
<th>Agree a little</th>
<th>Agree strongly</th>
</tr>
</thead>
<tbody>
<tr>
<td>is outgoing, sociable</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>tends to criticize others</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>does a thorough job</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>gets nervous easily</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>has an active imagination</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Thank you for your co-operation!
Appendix D: R source code of generating a synthetic dataset with N choice scenarios

dat<-gen.factorial(c(2,2,5,2,2,5,2), factors="all")
design<-optFederov(~.,dat,N.eval=TRUE)
data<-data.frame(design$design)
data$X1<-ifelse(data$X1==1,35,60)
data$X2<-ifelse(data$X2==1,3,8)
data$X3<-ifelse(data$X3==5,30,data$X3)
data$X3<-ifelse(data$X3==4,25,data$X3)
data$X3<-ifelse(data$X3==3,20,data$X3)
data$X3<-ifelse(data$X3==2,15,data$X3)
data$X3<-ifelse(data$X3==1,10,data$X3)
data$X4<-ifelse(data$X4==1,1.2)
data$X5<-ifelse(data$X5==1,1,5)
data$X6<-ifelse(data$X6==1,10,30)
data$X7<-ifelse(data$X7==5,30,data$X7)
data$X7<-ifelse(data$X7==4.25,data$X7)
data$X7<-ifelse(data$X7==3.2,5,30)
data$X7<-ifelse(data$X7==2.15,data$X7)
data$X7<-ifelse(data$X7==1.1,10,30)
data$X8<-ifelse(data$X8==1,1,2)
beta11<-rep(-0.007,length(data$X7))
beta12<-rep(-1.347,length(data$X7))
beta13<-rep(-0.281,length(data$X7))
beta14<-rep(2.256,length(data$X7))
beta21<-rep(1.574,length(data$X7))
beta22<-rep(0.018,length(data$X7))
beta23<-rep(-0.122,length(data$X7))
beta24<-rep(1.24,length(data$X7))
choice<-rep(0,length(data$X1))
U1<-beta11*data$X1+beta12*data$X2+beta13*data$X3+beta14*data$X4
U2<-beta21*data$X5+beta22*data$X6+beta23*data$X7+beta24*data$X8
prob_1<-exp(U1)/(exp(U1)+exp(U2))
prob_2<-exp(U2)/(exp(U1)+exp(U2))
random_number<-runif(length(data$X1),min=0,max=1)
for(i in 1:length(data$X1)){
  if (random_number[i]< prob_1[i])
    choice[i]<-1 else choice[i]<-2
}
choice <- as.matrix(choice)
input_data <- cbind(data,choice)
write.table(input_data,file="C:/Users/yunlei hu/Documents/input_.txt")