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Investigating the travel behaviour dynamics of Bus Rapid Transit passengers

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Abstract

The long-term prevalence of car dependency has resulted in a series of persistent urban problems, including congestion, environmental pollution and social inequity, and threatens the survival of urban public transport (UPT). One response to these problems has been an international rising trend to implement Bus Rapid Transit (BRT) as a cost-effective means to progress towards more sustainable urban transport. Despite the growing popularity of BRT implementation worldwide, little is known about the travel behaviour dynamics associated with BRT. Given that the understanding of travel behaviour is a critical component for public transport planning and policy, this deficit may critically hinder our ability to inform future BRT-related policy.

This research presents three empirical investigations of interrelated travel behaviour dynamics of BRT passengers, providing an enhanced evidence base on which future BRT-related policy can be founded. Drawing on Brisbane (Australia) as the case study coupled with three distinct datasets (i.e., census, smart card and primary survey data), BRT passenger travel behaviour is investigated from three complementary perspectives, namely, modal share patterns of BRT catchments, spatial-temporal dynamics of current BRT usage and behavioural intentions of BRT passengers. Examinations from these three perspectives capture a broad spectrum of travel behaviour dynamics that collectively render a more holistic understanding of BRT usage.

First, the modal share patterns of BRT catchments are examined before and after BRT implementation to shed light on the extent to which the travel behaviour was altered by the implementation of BRT. Drawing on census data from three periods, marked increases in bus and walk shares, and decreases in private car share for work trips were revealed after BRT implementation at both walk-in (800-metre) catchments and the bus-in/drive-in catchments (up to three kilometres). Regression modelling highlights marked increases in female, lone person commuters as well as ‘choice’ passengers who have access to private cars within the vicinity of BRT stations.

Next, drawing on smart card data, the spatial-temporal dynamics of current BRT usage are examined to reveal the role of the BRT embedded within the UPT network in catering for passengers’ travel needs. To exploit the utility of smart card data, a geo-visualisation-based method (the flow-comap) is developed to visualise and analyse the spatial-temporal patterns of BRT-related trips. The results highlight distinct trip characteristics and spatial-temporal patterns of BRT-related trips against the remaining on-road bus trips. The spatial heterogeneity of passenger trip patterns using the exclusive busway of the BRT across the bus network is also revealed, this encompasses: (1) the South East Busway (SEB), which serves as a stronger corridor in collecting trips around Brisbane than the Northern Busway (NB) and (2) differing temporal trip patterns which are associated with the SEB rather than the NB.

Last, to capture the attitudinal mechanisms of travel behaviour, BRT passengers' behavioural intentions (i.e., loyalty, intention to increase BRT use and intention to shift to private car use) are modelled by using primary survey data. A number of small yet significant differences in the behavioural intentions are revealed in association with the socio-demographic and behavioural characteristics of passengers. More importantly, a series of regression models highlight that the loyalty and intention of passengers to increase BRT use were positively associated with their evaluations of BRT service and pro-environmental responsibility, while their intention to change to private car use negatively related with these attitudinal factors. Furthermore, regressing passengers' loyalty on their attitudes related to private car use results in a positive relationship.

The thesis contributes to knowledge in the area of travel behaviour dynamics related to BRT through drawing on a suite of datasets to capture three complementary dimensions of behavioural dynamics of BRT passengers. Methodological and theoretical contributions are also rendered in this research, including (1) the proposed geo-visualisation-based method (the flow-comap) to enhance the utility of smart card data for the examination of travel behaviour and (2) a more comprehensive inclusion of behavioural intentions coupled with the considerations of alternative transport to better understand UPT passengers' attitudinal mechanisms. In the context of the case study, this thesis has some implications for the potential to inform (1) the service provision and infrastructure expansion of BRT to better meet the travel needs of passengers and (2) the design of marketing strategy and soft policy (e.g., information-based approach) to maintain and promote BRT usage.

In conclusion, through a series of empirical investigations, this thesis helps realise the potential of BRT to offer a way in which urban environments can progress towards sustainable UPT systems. It is also hoped that this thesis may stimulate future research in this area that can help inform and guide the implementation of smarter BRT systems.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications during candidature

Journal Publications

Tao, S., Corcoran, J., Mateo-Babiano, I. & Rohde, D. 2014. Exploring Bus Rapid Transit passenger travel behaviour using big data. *Applied Geography*, 53, 90-104.

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Tao, S., Corcoran, J. & Mateo-Babiano, I. Submitted. Modelling Bus Rapid Transit passengers' loyalty and behavioural change intentions. *Transportation*.

Conference paper

Tao, S., Corcoran, J. & Mateo-Babiano, I. 2013. Bus Rapid Transit: An examination of changes of travel patterns for journey to work and socio-demographic characteristics. *Australasian Transport Research Forum (ATRF)*. Brisbane, Australia.

Publications included in this thesis

This thesis contains three jointly authored published papers and one jointly authored paper currently under review for publication. Contributions by co-authors are indicated below.

Tao, S., Rohde, D. & Corcoran, J. 2014. Examining the spatial–temporal dynamics of bus passenger travel behaviour using smart card data and the flow-comap. *Journal of Transport Geography*, 41, 21-36. – partially incorporated as paragraphs in Chapters 4 and 6.

Contributor	**Statement of contribution**
S. Tao	Conceptual design (70%) Data analysis (70%) Writing and editing the paper (75%)
D. Rohde	Data analysis (30%) Writing and editing the paper (10%)
J. Corcoran	Conceptual design (30%) Writing and editing the paper (15%)

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S. Tao	Conceptual design (80%) Data analysis (100%) Writing and editing the paper (80%)
J. Corcoran	Conceptual design (20%) Writing and editing the paper (10%)
I. Mateo-Babiano	Writing and editing the paper (10%)

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S. Tao	Conceptual design (80%) Data analysis (90%) Writing and editing the paper (80%)
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D. Rohde	Data analysis (10%)

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S. Tao	Conceptual design (80%) Survey and data collection (100%) Data analysis (100%)

	Writing and editing the paper (80%)
J. Corcoran	Conceptual design (10%) Writing and editing the paper (10%)
I. Mateo-Babiano	Conceptual design (10%) Writing and editing the paper (10%)

Contributions by others to the thesis

While all the chapters were written by the candidate, my supervisors—A/Prof Jonathan Corcoran, Dr. Derlie Mate-Babiano and Dr. David Rohde have contributed substantially to this research in terms of the conceptual development, data collection, technical support and editing process.

Statement of parts of the thesis submitted to qualify for the award of another degree

None.

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Keywords

Bus Rapid Transit, passenger travel behaviour, multi-database, evidence-based planning

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List of Abbreviations

ABS	Australian Bureau of Statistics
ADC	Automatic Data Collection
AFC	Automatic Fare Collection
ANZAC Day	Australian and New Zealand Army Corps Day
AVL	Automatic Vehicle Location
BI	Behavioural Intention
BITRE	Bureau of Infrastructure, Transport and Regional Economics
BRT	Bus Rapid Transit
BSD	Brisbane Statistical Division
BUZ	Bus Update Zone
CA	Car attitudes
CBD	Central Business District
CD	Collection District
CV	Coefficient of Variance
DETA	The Department of Education, Training and Employment
EB	Eastern Busway
FV	Flow Volume
GIS	Geographic Information Systems
GPS	Global Positioning System
GTFS	General Transit Feed Specification
IRSAD	The Index of Relative Socio-economic Advantage and Disadvantage
ITS	Intelligent Transport System
JTW	Journey-to-Work
LF	Load Factor
LRT	Light Rail Transit
MANOVA	Multivariate Analysis of Variance
MTW	Method for Travel to Work
NAM	The Norm Activation Model
NB	Northern Busway
OD	Origin-Destination
PBC	Perceived Behavioural Control
PHS	Personal Hand-phone System
PN	Personal Norm

PSQ	Perceived Service Quality
PV	Perceived Value
SA1	Statistical Level 1
SEB	South East Busway
SEIFA	Socio-Economic Indexes for Areas
SEQ	South East Queensland
SN	Social Norm
TPB	The Theory of Planned Behaviour
UK	United Kingdom
UPT	Urban Public Transport
VIF	Variance Inflation Factor
WWII	World War II

Chapter 1 Introduction

1.1 Overview of the thesis

With the rapid global rise in motorised transport over the past five decades, urban public transport (UPT) systems in developed countries have been struggling to compete with private cars for people to fulfil their travel needs (Newman and Kenworthy, 1999a). A transport survey including 37 developed cities across North America, Australia and Europe reported that only seven cities had UPT modal shares over 20%, while for 22 other cities the share was less than 10% of all trips (Kenworthy and Laube, 1999; Newman and Kenworthy, 1999). The long-term imbalance between UPT use and private car use in many cities has resulted in a number of persistent urban problems that include congestion, environmental pollution and social inequity, and threatens the survival of UPT worldwide. Overlooking such issues can seriously damage the efficiency of urban transport and the economy, public health and life quality, especially of those who rely on UPT services to fulfil their mobility needs (Newman and Kenworthy, 1999a; Banister, 2008; Banister, 2011; Okata and Ieda, 2010; Litman, 2002; Dodson et al., 2004).

One response to the issues pertaining to unsustainable impacts of transport has been a rising international trend towards the implementation of Bus Rapid Transit (BRT) as a way to enhance UPT service and redress the imbalance between private car and UPT usage. Due to features including exclusive busway, intelligent transport information systems, BRT has proven to be able to deliver a rail-like service quality including high capacity and high frequency with a relatively low construction and maintenance cost (Levinson et al., 2002; Wright and Hook, 2007; Hoffman, 2008). The implementation of BRT has achieved positive outcomes, including enhanced UPT service (such as higher capacity and operational speed) and considerable increases in UPT patronage in a number of cities (Hensher and Golob, 2008; Levinson et al., 2003b). However, given the relatively low mode share of UPT in highly motorised contexts (such as Australian cities with UPT shares around 10%), the challenge of maintaining and enhancing the use of BRT remains critical.

A core component of overcoming this challenge is the development of an enhanced understanding of travel behaviour and the underpinning attitudinal mechanisms of BRT passengers through which future BRT policy and planning can be better informed. However, despite the growing popularity of BRT implementation worldwide little is known about the travel behaviour dynamics related to BRT. This deficit may have the potential to thwart our ability to inform future BRT provision and promotion as a way to progress towards more sustainable transport outcomes.

This thesis seeks to bridge the knowledge gaps identified by drawing on three distinct datasets (i.e., census data, smart card data and survey data) that permit the investigation of BRT dynamics from complementary behavioural dimensions. First, drawing on census data, the changes in modal share patterns and associated socio-demographic characteristics of the BRT catchments were investigated to shed light on the effects of BRT in shaping greener travel behaviour of urban populations. Second, a large smart card dataset was drawn upon to capture the spatial-temporal dynamics of BRT-based trips across different calendar events (i.e., a workday, a Saturday, a Sunday, a public holiday and a school holiday), revealing how bus passengers use BRT to fulfil their travel needs across the UPT network. Last, using a survey-based method, primary data was collected for the modelling of BRT passengers' behavioural intentions (i.e., loyalty, the intention to shift to private car use and the intention to increase BRT use) to help in understanding the attitudinal dimensions having impacts on their future use of BRT and alternative transport, in particular private cars.

Through these empirical investigations, the results of this study collectively provide a more holistic understanding concerning the dynamics of BRT passenger travel behaviour that has the potential to inform and guide future BRT-related policy and planning in terms of: (1) the service provision and infrastructure expansion of BRT in better meeting the travel needs of passengers, and, complementary to this first perspective, (2) the design of marketing and soft policy options (e.g., information-based approach) to maintain and promote passengers' usage of BRT as another critical component of establishing sustainable transport.

Methodological and theoretical contributions are also progressed in this thesis. From an overarching perspective, this research presents a methodological design of the application of various, formerly disparate, data sources in investigating complementary dimensions of BRT passenger travel behaviour. This paradigm can serve as a foundation on which future research can draw to investigate UPT passengers' behaviour. Methodologically, a geo-visualisation-based method (the flow-comap) (Tao et al., 2014a) is developed and applied to a large smart card dataset to unveil the spatial-temporal dynamics of BRT usage at a stop-to-stop level of granularity, as such enhancing the utility of smart card data as a data source of growing importance for the examination of UPT passenger travel behaviour. From a theoretical perspective, it is shown in this research that through an empirical investigation of primary survey data, a more comprehensive inclusion of behaviour intentions as well as a suite of attitudinal factors, has the potential to allow a better understanding of UPT passengers' attitudinal mechanisms related to their travel behaviour.

1.2 Problem statement

The provision of road or rail-based UPT alternatives to private cars is a key prerequisite for sustainable urban transport (Newman and Kenworthy, 1999a; Wright and Fjellstrom, 2003). Rail-based transit has been commonly praised for its high service quality (e.g., high reliability and speed) and capacity to carry relatively large numbers of passengers, typically, between 10,000 and 30,000 passengers per hour per direction during peak hours (Wright and Fjellstrom, 2003; Currie, 2005). However, weaknesses including inflexibility of route identification coupled with the relatively high construction and maintenance costs reduce the feasibility and attractiveness of rail-based transit in many developed and developing cities (Wright and Fjellstrom, 2003). On the other hand, Despite its lower funding requirements, the on-road bus service has commonly been deemed as less unreliable and overall, an unattractive transit mode for the public (Wright and Fjellstrom, 2003; Deng and Nelson, 2010). Given this, UPT alternatives have been sought in the hope of providing a transit service with high service quality for passengers and relatively low investment requirements.

Over the past two decades, more cities across the world have opted for Bus Rapid Transit (BRT) as a cost-effective alternative to rail-based transit in progressing towards sustainable urban transport (Deng and Nelson, 2010; Hensher and Golob, 2008; Hoffman, 2008). BRT combines the service pattern of rail-based transit (e.g., exclusive busway, enhanced stations, higher service frequency and intelligent transport system) with the low cost of bus transit. BRT normally has the capacity to carry 3,000 to 8,000 passengers (in some cases such as Bogota, Columbia, 20,000 passengers) per hour per lane per direction during peak hours (Levinson et al., 2003b; Hensher and Golob, 2008). In comparison to rail-based transit, a BRT system is assumed to be 4~20 times cheaper than a Light Rail Transit (LRT) system and 10~100 times cheaper than a metro system (Deng and Nelson, 2010; Wright and Hook, 2007). In addition, BRT offers door-to-door and higher flexibility service with an open design that allows on-road bus access to the busway (Levinson et al., 2003a; Wright and Hook, 2007). Such flexibility is unachievable for LRT or metro systems. These features (e.g., rail-like service features, lower costs and higher flexibility) collectively render BRT a cost-effective alternative to rail transit services in both developed and developing city contexts. To date, a total of 180 cities across the world have operated BRT within their UPT networks (Figure 1.1) (Global BRT Data, 2014). There has also been a marked increase of BRT implementation worldwide since 2000 (Hensher and Golob, 2008) (Figure 1.2).

Figure 1.1 BRT across the world, source: Global BRT Data (2014)

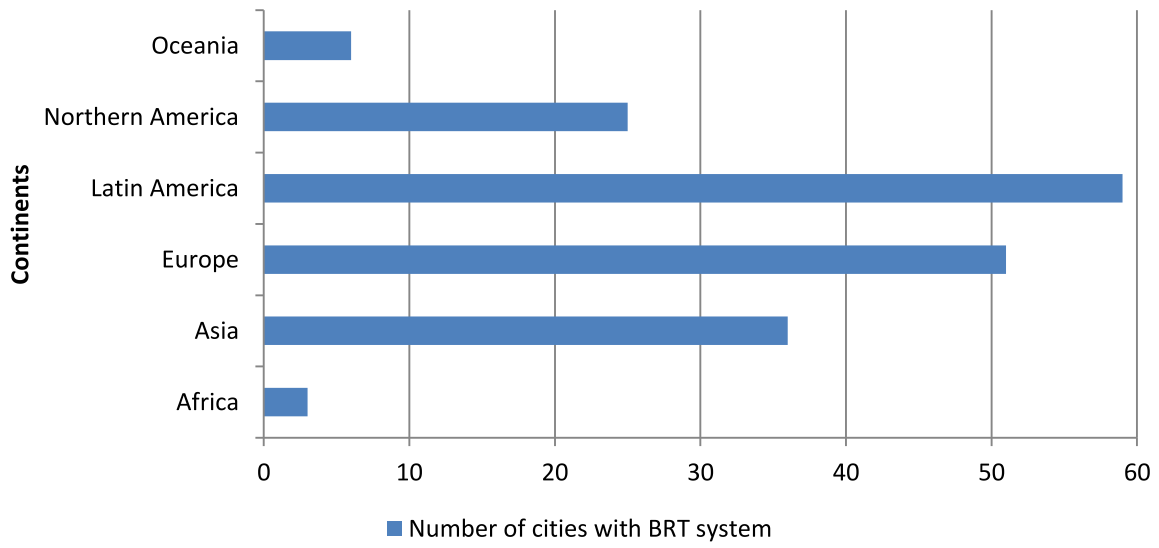
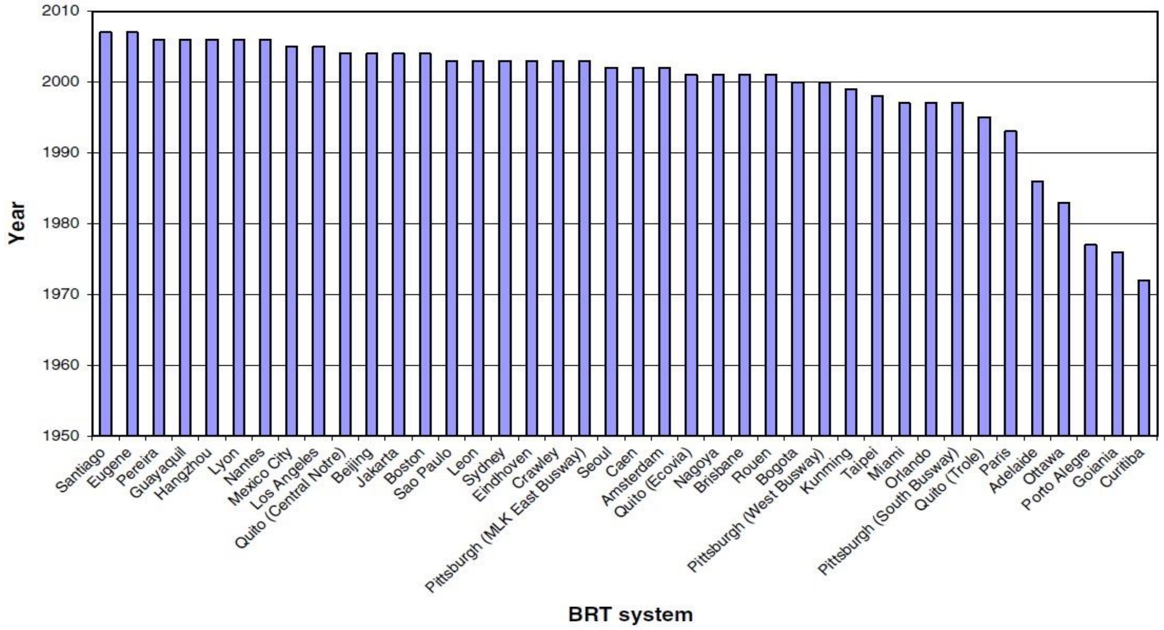


Figure 1.2 Age profile of BRT systems, source: Hensher and Golob (2008)



Given the increasing worldwide trend towards BRT implementation, academic attention has begun to focus on the examination of the performance of BRT systems to offer a mechanism through which future BRT programs can be informed (Currie and Delbosc, 2010; Deng and Nelson, 2010; Hensher and Golob, 2008; Levinson et al., 2003b). Considerable attention has been paid to the examination of ridership change for passengers associated with BRT implementation. Studies have found that marked increases in ridership (e.g., 20-50%) were achieved along the BRT corridors (e.g., exclusive busway) shortly after their implementation (e.g., 1-6 months) within both developed (Callaghan and Vincent, 2007; Levinson et al., 2003a; Currie, 2006) and developing city contexts (Hidalgo and Graftieaux, 2008; Deng and Nelson, 2013; Ernst, 2005; Hensher and Golob, 2008).

The accumulating evidence indicates that BRT is a cost-effective UPT option with enhanced performance compared to the on-road buses and some metro systems. Nonetheless a scrutiny of existing literature indicates that the knowledge concerning travel behaviour dynamics associated with BRT is rather limited (Lleras, 2002; Estupiñán and Rodríguez, 2008; Tao et al., 2014). Limited studies have examined the extent to which the implementation of BRT actually drives the changes in travel behaviour in a more sustainable direction across an urban space, particularly encouraging people's use of public transport instead of private motorised vehicles (Lleras, 2002; McDonnell and Zellner, 2011) and what socio-demographic cohorts of urban population are more likely to use BRT (Tao et al., 2013). Given that increasing public transport shares while reducing car dependency of urban populations has been highlighted as one of the core motives for initiating BRT programs worldwide (Wright and Hook, 2007; Lleras, 2002), a more explicit examination of changes in travel behaviours (in particular modal share patterns) and associated socio-demographic characteristics is needed to further clarify the effects of BRT in driving greener travel behaviour.

Apart from the examination of changes in travel patterns, two additional dimensions of travel behaviour, namely, the spatial-temporal dynamics of BRT usage and the attitudinal mechanisms of BRT passengers (in particular their behavioural intentions) also deserve particular attention.

The understanding of the spatial-temporal characteristics of people's travel behaviour has long been a critical topic in transport studies (Hanson and Huff, 1986; Kitamura, 1988; Pas and Koppelman, 1987), given that it serves as a fundamental component for informing transport policy and planning (Ortuzar and Willumsen, 2001; Pelletier et al., 2011; Farzin, 2008; Trépanier et al., 2007). Renewed interest has been seen in this field of studies over the past decade (Chu and Chapleau, 2010; Morency et al., 2006; Munizaga and Palma, 2012; Nassir et al., 2011), which to a considerable extent pertains to the emergence of smart card data as an enhanced data source for investigating UPT passenger travel behaviour compared to the conventional travel survey data in providing richer spatial and temporal trip information (Bagchi and White, 2005; Pelletier et al., 2011). The emergence of smart card data as such offers new opportunities to obtain a more detailed understanding of the geographic and temporal behavioural patterns of transit passengers. Existing research on BRT usage has been mostly carried out at corridor level, e.g., Callaghan and Vincent (2007), Currie and Delbos (2010), while little knowledge exists concerning how BRT is used in tandem with the wider transit network to fulfil people's travel demands. Redressing this knowledge gap using smart card data therefore may have the capacity to inform future BRT planning from a more network-based perspective, for example, adjusting BRT-based services' spatial configuration and frequency in accordance with passengers' varying travel demands over space and time, and by doing so better integrating BRT within an UPT network.

Further to the spatial-temporal patterns, the investigation of the attitudinal dimensions of BRT passengers can provide additional behavioural insights. Increasingly recognised has been that people use public transport for different reasons. It has been revealed that a variety of attitudinal factors such as lack of private vehicles, preference and pro-environmental concerns may influence people's decisions of choosing public transport to fulfil their travel needs (Bamberg et al., 2007; Anable, 2005; Parkany et al., 2004). Given this, capturing the attitudinal dimensions related to public transport use may enable more market-targeted approach (for example, identifying and acting on service aspects valued by certain passenger groups) to preserve and increase patronage for a transit service (Anable, 2005; Jen et al., 2011). Furthermore, attaining existing passengers' favourable behavioural intentions (for example, the willingness to continue patronise) towards a transit service has been highlighted as a key strategy to achieve such goal for a transit agency over the long run (Figler et al., 2011; Foote et al., 2001; Lai and Chen, 2011). Within the BRT context, however, few have explored BRT passengers' behavioural intentions and related attitudes. Considering the increasingly important role of BRT within the UPT context globally, investigating the attitudinal mechanisms of BRT passengers forms another key focus of this study.

In summary, given the growing popularity of BRT implementation worldwide, there is a compelling need to better understand the travel behaviour dynamics related to BRT to provide a platform through which future BRT-related policy and planning can be informed. Achieving this goal requires consideration and investigation from complementary behavioural perspectives that encompass the changes in travel patterns, the spatial-temporal dynamics of trip-making and the attitudinal dimensions of behavioural intentions. Doing so will render a more holistic and multi-layered understanding of BRT passenger travel behaviour and as such, provide valuable recommendations for BRT systems to improve the sustainability of urban transport. Given this, the investigation of the travel behaviour dynamics of BRT passengers underpins the impetus of this thesis.

1.3 Research question and objectives

Given the knowledge gaps identified, this thesis addresses the following research question:

What are the travel behavioural dynamics of BRT passengers and how can our understanding of these dynamics enhance understanding about BRT passengers' loyalty and change intentions?

Four objectives are proposed to answer this overarching question:

Objective 1: To examine changes in modal share patterns and socio-demographic characteristics of BRT catchments.

Objective 2: To capture the spatial-temporal dynamics of BRT usage.

Objective 3: To model the behavioural intentions of BRT passengers.

Objective 4: To draw on the outcomes from Objectives 1, 2 and 3 to develop recommendations for future BRT policy and planning.

1.4 Research significance and contributions

While there are over 180 BRT systems currently implemented within the UPT networks of cities across the world, as outlined in Section 1.2, little is known about how BRT shapes and facilitates people's travel behaviour, as well as influences BRT passengers' loyalty and behavioural change intentions. This thesis aims to address these knowledge gaps and ultimately render an enhanced evidence base that has the capability to inform future BRT policy and planning. As outlined in Section 1.3, this thesis primarily seeks to contribute to the understanding of travel behaviour dynamics related to BRT from complementary behavioural dimensions by fulfilling the first three research objectives:

- Drawing on census data, Objective 1 aims to reveal the extent to which people's travel behaviour can be altered by BRT as a core concern of implementing BRT globally. It examines the modal share patterns (e.g., public transport and private car shares) for work trips from a before-and-after perspective, as well as in association with the socio-demographic characteristics of the BRT catchments.

- Drawing on a large smart card dataset, Objective 2 seeks to investigate the spatial-temporal patterns of BRT usage of passengers. It is expected that the revealed patterns can elucidate the spatial-temporal differences between BRT-related trips and the on-road bus trips, as well as the more nuanced spatial heterogeneity of passenger trip patterns using the BRT busway, since such knowledge critically relates to the understanding of the roles of BRT in catering for passengers' travel needs across a UPT network.

- Finally, drawing on a primary survey dataset, Objective 3 aims to understand the attitudinal mechanisms related to BRT passengers' behavioural intentions as the last component of travel behaviour investigations in this research. Particular attention is paid to the modelling and understanding of passengers' loyalty, behavioural change intentions and related attitudinal dimensions, considering their potentially critical roles in influencing passengers' short and long term use of BRT.

By fulfilling the first three objectives, it is expected that some valuable recommendations for future BRT policy and planning as a way to achieve more sustainable urban transport can be developed, that encompass:

- The findings derived from Objective 1 may provide clearer evidence concerning the capability of BRT in driving greener travel behaviour.

- The findings of Objective 2 may inform BRT provision in terms of adjusting BRT service in better reaction to passengers' travel needs.

- The findings of Objective 3 may help BRT agency to identify possible means to maintain current patronage especially within car-oriented contexts.

Apart from the knowledge and practical contributions, methodological and theoretical contributions are also expected to be achieved in this study, from which future studies investigating BRT and broader UPT passenger travel behaviour can benefit:

- From an overarching perspective, a multi-database research paradigm is adopted in this study in order to better capture the complementary dimensions of BRT passenger travel behaviour. This paradigm can be drawn upon by future studies focusing on other BRT or UPT systems in order to attain a more holistic and multi-layered understanding of passengers' behaviour dynamics.

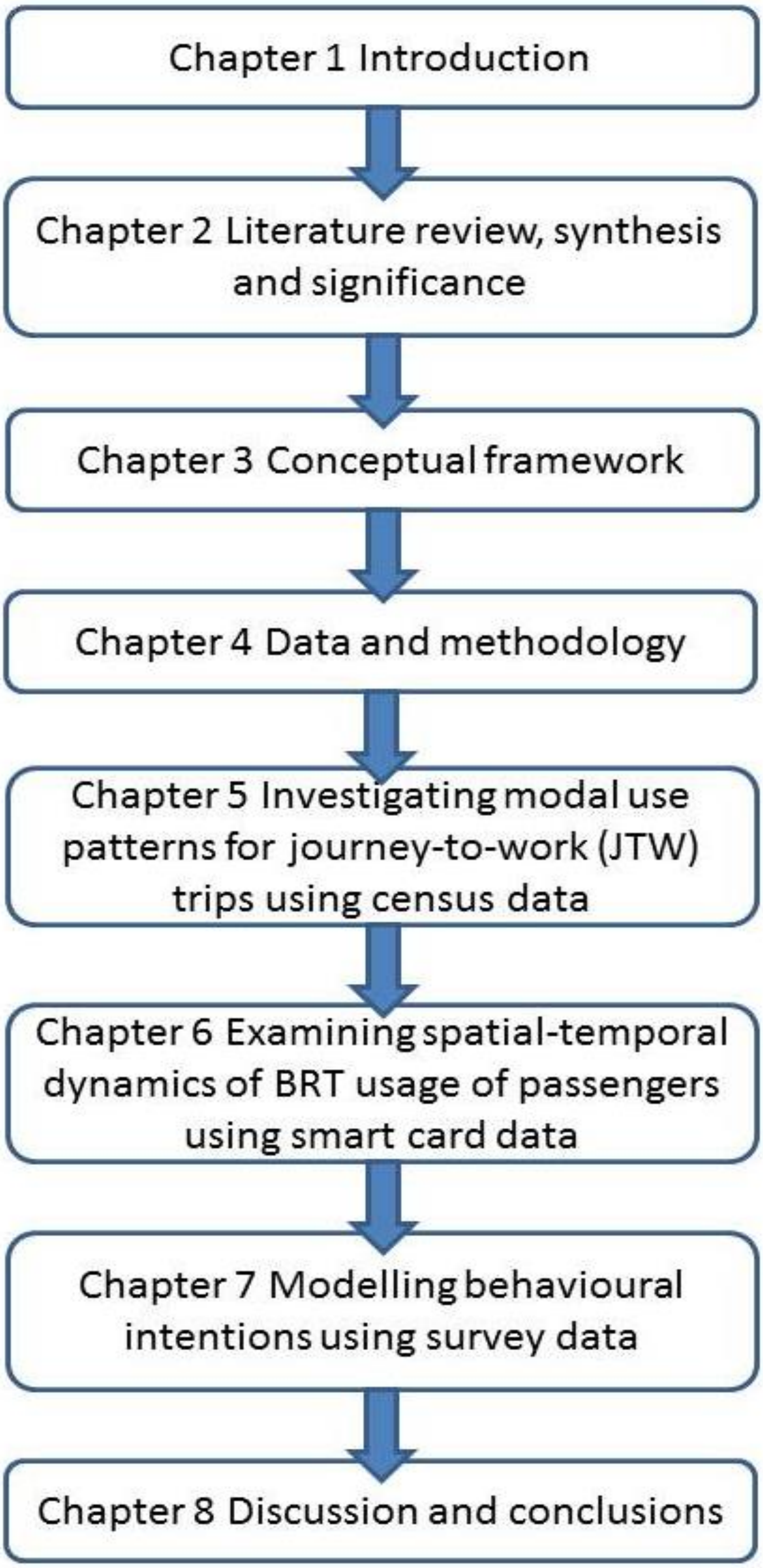
- This study develops a geo-visualisation-based method (the flow-comap) to analyse smart card data. This method seeks to enhance the utility of smart card data for travel behaviour investigations in two ways: (1) it allows the reconstruction of smart card records as travel trajectories at a stop-to-stop level of granularity; and (2) it uses expanded smart card data to compute conditional flow-maps (or flow-comaps) and weighted flow-comaps to capture the nuanced flow patterns of passengers across the UPT network previously unattainable. Given these two strengths, the method may be applied to other smart card datasets to understand the spatial-temporal dynamics of other BRT and UPT systems.

- In the modelling of behavioural intentions, this study establishes and tests a series of regression models with a more comprehensive inclusion of behavioural intentions (i.e., loyalty coupled with behavioural change intentions) as well as the considerations of alternative transport, in particular private car use. Further empirical studies may build upon these models to offer an enhanced understanding of the attitudinal mechanisms related to UPT passengers' behavioural tendencies towards their future use of UPT and alternative transport, particularly private cars, considering them as a key barrier to UPT use.

1.5 Structure of the thesis

The remainder of the thesis is organised as follows. Chapter 2 provides a critical review of the salient literature related to the investigation of BRT passenger travel behaviour, synthesises research significance and finally proposes the overarching research question. Chapter 3 establishes the conceptual framework to guide this research, as well as identifying research objectives underpinning the research question. Chapter 4 introduces and justifies the choice of Brisbane as the case study for this research, and explains the data and methodology used in this research. Chapter 5 examines the modal share patterns for journey-to-work (JTW) trips within BRT's catchment areas. Chapter 6 captures the spatial-temporal dynamics of BRT passenger travel behaviour by analysing smart card (Go Card) data using a series of geo-visualisation techniques (e.g., the flow-comap). Chapter 7 models the key attitudinal aspects related to BRT passengers' loyalty and behaviour change intentions. Finally, Chapter 8 draws together the findings and contributions from the empirical investigations of Chapters 5, 6 and 7 to develop recommendations for future BRT policy and planning. Limitations of the study and future research avenues are discussed allied to drawing a set of tentative conclusions. Figure 1.3 depicts the overall workflow of the thesis.

Figure 1.3 The overall workflow of the thesis



Chapter 2 Literature review, synthesis and significance

This chapter provides a critical review of the related literature in three sections. Section 2.1 introduces Bus Rapid Transit (BRT) as a means towards sustainable urban transport and its implementation in both a global and Australian context, highlighting the currently limited knowledge concerning travel behaviour related to BRT. Section 2.2 reviews the literature focusing on examining the spatial-temporal dynamics of travel behaviour, and highlights the emergence of smart card data and its utility for the examination of UPT passenger travel behaviour. Section 2.3 reviews the literature related to the investigation of the attitudinal mechanisms of UPT passengers that largely draws on attitudinal theories in the field of social and environmental psychology and concepts in the service marketing literature. Section 2.4 summarises the knowledge gaps identified concerning the investigation of BRT as well as the general UPT passenger travel behaviour. Finally, drawing on the presented literature the overarching research question is proposed in Section 2.5.

2.1 Bus Rapid Transit (BRT) as a means towards sustainable urban transport

With the long-term car dependency positing a series of persistently unsustainable issues globally, an increasing international trend has been the implementation of BRT systems as one of the key means to help establish more sustainable transport. This section elaborates on this point and establishes the BRT system as a critical context for studying travel behaviour with a capacity of informing future BRT-related policy.

2.1.1 Sustainable urban transport

The global motorisation over the past five decades has generated an increasing number of car-dependent cities across the world, in which private cars have become the dominant means for people’s daily commuting trips as well as trips for other purposes such as shopping and recreation (Newman and Kenworthy, 1999a). Drawing on the results of a study covering 37 cities across the world, it has been indicated that serious imbalance persists between the shares of private cars and other transport modes including public transport and walking (for example, 90% versus 10%) in fulfilling people’s travel needs (Kenworthy et al., 1999; Kenworthy and Laube, 1999). Such a pattern (or car dependency) is considered detrimental to the sustainability of urban transport and development.

The issues originating from the rising levels of car dependency can be understood from the environmental, economic and social aspects of sustainability (Himanen et al., 2005). Concerning the environmental aspect, car emissions have been highlighted as one of the major issues at both local and global levels. At a local level, emission resulting from private car use has contributed to the increase in the incidence of asthma among city populations over recent years (Newman and Kenworthy, 1999). At the global level, the over-consumption of unrenewable natural resources (e.g., fossil fuels) directly contributes to the energy crisis that has not only affected car dependent cities, but also cities with lower level of motorisation (Newman and Kenworthy, 1999). In addition, the greenhouse gas (e.g., carbon dioxide) emissions originating from car dependency are a well-recognised driver behind the global climate change that endangers the lives (human and other lives) on earth (Greene and Wegener, 1997; Jain and Guiver, 2001; Banister, 2011).

In respect to the economic aspect, car dependency has the capacity to compromise the cost-efficiency of an urban system (Black, 2000; Kenworthy and Laube, 1999; Banister, 2005). The immediate impacts of car dependency are commonly reflected by traffic congestion, which can generate considerable external costs. Based upon a series of comparative analysis of both car-dependent and transit-oriented cities, Newman and Kenworthy (1999), Kenworthy and Laube (1999) showed that to cater for the demand of car use, car-dependent cities (such as cities in North America, Australia) faced considerably higher costs for road construction and maintenance and a lower level of transit cost recovery than more transit-oriented cities (such as Hong Kong, Tokyo). The former circumstances force uneconomic decisions for infrastructure development, for example, excessive expansion of road networks, which has the potential to foster sprawled urban form and therefore more car-dependence in a vicious cycle (Kenworthy and Laube, 1999; Kenworthy and Hu, 2002).

Last, car dependency can also unfavourably influence aspects such as safety, social equity and even quality of life especially for mobility-impaired cohorts (e.g., without access to private cars, residing in remote urban areas) (Steg and Gifford, 2005; Litman, 2002; Delbosc and Currie, 2011; Dodson et al., 2004). It has been revealed that fatality rates caused by road accidents were considerably higher in car-dependent cities (e.g., North American cities) in comparison to transit-oriented cities (Newman and Kenworthy, 1999). Social exclusion (i.e., lacking the opportunities to participate into social activities) was also revealed to be more serious in car-based cities for people facing mobility-disadvantages (Delbosc and Currie, 2011). Such issues as the aggravation of road safety and social exclusion are collectively considered as signals of deteriorating life quality and as such, have the potential to threaten the well-being (e.g., satisfaction, happiness with life quality) of people facing such issues (Delbosc and Currie, 2011; Steg and Gifford, 2005).

Apparently the costs of car dependency at both local and global levels can to a considerable degree overshadow the benefits to individuals in the long run. Therefore there has been a pressing need to enhance the service quality and usage for Urban Public Transport (UPT) (e.g., bus transit, rail-based transit). This is one of the key strategies to improve the sustainability of urban transport systems (Currie and Wallis, 2008; Marshall and Banister, 2000; Rhindress et al., 2008; Mees and Dodson, 2011).

Ideally, a sustainable transport system is envisaged to be one that is well balanced between car use and UPT use (as well as other greener transport modes such as walking, cycling), based on which, desirable improvements including efficient use of road space, enhanced safety for pedestrians and cyclists, enhanced air quality and social equity can be achieved (Banister, 2008; 2011). However, the tasks to maintain and enhance the patronage for UPT remain challenging due to the persistent car dependency internationally. Some published evidence suggests that UPT use has been largely and persistently quenched by car ownership in car-dependent cities, e.g., Kitamura et al (1997), Bagley and Mokhtarian (2002), Simma and Axhausen (2001), Cosgrove (2011). Furthermore, favourable attitudes held by urban populations towards private cars over UPT in terms of trip experience (e.g., flexibility, reliability) and other aspects (e.g., the affective and symbolic appeals) have been revealed across various city contexts, e.g., Cullinane and Cullinane (1999), Jensen (1999), Ibrahim (2003), Steg (2005), Beirao and Sarsfield Cabral (2007), Grdzelishvili and Sathre (2011), Van and Fujii (2011). The rising car-favouring culture only enhances the difficulty of promoting UPT use for transit agents. To overcome this issue, it is important to have a thorough understanding of the travel behaviour related to people's use of UPT instead of private cars, so as to provide an evidence base to inform sustainable transport policies (Miller et al., 1999; Rhindress et al., 2008; Ampt, 2004; Bamberg et al., 2011).

2.1.2 Bus Rapid Transit (BRT)

The provision of UPT service to meet people's travel needs has been a challenging task. Traditionally, rail-based transit has been avidly advocated for its service quality, such as high speed, reliability and capacity—typically, between 10,000 and 30,000 passengers per hour per direction during peak hours (Wright and Fjellstrom, 2003). However, weaknesses including lower flexibility of route identification coupled with the expensive construction and maintenance costs largely impair the feasibility of launching a rail transit program for cities with relatively low population and density (Zhang, 2009). With a considerably lower funding demand, conventional on-road bus service, however, has commonly been deemed as relatively time-consuming, unreliable and overall an unattractive transit mode for people's regular trips (Wright and Fjellstrom, 2003; Deng and Nelson, 2010).

Over the past two decades, Bus Rapid Transit (BRT) has been increasingly considered as a cost-effective choice for enhancing service quality and patronage for UPT services across cities globally (Levinson et al., 2002; Deng and Nelson, 2010; Hensher and Golob, 2008). While there has not been a unanimous definition for BRT, it is essentially an enhanced bus transit service that encompasses a diverse range of specific forms (Figure 2.1). Depending on different political initiatives and available resources, the implementation of BRT varies from integrating signal priority for bus transit services within a mixed traffic system to dedicated busways coupled with distinct vehicles and intelligent transport systems (ITS) (Levinson et al., 2003a; Wright and Hook, 2007; Cain et al., 2009). Despite the variability of BRT implementation, an exclusive busway is considered as the key component of a BRT system, as it is the essential element that can realise the high capacity, reliability, speed and enhanced image of a BRT service (Deng and Nelson, 2010; Hoffman, 2008). Figure 2.1 provides a snapshot of a BRT system, located in Brisbane, Australia.

Figure 2.1 Spectrum of BRT definition (Source: Cain et al 2009)

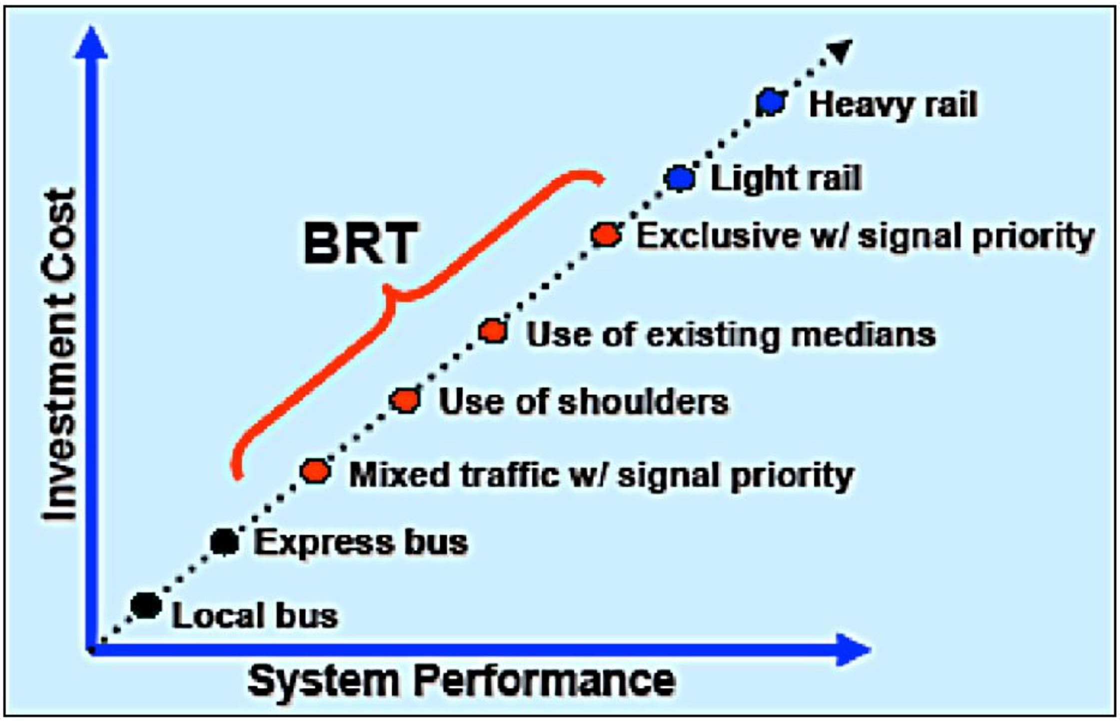


Figure 2.2 An example of BRT system

In comparison to rail transit, it usually takes a shorter time period (e.g., six months to one year compared to at least two years for a metro system) to construct the infrastructure for BRT (e.g., exclusive busway, stations) with considerably lower costs, e.g., four to 20 times cheaper than a Light Rail Transit (LRT) system and 10 to 100 times cheaper than a metro system (Deng and Nelson, 2010; Wright and Hook, 2007). BRT can also provide a more flexible transit service than rail transit service, in that a door-to-door service can be realised with an open design that allows on-road buses access to the busway infrastructure (Levinson et al., 2003a; Wright and Hook, 2007). However, such flexibility is infeasible for LRT and Metro systems. These features (e.g., rail-like service features, lower costs and higher flexibility) collectively render BRT a cost-effective alternative to rail transit services in delivering a transit service with considerably higher capacity and service quality in comparison to conventional on-road bus transit services.

2.1.3 BRT implementation across the world

A number of cities across the world have opted for BRT as an alternative to rail-based transit in progressing towards sustainable urban transport. The first BRT system can be tracked back to Chicago's 1937 plan that converted a rail transit line to an express bus line (Levinson et al., 2002). A few BRT programs were initiated between the 1940s and the 1970s in North America and Europe, including the Washington D.C. Plan between 1955 and 1959, the St. Louis Plan in 1959, and the Milwaukee Transitway Plan in 1970 in the US (Levinson et al., 2002) and Runcorn's busway plan in 1971 in the UK (Deng and Nelson, 2010).

The first BRT system that has gained wide recognitions is Curitiba, Brazil's BRT system (Rede Integrada de Transporte, or RIT) opened in the 1970s (Hidalgo and Graftieaux, 2008). The credits received by Curitiba's RIT are largely attributed to the reduced traffic congestion in the corridor where it operates, as well as the enhanced reliability of the local bus transit service (Lindau et al., 2010). Over the past two decades, there has been a marked growth of BRT implementation within UPT networks across the world in the past two decades with the aim of improving UPT service performance. Examples of BRT implementation can be found in South America, e.g., Quito (Ecuador), Sao Paulo (Brazil), Mexico City (Mexico) (Hidalgo and Graftieaux, 2008); North America, e.g., Boston, Cleveland, Los Angeles (US), Ottawa (Canada) (Levinson et al., 2003b); and Asia, e.g., Nagoya (Japan), Beijing, Guangzhou (China), and Jakarta (Indonesia) (Satiennam et al., 2006).

Given the increasing trend of BRT implementation at the global scale, a growing body of studies in recent years have been conducted to examine the performance, costs and benefits and planning process of BRT systems across the world to inform future BRT implementation, e.g., Levinson et al (2003b), Currie (2006), Hidalgo and Graftieaux (2008), Hensher and Golob (2008), Deng and Nelson (2010).

In terms of performance, ridership levels achieved by BRT implementation are of primary concern. Through comparing 44 BRT systems, it has been found that most BRT systems have a peak hour ridership between 2,000 and 8,000 passengers per hour per direction (Hensher and Golob, 2008). Higher ridership (e.g., 20,000 passenger per hour per direction and above) is more concentrated in BRT systems in Latin America, which renders government subsidies less critical for BRT systems there (Levinson et al., 2003b; Hensher and Golob, 2008). The varying levels concerning BRT ridership can be attributed to the intrinsically distinct natures of city contexts in terms of urban form, population, density and level of motorisation. Some researchers developed regression models to investigate the drivers behind ridership level, e.g., Currie and Delbosc (2011), Hensher and Golob (2008). It has been revealed that service frequency, travel time and reliability are among the key performance dimensions that influence ridership for BRT (Currie and Delbosc, 2011; Hensher and Golob, 2008).

An examination of costs and benefits renders a varying picture across existing BRT systems. The construction costs for BRT range from 0.35 million dollars per kilometre in Taipei to 8.2 million dollars per kilometre in Bogota (Hensher and Golob, 2008). While the construction costs for BRT are highly linked to local economic situations and labour costs, upgraded busways (e.g., tunnel, uplifted busway) commonly costs more than busways using existing median lanes of roads (Hensher and Golob, 2008). In addition, Wright and Hook (2007) found that in general, the construction costs of BRT are considerably cheaper (four to 100 times) than rail transit systems. Regarding operation costs, despite higher overall costs associated with rail transit, it usually outperforms BRT, LRT and bus at a per passenger/kilometre level, with the latter being the least cost-saving, e.g., Zhang (2009), Wright and Hook (2007). Taken together, it appears that BRT can provide a service level (e.g., capacity, operational speed) similar to a LRT system with a relatively lower cost (Cain et al., 2009; Hensher and Golob, 2008). However, a more comprehensive and definitive evaluation of the cost-recovery rate of BRT systems is still lacking and in demand to further quantify the financial performance of BRT.

The impact of BRT on its proximate land use is another issue of interest concerning the benefits of introducing a BRT system. As a form of mass transit, BRT arguably has the capacity to stimulate high-density land development as well as enhance land value along its corridor. Supportive evidence on this issue has emerged in recent studies. Drawing on Seoul, South Korea as a case study, Cervero and Kang (2011) showed that there was a 5-10% increase in the residential land price within the 300 metre bandwidth along the BRT corridor after its implementation. Using a before-and-after hedonic model, Rodriguez and Mojica (2009) found that Bogota's BRT system contributed to higher property prices (13-14% increase) in adjacent areas. Similar impacts of BRT on land values were also found in North America and Australia (Levinson et al., 2003a).

Current literature focusing on BRT implementation partially supports BRT as a cost-effective transit option towards sustainable urban transport, as it has the capacity of enhancing transit service quality (e.g., higher speed, improved reliability) with relatively low construction and maintenance costs, attracting and moving large numbers of passengers as well as stimulating transit-oriented development (TOD) in different city contexts. To launch and maintain a high quality BRT system, factors including strong political wills and reinforcement, marketing and branding, well-defined public-private partnership and integration with land use also play significant roles and need to be achieved in the planning process as well (Deng and Nelson, 2010; Hidalgo and Graftieaux, 2008; Wright and Hook, 2007; Diaz et al., 2004).

2.1.4 BRT implementation in the Australian context

Four Australian capital cities (Adelaide, Brisbane, Melbourne and Sydney) have implemented BRT within their UPT networks (Currie, 2006; Currie and Delbosc, 2010). Substantial money (in total over $1 billion) has been invested to fund the construction of BRT infrastructures (e.g., exclusive busway, enhanced BRT stations). From 2006 to 2010, the total length of BRT networks in Australia increased 194% to 318 kilometres backed by an increase of 130% (36.6 million to 84 million) in the annual number of passengers carried. In addition, further expansions of BRT networks are planned over the next four to five years, which will result in an additional 100 kilometres of BRT network across Australia.

A relatively limited number of studies have investigated the performance and impacts of BRT within Australian city contexts. Currie (2006) and Currie and Delbosc (2010) reviewed the development history of BRT systems in the Australasian region from 2001 to 2010, coupled with overviews of the enhanced efficiency of BRT carrying passengers in cities of Australia (i.e., Adelaide, Sydney, Brisbane and Melbourne) and New Zealand (i.e., Auckland). These two studies found steady growth of BRT ridership across Australia between 2001 and 2010, and reinforced the notion of BRT being an attractive alternative to rail transit. Opportunities to enhance BRT service such as off-board fare payment were suggested as well. In addition, Bitzios et al. (2009) examined the benefits from the operation of the South East Busway (SEB) in Brisbane between 2002 and 2006. They contended that while monetary cost-benefit evaluation of BRT implementation did not render convincing results of viable economic benefits, it was limited in considering other aspects such as public attitudes towards public transport, promoting public transport use and environmental impacts. Positive feedbacks concerning these aspects such as enhanced satisfaction of bus passengers and reduced car use along the BRT corridor were found (Bitzios et al., 2009).

2.1.5 The impacts of BRT on travel behaviour

In addition to the operational aspects of BRT systems, a number of studies focused on examining the impacts of BRT on travel behaviour. From a before and after perspective, immediate increase in ridership and time-saving has been tangible after introducing BRT systems in many cities. Markedly, 20-50% gains in ridership coupled with time-saving (10-15%) have been achieved in the BRT systems in Los Angeles (US), Vancouver (Canada), Leeds (UK) and Adelaide (Australia) (Levinson et al., 2003b; Callaghan and Vincent, 2007). In developing city contexts, lower yet notable increases in ridership have been observed for the BRT systems in Beijing, China (7.4% increase in ridership) (Deng and Nelson, 2013) and Jakarta, Indonesia (14% increase of new passengers) (Ernst, 2005). While there is evidence suggesting short-term increase of ridership can be achieved after BRT implementation, little evidence exists pertaining to the long-term trend of BRT impacting ridership.

Apart from the above examinations, some researchers also investigated passengers' perceptions of and satisfactions with the performance of BRT systems. Lleras (2002) found that Bogota's BRT (Colombia) has resulted in an enhanced travel experience (in particular, less 'distasteful' time perceived when riding the BRT) compared to the on-road bus services for transit passengers. Baltes (2003) investigated passengers' satisfaction with BRT service in Miami and Orlando (the US) and showed that comfort, service frequency and reliability were importantly related to passenger satisfaction. Currie (2005) investigated passengers' perceptions towards BRT in comparison to conventional on-road bus transit and rail transit (i.e., LRT, Metro). His findings suggest that passengers tended to value BRT and rail transit similarly and both as superior options to on-road bus transit. Moreover, Deng and Nelson (2012) revealed that Beijing's BRT system received favourable perceptions from passengers in terms of time-saving and enhanced reliability, as well as increasing the attractiveness of residential property along the BRT line.

The above studies provided some evidence that BRT can be a cost-effective option in increasing UPT ridership as well as benefiting passengers in terms of time-saving and travel experience. However, the effects of BRT in shaping more sustainable travel behaviour have not been fully captured and understood. In particular, although increasing public transport use while reducing car dependency has been highlighted as one of the core motives for implementing BRT systems (Wright and Hook, 2007; Lleras, 2002), an examination of the above studies indicates that few have explicitly examined the extent to which BRT altered people's usage of the two transport modes (i.e., public transport and private cars) across an urban space, and relatedly, what demographic cohorts are more likely to be attracted to using BRT than others, given private cars as an attractive alternative?

Clarifying these issues has the potential to provide additional evidence concerning travel behaviour change associated with BRT implementation, and hence warrants examination.

Further to the examination of changes in travel patterns, the understanding of the travel behaviour dynamics related to BRT will be incomplete without considering another two aspects of travel behaviour. First, while BRT has formed an integral component of UPT infrastructure across 180 cities worldwide, its role in facilitating people's trip-making across a UPT network expressed in their spatial-temporal trip dynamics remains largely unknown (Lleras, 2002; Tao et al., 2014). The deficit of such a comprehensive picture may compromise our ability of ongoing management of BRT in a less responsive and adaptive manner, especially considering the complex geographical patterns inherently associated with transportations activities (Mesbah et al., 2012; Tribby and Zandbergen, 2012). Therefore, considering that capturing the spatial-temporal patterns of passengers' travel behaviour can better inform the evidence-based UPT planning in reaction to passengers' travel needs (Ortuzar and Willumsen, 2001; Pelletier et al., 2011), this deficit related to the BRT usage dynamics warrants in-depth investigation to inform future BRT service and infrastructure provision.

Second, the attitudinal mechanisms of BRT passengers related to their behavioural intentions have received limited research attention and also deserve particular research attention (Joewono et al., 2012). Over the past three decades, it has been increasingly realised that in addition to the supply-oriented approach (e.g., the provision of UPT service and infrastructure), the increase of public transport use in the face of persistent car dependency requires more proactive approaches that target people's attitudinal mechanisms related to their mode choice behaviour (Bamberg et al., 2011; Richter et al., 2011; Brög et al., 2009; Bonsall et al., 2004; Tertoolen et al., 1998; Gilbert and Foerster, 1977). Within the UPT context, passengers' with favourable intentions towards a transit service were found to be more loyal (that is keeping using a transit service over long run) and more willing to spread good word-of-month about a transit service (Foote et al., 2001, Jen et al., 2011, Lai et al., 2011, Joewono et al., 2012). As such, it is also of value to investigate BRT passengers' behavioural intentions in order to identify possible ways to maintain and promote BRT usage.

Given the knowledge gaps initially outlined above, Sections 2.2 and 2.3 critically review the literature related to the investigation of the spatial-temporal dynamics and the attitudinal mechanisms of travel behaviour, and highlight the currently critical methodological (i.e., the use of smart card data) and theoretical challenges (i.e., the understanding of behavioural intentions) that need to be addressed in the investigation of travel behaviour dynamics related to BRT passengers.

2.2 Understanding the spatial-temporal dynamics of travel behaviour

The spatial-temporal dynamics of people's travel behaviour has been established as one of the key research foci in transport studies. This section reviews the previous literature in this area and pays particular attention to the emergence and application of large automatically collected data within the UPT context.

2.2.1 The significance of understanding the spatial-temporal dynamics of travel behaviour

The significance of understanding human mobility in terms of their spatial and temporal characteristics has been well recognised in the transportation domain (Ortuzar and Willumsen, 2001; McNally, 2008). For example, the classic four-step model predicts people's trip generation based on information including the spatial distribution of origin-destination of people's trips associated with the existing land-use patterns, the assignment of trip routes and the choice of transport mode for making trips (Ortuzar and Willumsen, 2001). Such a modelling process is often carried out at a geographically aggregate level, e.g., pre-defined traffic analysis zones (McNally, 2008). Considering that people's trip making is a demand derived from fulfilling their everyday activities (e.g., working, shopping), a growing body of research has adopted an activity-based approach with the aim of attaining a more detailed understanding concerning people's daily activities and related travel behaviour patterns reflected in space and time (Axhausen and Gärling, 1992; Buliung and Kanaroglou, 2007; Kitamura, 1988). Concepts such as activity types, scheduling and intra-household interactions, have been applied in travel behaviour studies to offer enhanced explanations concerning the spatial and/or spatial-temporal patterns of people's trip making, e.g., Kitamura (1988), Newsome et al (1998), Buliung et al (2008), Shaw and Yu (2009).

Allied with the need to better understand the complexity of travel behaviour patterns, the search and application of alternative data sources to the travel survey data emerges as another critical challenge in the field of travel behaviour studies. This is largely due to the limitations associated with the travel survey data, including high collection costs, low response rate, inaccuracy of spatial and temporal information and generalisability of samples, and as a result, their potential to compromise the affordability and the results of travel behaviour investigation (Noland and Polak, 2002; Rickwood and Glazebrook, 2009; Chu and Chapleau, 2010).

A key focus of public transport planning closely relate to the planning and management of transit service in terms of such aspects as service frequency, time table, operation speed and route configuration to better meet people’s travel needs (White, 2009; Mees and Dodson, 2011). The premise of properly handling these aspects resides in a detailed understanding of the spatial and temporal properties of people’s public transport use (Arana et al., 2014; Hofmann and O'Mahony, 2005; Munizaga and Palma, 2012). In this regard, the worldwide implementation of automatic data collection systems (in particular, smart card systems) and the resulting smart card data have received increasing attention in the investigation of spatial-temporal travel patterns of UPT passengers, which may serve as an enhanced platform to support evidence-based UPT planning compared to the traditional survey data (Bagchi and White, 2005; Pelletier et al., 2011). Given the typically high resolution of spatial and temporal information of smart card data, these data offer new opportunities for better understanding the spatial-temporal trip patterns associated with BRT systems.

In the following sections, the existing literature that investigated the spatial-temporal dynamics of travel behaviour is first reviewed, followed by the discussion concerning the implications attained. Next, issues and challenges encountered in pursuing greater details and accuracy of people’s travel behaviour by the use of smart card data are highlighted, due to its rising significance in the travel behaviour studies within the UPT context.

2.2.2 Spatial-temporal analysis of travel behaviour

Numerous studies have investigated people’s travel behaviour patterns in space and time. A broad spectrum of research topics has been established and explored in this field, from spatial-temporal characterisation of travel patterns, e.g., Hanson and Huff (1986), Schlich et al (2004), to the social implications (such as social exclusion, life quality) of spatial-temporal travel patterns, e.g., Schönfelder and Axhausen (2003), Dodson et al (2010), Roorda et al (2010). Given that this thesis seeks to establish an initial step in understanding BRT usage from the spatial-temporal perspective, it appears appropriate to concentrate more on the discussion of the existing literature in terms of the exploratory analysis of travel behaviour. Hence the key aim here is to critically review the measures, methods and key findings of the spatial-temporal investigation of people’s travel behaviour.

Earlier studies investigating the spatial-temporal patterns (or one aspect, e.g., spatial or temporal dynamics) of people’s travel behaviour are largely characterised by the application of statistical and mathematical methods to measure and examine travel behaviour patterns of people (Pas, 1985; Buliung et al., 2008). A major concern of these studies was to examine the intrapersonal variability of travel or activity-travel patterns over time, in particular, multiple days.

Drawing on a 5-week travel diary dataset collected in Uppsala, Sweden, Hanson and Huff conducted a series of studies examining intrapersonal variability of travel behaviour by calculating and comparing the variance on a number of travel characteristics including trip frequency, purposes, distance, timing and number of stops made of individual persons over multiple days (e.g., five weeks). Their findings indicate that individual travel behaviour commonly demonstrates significant variability on day-to-day basis in terms of spatial (e.g., revisit to a location) and temporal (e.g., trip timing) aspects (Hanson and Hanson, 1981; Hanson and Huff, 1981; Huff and Hanson, 1990), suggesting the need to use multi-day data to fully capture travel behaviour dynamics. Furthermore, by linking trip patterns with activity types, quite a few studies, e.g., Jones and Clark (1988), Huff and Hanson (1990), have revealed that trips associated with activities that has a more ‘obligatory ’ component (e.g., going to work) tend to be more spatially and temporally repetitious compared to other types of activities such as shopping, recreation.

Using a series of statistical analysis (e.g., principal component, regression and discriminant analysis) on a number of travel behaviour measures and socio-demographic characteristics (e.g., gender, employment status, income, household composition), Hanson and Huff further detected that different socio-demographic groups were also associated with significantly different patterns of travel behaviour (Hanson and Hanson, 1981; Hanson and Huff, 1986). For example, female travellers living in multi-person households tended to make a limited number of short trips dominated by shopping purposes; by contrast, full-time employed males were likely to make more trips (and usually by cars), among which fewer trips were shopping-related but rather with socialising purposes (Hanson and Huff, 1986), suggesting the one’s social and household duties (e.g., looking after children, working) impose spatial-temporal constraints that play significant roles in shaping their travel patterns.

Related studies focusing on intrapersonal travel patterns have also been carried out drawing on travel diary data in other contexts, including studies in England, e.g., Pas (1988), Pas and Koppleman (1987), Pas and Sundar (1995), Germany, e.g., Schlich and Axhausen (2003), Schlich et al (2004) and Susilo and Kitamura (2005) and the US, e.g., Misra and Bhat (2000), Lockwood et al (2005). Despite the different study contexts and statistical methods used (see Schlich and Axhausen (2003) for a more comprehensive discussion on this matter), the findings of these previous studies to a considerable extent support the studies by Hanson and Huff, that the complexity of travel behaviour patterns in space and time were to a considerable degree related to one's activity patterns and socio-demographic characteristics. Additionally, the effects of different calendar events on the spatial-temporal variety of people's travel behaviour have been highlighted. Drawing on the analysis of six-week travel dairy data in Germany, Schlich and Axhausen (2003), Schlich et al (2004) found that individuals' travel patterns on weekdays were markedly more stable compared to weekends. Within the US context, some studies such as Lockwood et al (2005) also highlighted that the activity-travel patterns in terms of stop-making and trip-chaining were more spontaneous than systematic on weekends.

Through applying statistical-mathematical measures and methods, valuable knowledge has been attained concerning the spatial-temporal dynamics of people's travel behaviour and shed light on the impacts of socio-demographic characteristics and different calendar events (e.g., workday-to-weekend) on travel behaviour. However, as identified by Buliung et al (2008), despite the focus on spatial-temporal dynamics, the variables and indicators used in these studies are largely 'aspatial' (e.g., trip frequency, distance and timing). The actual spatial characteristics of people's travel patterns such as spatial extent and trajectories associated with one's daily activity have largely remained unexplored, rendering the actual spatial-temporal travel patterns of people not fully captured. Given this, while the above studies are useful in developing mathematical models in predicting travel demand (e.g., number of trips) at an aggregate level (e.g., a city level), they are less effective in providing an evidence base from which more localised transport policies can be developed.

Given the limitations of the statistics-mathematical based studies, another group of studies drew on more spatial-based concepts and methods in order to better capture the actual spatial dynamics of travel behaviour. In achieving this, one well-received tool is 'action space' (or activity space) derived from the concept of 'prism' of time geography (Hägerstrand, 1970; Lenntorp, 1976). A prism consists of *'a set of positions in space-time for which the probability of being included in the individual path is greater than zero'* (Dijst and Vidakovic, 2000, pg. 3). An action space is the projection of a prism onto a space. Four indicators have been identified as key conditions in defining the size and shape of an action space: the distance between bases (commonly home and working place), available time interval (the total time for carrying out activities at places other than the bases), travel speed (usually determined by travel mode) and travel time ratio (the ratio of time for travelling between places accounting for the available time interval) (Dijst and Vidakovic, 2000; Ritsema van Eck et al., 2005; Dijst, 1999). Based on the specification of the four conditions, the common forms of an action space can be a linear, a circular or an elliptic area (Dijst, 1999; Ritsema van Eck et al., 2005).

While an action space primarily reflects an individual's potential activity choices of space and time, it can be easily operationalised as the actual spatial extent for one's activity and travel behaviour. A common method used in calculating actual action space is considering the furthest travel distance from the bases (home or working space) in the calculation of an elliptic area, e.g., Susilo and Kitamura (2005), Ritsema van Eck et al (2005), Buliung et al (2008). To a lesser extent, other indicators for calculating actual action space include kernel density of visited locations, e.g, Schönfelder and Axhausen (2003), and number of unique locations visited and activity duration, e.g., Kamruzzaman et al (2011).

Drawing on the concept of action space, a number of studies have furthered the understanding of the spatial-temporal patterns of people's travel behaviour in conjunction with variables including socio-demographic characteristics, calendar events and certain spatial-related variables such as home location, spatial configuration, e.g., Newsome et al (1998), Dijst (1999), Schönfelder and Axhausen (2003), Susilo and Kitamura (2005), Ritsema van Eck et al (2005), Buliung and Kanaroglou (2006), Buliung et al (2008), Kamruzzaman et al (2011). Using data from a 1985 household travel survey in Charlotte (US), Newsome et al (1998) compared three indicators of activity areas (elliptic areas, axis ratio and activity duration) of work-based linked trips across different socio-demographic and locational characteristics of households. Their results indicated that household size and residential location (e.g., near city-centre, suburbs) had the strongest power in explaining different types of activity areas in particular in terms of axis ratio and activity ratio, followed by income, age and race. Some conventionally 'critical' variables including gender, however, failed to account for the different activity-travel patterns.

Within other city contexts, studies have continued to explore the utility of action space in characterising people's activity-travel patterns. For example, the results of a Dutch study by Ritsema van Eck et al (2005) highlighted that the levels of spatial concentration surrounding transit nodes and urban density were related to the diversity of the types of people's action space. Similarly, other published evidence including Susilo and Kitamura (2005) (Karlsruhe and Halle, Germany), Buliung et al (2008) (Toronto, Canada) and Kamruzzaman et al (2011) (Northern Ireland, UK) substantiated the findings by Newsome et al (1198) and Ritsema van Eck et al (2005), that spatial and locational variables indeed critically impacted on the distinctions of intrapersonal or household action space. In another related study, drawing on two Dutch cities (Utrecht and Houten), Dijst (1999) confirmed that time-space constraints (e.g., distance between bases, available time interval) and transport modes used (e.g., cars, public transport) had significant impacts on the types and distinctions between male and female of two-earner households. These studies highlighted that in addition to the socio-demographic and socio-economic variables, spatial-based variables such as residential location, density and spatial configuration should also be taken into account in further dismantling the complexity of people's spatial-temporal travel patterns.

With the technological advancement in Geographic Information System (GIS) over the past two decades, more recent studies have managed to develop three-dimensional GIS environment and related tools by essentially adding a time axis to a two-dimensional space (Miller, 2005; Miller and Bridwell, 2008; Yu, 2008; Neutens et al., 2010). In doing so, it becomes possible to represent and analyse intrapersonal or household activity-travel behaviours in a more time-space integrated manner (e.g., creating time-space path, prism). For example, Kwan (2000), Chen et al (2011), and Shaw et al (2008) demonstrated that by generating generalised time-space paths and conducting spatial clustering, representative time-space trajectories of a relatively large amount of individuals (e.g., thousands of persons) can be easily extracted to identify the embedded typical activity-travel groups.

From the perspective of more complicated behavioural phenomenon, some researchers including Yu (2008), Kang and Scott (2008) developed GIS-based tools to quantify and visualise activity-travel behavioural interactions between persons, and relatedly their spatial-temporal distributions. These GIS-based tools achieved such goals by identifying joint episodes between individual-based activity-travel paths in space and time based on a series of criteria, including joint activity purpose, joint time and joint location. In another relevant study, Fang et al (2011) developed a multi-objective approach for activity scheduling of multiple persons, which proved to be useful in simulating the spatial and temporal choice of joint activity participation given the occurrence of a certain circumstance, such as congestion. Furthermore, given the ubiquity of information and communication technologies globally, some researchers, e.g., Yu and Shaw (2008), Shaw and Yu (2009), extended the above GIS-based time-space concepts and methods to capture behaviours in a hybrid physical-virtual environment. It is imaginable that tools can be used to study people’s trade-off between actual travel and its substituting choice due to the impacts of communication technologies, although empirical studies on this issue appear to be limited.

Last, another group of studies worth mentioning here are characterised by the application of spatially expanded modelling approaches that explicitly consider the spatial heterogeneity of travel behaviour patterns and influencing factors. A commonly applied method uses Geographically Weighted Regression (GWR) (Brunsdon et al., 1996) that assigns a spatial weight to each data point based on the location (usually captured by the geographic coordinate) in the construction of a linear regression model. Drawing on GWR, a number of studies modelled local relationships between travel behaviour (e.g., trip generation, stop-level ridership and travel distance) and influential factors as well as their variations across space, e.g., Zhao and Park (2004), Clark (2007) , Morency et al (2011), Cardozo et al (2012). Additionally, some researchers managed to incorporate the concept of spatial weight with other modelling approaches, e.g., probit modelling in modelling ordinal and nominal travel behaviour indicators (Páez, 2006; Páez et al., 2007). The results of these studies further strengthen the significance of considering spatial effects in the investigation of spatial-temporal travel patterns. For example, focusing on similar socio-demographic groups (elderly, low-income and single-parent households), Morency et al (2011) found that significant spatial variation existed regarding their mobility patterns (travel distance) as well as the effects of demographic and economic variables (e.g., ownership of car). Linking such spatial variation with specific context in terms of spatial density, location and configuration can render more detailed implications for transport policy-making.

In this section, through a critical review of existing literature that has a particular focus on the spatial-temporal analysis of travel behaviour, two groups of studies with relatively different aims and methods applied can be identified. The first group of studies relies on the use of statistical-mathematical measures and methods to quantify and categorise the spatial-temporal travel patterns of people. While these studies have yielded valuable information for travel demand modelling at an overall level (e.g., city level), they are limited in capturing the actual spatial-temporal dynamics of travel behaviour, due to the ‘aspatial’ nature of the methods and aims in these studies. In addressing this limitation, the second group of studies draws on a series of spatial-based concepts (e.g., action space, time geography) and GIS-based methods to provide enhanced capacity to reveal the spatial-temporal dynamics of travel behaviour. Different from the first group of studies, these studies pay more attention to the better representation of travel behaviour in space and time as the basis for studying and interpreting spatial-temporal travel patterns. Therefore, the findings of these studies are more ready for informing context-specific transport policy-making.

As identified in Section 2.1.5, the existing studies examining travel behaviour related to BRT (Callaghan and Vincent, 2007; Deng and Nelson, 2013; Ernst, 2005; Hensher and Golob, 2008; Levinson et al., 2003b) largely belong to the ‘aspatial’ group of travel behaviour studies, given that they also mainly draw on statistical-based measures (e.g., change in ridership of the BRT corridor). Studies characterised by more spatial-based analysis methods are however scarce within the BRT context, despite their potential to provide localised implications for BRT planning, e.g., Delmelle and Casas (2012). Specifically, the questions such as how BRT caters for people’s trip-making across an urban space, and is there any marked difference concerning BRT usage over space and time may be better understood, and therefore inform spatial prioritisation of BRT-based services accordingly (Tao et al., 2014). To address this deficit, a key challenge that should be addressed is the use of suitable data sources, which is elaborated in the following two sections.

2.2.3 Alternative travel behaviour data sources

As discussed in the last section, considerable methodological and theoretical progress has been achieved in the spatial-temporal investigation of travel behaviour. A persistent challenge in this field of studies, however, relates to seeking reliable travel behaviour data sources.

In travel behaviour research, survey-based methods (e.g., questionnaire survey, telephone-based survey) have long been the major method for collecting travel behaviour data, well-known survey datasets including the 1971 Uppsala data, Sweden (Hanson and Huff, 1988), the 1973 Reading data, England (Pas and Koppelman, 1987), and the 1999 Mobidrive data, Germany (Susilo and Kitamura, 2005). Despite the prevalence of the survey-based method, it has also been recognised that travel survey data inherently suffer from certain methodological limitations that may critically compromise the data quality (Pas, 1985; Noland and Polak, 2002; Richardson et al., 1996; Greaves, 2006; Clarke et al., 1981).

One-day record of travel survey has been commonly criticised for its assumption that people’s travel behaviour is highly routinised on a day-to-day basis (Hanson and Huff, 1988;

Huff and Hanson, 1986). Multi-day survey (or travel diary survey), while partially addressing such issues, also creates its own hazards stemming from the survey process. The fact that multi-day survey data require days to weeks of self-administered recording of travel details apparently places a non-trivial burden (psychologically or physiologically) on the participants, that further causes non-responses either at the stage of recruiting participants (i.e., not participating at all) or during the survey process (e.g., dropping from the survey, or providing incomplete responses) (Clarke et al., 1981; Pas, 1985). The commonly low response rate of travel surveys (e.g., 10-20%) speaks for this point. In such cases, the resulting samples are likely subject to 'non-response bias', compromising the generalisability of the samples collected (Clarke et al., 1981; Pas, 1985; Richardson et al., 1996).

Additionally, travel information collected faces the issue of inaccuracy, since participants may provide inaccurate information (location or time) or omit certain trips due to reasons such as fatigue over multi-days of completing the survey, or considering a trip insignificant (Clarke et al., 1981; Richardson et al., 1996). These issues apparently also have the potential of compromising the results of spatial-temporal analysis of travel behaviour. Last, the costs of a survey can easily be substantial, since it usually involves the employment and training of a number of surveyors and the deployment of facilities (telephones, post) in order to approach a large number of participants to do the survey. The high costs of travel surveys posit barriers for the renewal of travel behaviour data in a timely manner, and therefore resulting in the use of dated travel behaviour data (Bagchi and White, 2005).

Given the aforementioned drawbacks of travel survey data, it becomes compelling to search for alternative data sources that have the capacity to offer more accurate and reliable travel behaviour information with less costs for data collection and a lower burden for the participants.

Census data has been applied as an alternative data source to survey data for investigating travel behaviour patterns from a time-series perspective (Milthorpe and Raimond, 1998; Shuttleworth et al., 2000; Cosgrove, 2011). Census data is normally collected at a regular time interval (e.g., every five years) for analysing and publishing socio-economic and demographic characteristics of the population of a relatively large geographic area (e.g., a country) (United Nations, 2008). With regards to the travel behaviour of a population, many censuses also collect information concerning the population's travel patterns for work trips (e.g., modal share, number of people travelling between employment and residential locations), due to the primary interest of governments in work trips because of the traffic burdens generated during peak hours (Mees et al., 2008; Senior, 2009). Compared to travel survey data, census data is considered to be superior in providing travel information with a much more comprehensive population and geographic coverage (Mees et al., 2008; Rickwood and Glazebrook, 2009). As such, it to a degree avoids the issue of generalisability of sample of the travel survey data.

A number of studies have drawn on census data to investigate the travel patterns of country-wide or city-wide populations in relation to other socio-demographic variables (e.g., employment-residence ratio), e.g., Giuliano and Small (1993), Shuttleworth et al (2000), Weber and Sultana (2007), Mees et al (2008), Senior (2009), Li et al (2012). In terms of spatial-temporal analysis of travel behaviour, the strength of census data is that it allows the investigation of travel behaviour spatial patterns at various aggregated levels, given that census data are usually provided on a variety of geographic units (e.g., postcode area, local government area). Related to the aggregated nature, census data has some critical limitations as well. First, the observation of individual or household travel behaviour is not possible for census data. Additionally, the trip information of census data usually focuses on work-based trips on the census date while omitting other types of trips such as shopping and recreation on weekends. Finally, the common collection interval of several years (e.g., five years) renders the census unsuitable for more continuous analysis of travel behaviour (e.g., day-to-day).

Apart from the census data, the emergence of ‘big data’ has received growing attention in transport studies in the past two decades. ‘Big data’ are usually characterised by large quantities of information, high velocity of data collection and high resolution of data details (Boyd and Crawford, 2012; Kitchin, 2013; Miller, 2010). The ‘big data’ collected by location-aware systems, such as Global Positioning System (GPS) and automatic data collection (ADC) within the UPT context are worth mentioning here.

Rather recently, location-aware systems, including GPS and personal handy-phone system (PHS), have been increasingly applied in providing enhanced trip information for spatial-temporal travel behaviour studies (Wolf et al., 2001; Ohmori et al., 2000; Asakura and Hato, 2004; Stopher et al., 2007). Facilitated by location-positioning satellites, a location-aware instrument (e.g., a GPS tracker, or a cellular phone) can continuously track and record the spatial location (i.e., coordinates) and the associated temporal stamps of its carrier (e.g., a survey participant) at a small interval (e.g., 15 seconds) over time (e.g., several days to weeks) (Ohmori et al., 2000; Asakura and Hato, 2004). Hence, the trip information collected by such an approach (location-tracking data) is usually considered of high spatial and temporal resolution. It has been shown that location-tracking data surpass the traditional survey data in reducing the issues of omitting certain trips and reporting inaccurate geographic and time information associated with the trips of the participants (Bohte and Maat, 2009; Stopher et al., 2007). Additionally, considering the automatic manner of location-aware systems in collecting trip data, the burden for the participants in the survey process is arguably much smaller compared to the traditional survey method (Bohte and Maat, 2009).

A growing body of studies has exploited the utility of GPS and other location-tracking datasets such as PHS-based data and revealed detailed spatial-temporal dynamics of individual and vehicular travel behaviour, e.g., Wolf et al (2003), Stopher et al (2003), Demissie et al (2013), Guo et al (2012). A critical limitation of location-tracking data, however, is that certain important trip information, including travel mode and purposes are not recorded by location-aware instruments (Asakura and Hato, 2004; Bohte and Maat, 2009). An examination of existing literature shows that methods (e.g., additional survey) have been developed to deal with such issues (Bohte and Maat, 2009). Furthermore, location-aware systems, while able to record detailed trip information of individuals, have been essentially applied as a survey tool with relatively small sample sizes ranging from dozens to a few thousand participants (or subjects) in the existing literature. Large scale application of location-aware systems in travel behaviour studies appears to be rather limited (Bohte and Maat, 2009). This might be attributed to that the fact that large-scale application of location-aware instruments is not easily fulfilled from both an expenditure and feasibility point of view.

Last, with the growing prevalence of the ADC systems in the UPT context globally, the resulting data has received particular research attention in investigating UPT passenger travel behaviour (Bagchi and White, 2005; Pelletier et al., 2011; Chu, 2004). ADC systems, in particular automatic fare collection (AFC) have been introduced in the UPT context with the initial aim of improving the efficiency of UPT system operation, such as automating ticketing processing. Given the case of AFC implementation with an exhaustive network-coverage, the trip information (e.g., passengers' boarding and alighting location and time) collected is typically characterised by very large quantity (e.g., hundreds of thousands of data entries on daily basis) and relatively high spatial-temporal resolution. Given such characteristics, AFC-based data to a degree encompass the strengths of both census and GPS data in providing relatively detailed spatial-temporal trip information with a sample size that approximates to an entire population (e.g., UPT passengers of a city).

Considering that BRT has formed an integral component of UPT infrastructure across more than 180 cities worldwide, AFC-based data, if available, are arguably more suited for investigating the tangible aspect of BRT system dynamics compared to other location-tracking data, e.g., GPS data. Bearing this point in mind, the next section provides a more detailed review concerning the application of AFC data as well as the implications and challenges for investigating BRT usage with such datasets.

2.2.4 Smart card data for investigating UPT passenger travel behaviour

Over the past decade, AFC systems have been adopted by more transit agencies to replace the traditional paper ticket method and enhance the management of passenger fare collection (Bagchi and White, 2005; Pelletier et al., 2011). In an AFC system, the use of smart cards for fare collection is usually accomplished by the implementation of a group of devices within a UPT system, typically including the smart cards (i.e., credit-card sized plastic cards embedded with memory chips), on-board card readers, on-board GPS trackers and a central server. A smart card commonly stores the information of a unique card ID (e.g., a series of numbers), card type (e.g., adult, children, senior card user) and fare deposit balance. The central server stores the service information such as routes and schedules that is regularly transferred to the on-board card readers. When boarding (and sometimes alighting) a transit vehicle, a passenger touches his or her smart card to the on-board card readers that verify card and service information. Transaction records are generated in this way and stored in the central server. A smart card record normally contains information including date, card ID, route ID, route direction, boarding stop ID and time (and sometimes alighting stop ID and time), vehicle ID and employer ID.

Initially serving as a new mechanism for fare charging, the transaction records collected by smart card (or smart card data) apparently provide rather detailed and continuous travel behaviour itineraries of UPT passengers. As such, smart card data can offer a much enhanced data source for studying UPT passenger travel behaviour and related activities in comparison to travel survey data. This enables the investigation of UPT passenger travel behaviour at more disaggregated levels (e.g., trip-based, activity-based) and over longer temporal ranges (e.g., months to years) (Pelletier et al., 2011; Yue et al., 2014).

A number of studies have utilised smart card data to investigate the behavioural dynamics of UPT passengers across the world. Some studies focused on examining the spatial and temporal variability of UPT passenger boarding behaviour, using a variety of techniques including cluster analysis, where Argard et al (2006) and Morency et al (2006; 2007) detected the temporal boarding patterns across different card holder groups in Gatineau, Canada. By enumerating the number of non-repeated passenger-boarding stops, Morency et al (2006; 2007) further explored the spatial variety of the card users' boarding behaviour. Focusing on the same study context, Chu and Chapleau (2010) applied a GIS-based visualisation method to reveal the anchor points of student card holders, where reoccurring boarding behaviours were tangible. Park et al (2008) examined temporal boarding patterns across different transit modes in Seoul, South Korea. In another related study, Nishiuchi et al (2013) compared the reoccurrence of boarding time and stops to identify spatial-temporal consistency of rail transit passengers in Kochi City, Japan, highlighting that travel patterns of student passengers were more consistent in comparison to other groups (e.g., adult, senior passengers).

In addition to passengers' boarding behaviour, many researchers also managed to estimate transfer stop and time of UPT passengers, shedding lighting on the more complicated phenomenon of transfer behaviour and linked trips within the UPT context. Rule-based algorithms are a commonly applied method in dealing with this issue. Drawing on experience data, many researchers used fixed time constraints (e.g., 30 minutes, 2 hours) to estimate alighting stop and time, and as such link trips into journeys, e.g., Bagchi and White (2005), Utsunomiya et al (2006), Hofmann and O'Mahony (2005) and Jang (2010). Using a similar method, Devillaine et al assigned activity types to different time periods, and generated and compared activity temporal patterns of bus and metro passengers in two cities (i.e., Santiago, Chile and Gatineau, Canada). Alternative to the fixed-time constraint method, fixed-distance methods that assume a common walking-distance between transfer stops (e.g., 400, 800 metres) were also applied in linking trips into journeys (Barry et al., 2002; Trépanier et al., 2009; Zhao et al., 2007).

Considering the arbitrary nature of the fixed-time/distance constraint methods, some researchers developed more sophisticated methods to estimate linked journeys. For instance, Seaborn et al (2009) developed an elapsed time threshold method that takes differences in multi-modal transfers to estimate multimodal trips. By taking a number of variables into account, e.g., planned departure and arrival times for each run, stop sequence and linear distance between stops, Chu and Chapleau (2008) developed a multi-rule algorithm to detect transfer patterns of individual passengers. Munizaga and Palma (2012) applied a generalised time approach to estimate alighting point and origin-destination (OD) matrix. Their method minimised the generalised time distance between two sequential boarding position-times, which is argued to be more accurate than the fixed-distance method. Drawing on various methods, by reconstructing the journey information and OD matrix, smart card data can be transformed from raw datasets into more prepared data for further policy-making processes and sophisticated mathematical demand modelling.

In addition to the aforementioned studies, another group of work has focused on estimating O-D matrices of UPT passengers. A critical limitation of smart card data is that many smart card systems only capture boarding information (i.e., boarding stop and time) in order to charge fares while omitting alighting information (Pelletier et al., 2011). In addressing this issue, some researchers have developed algorithms to estimate alighting stop based on the assumption of shortest walking distance between the destination of one trip and the origin of the next one, e.g., Barry et al (2002), Trépanier et al (2007). To attain more reliable estimations, smart card data has also been applied in conjunction with other datasets that contain detailed trip and geographic information of a transit service. For example, Zhao et al (2007), Farzin (2008), Munizaga and Palma (2012) have integrated smart card data with Automatic Vehicle Location (AVL) data (or Global Positioning System (GPS) data) to infer an O-D matrix of transit passengers (bus or rail passengers) within various situational contexts. In addition, Nassir et al (2011) demonstrated a related approach by joining smart card data with Automatic Passenger Count (APC) data and General Transit Feed Specification (GTFS) to infer passenger-alighting stops in their study of Chicago’s metro transit network, US.

Despite the great potential of smart card data demonstrated by the previous studies, smart card data has rarely, if not never, been applied to investigate BRT usage dynamics. While it is desirable to do so, some methodological challenges and limitations associated with smart card data should be carefully considered, as they critically relate to fulfilling the utility of smart card data in dealing with the issue of interest (i.e., passengers’ travel behaviour related to a BRT system).

As discussed in the last section, smart card data are essentially the ‘by-product’ of AFC systems with a primary aim of assisting the ticketing process, rather than providing travel behaviour data. Hence, smart card data still lack certain important trip and personal information (Bagchi and White, 2005; Pelletier et al., 2011). In terms of trip information, the actual geographic location (e.g., the coordinate of a boarding stop) is usually not provided in the smart card data. In dealing with this issue, the supplement of other datasets such as GPS data is necessary. In addition, personal information including trip purpose and the socio-demographic characteristics of passengers are normally unavailable in smart card data. This loss is largely due to the issue of personal privacy of smart card users (Pelletier et al., 2011; Utsunomiya et al., 2006; Yue et al., 2014). Establishing a personal registration system for smart card users has been identified as a potential solution (Pelletier et al., 2011; Utsunomiya et al., 2006). Yet, the privacy concerns of smart card users remain as a major drawback for this approach (Bagchi and White, 2005; Pelletier et al., 2011).

As elaborated in previous literature review of smart card data studies (Pelletier et al., 2011; Yue et al., 2014) and more general ‘big data’ application (Boyd and Crawford, 2012; Kitchin, 2013; Miller, 2010), big data sets (or data deluge) also posit critical methodological challenges for researchers, which particularly question the effectiveness of conventional statistical methods in extracting meaningful results from ‘big data’. Given a large dataset (e.g., hundreds of thousands to millions of data entries), it is imaginable that many statistical methods applied in the earlier travel behaviour studies will very likely render significant results that may contain little practical meaning. Hence it becomes a pressing issue to develop novel and tailored methods that can generate meaningful and interpretable results from big data (Kitchin, 2013; Miller, 2010).

In regards to spatial-temporal investigation of travel behaviour, spatial visualisation or geo-visualisation based methods have been widely advocated and applied in the exploratory analysis of big data (including smart card data) (Kwan, 2000; Kwan and Lee, 2004; Andrienko and Andrienko, 2008; Shaw and Yu, 2009; Yu, 2008). Spatial visualisation of big data commonly involves a series of steps including data processing (commonly spatial clustering and aggregation) and visualisation of the data. By doing this, big data can be reduced to a more manageable size of information (e.g., aggregated travel trajectories based on certain spatial nodes), and the attained results can well reflect the interactions between travel patterns and a spatial context. Given such strengths, spatial visualisation appears to be the proper analytic strategy for investigating BRT usage in this research. Therefore, the next section discusses the existing methods of spatial visualisation applied to big data and their implications for this research.

2.2.5 Spatial visualisation of ‘big data’

As discussed in the last section, a major concern pertaining to the use of ‘big data’ for the examination of travel behaviour dynamics has been the attainment of interpretable spatial-temporal patterns. In dealing with this issue, spatial visualisation has been identified as an effective strategy to reduce information redundancy and generate interpretable results. Before discussing empirical examples of spatial visualisation of ‘big data’ and their implications for applying smart card data to investigate BRT usage, it is necessary to first have an understanding of the theoretical underpinnings for the spatial clustering and aggregation precedent to the spatial visualisation.

Three aspects constitute the foundation for spatial clustering and aggregation of big data, i.e., Spatial (S), Temporal (T) and Attributive (A) aspects (Andrienko and Andrienko, 2008; Andrienko and Andrienko, 2010). Visualisation can be carried out based upon one single aspect. For example, plotting volumes of passenger boarding or alighting by time intervals is a common T approach, e.g., Morency et al (2006), while a kernel density approach usually generates S clusters, e.g., Kwan (2000). More complicated methods are established by combining two or more aspects. For instance, constructing origin-destination (OD) matrices in predefined grid cells over different times of a day is a common S×S×T×T (origin × destination × start-time × end-time) method in transport planning (Meyer and Miller, 2001). OD matrices can be further extended to an S×S×T×T×A aggregation by adding the categorical aspect of the movement, such as different socio-demographic groups. In addition to the above three aspects, other important aspects can be added in the process, i.e., Route (R) and Object (O). An example is that movement trajectories can be clustered and visualised based on the similarity of travel routes such as spatial or temporal proximity, which renders R clusters, e.g., Shaw et al (2008).

Two general conceptual views of movement, i.e., trajectory-oriented and situation-oriented views are proposed to guide the selection of different clustering and aggregation methods (Andrienko and Andrienko, 2008; 2010). The trajectory-oriented view focuses on the movement trajectories of a single entity over space and time, whereas the situation-oriented view focuses on the spatial positions of all entities coupled with other movement attributes such as direction and speed. In the field of transport studies, the situation-oriented view is more suitable for picturing the traffic condition of a transport network at certain time point. This approach can be helpful in a situation such as identifying the bottleneck of a road network by examining the traffic speed during peak hours. On the other hand, the trajectory-oriented view preserves the movement trajectories of all entities and allows grouping and comparing spatial-temporal similarities of trajectories.

Under each of the two views, two strands of tasks can be further distinguished, i.e., space-centred tasks and entity-centred tasks (Andrienko and Andrienko, 2010). In the space-centred tasks, by perceived movement as a property of space, it is the space and related subjects including accessibility, connectivity of places that are of interest. The identities of entities are usually ignored in the space-centred tasks. In contrast, the entity-centred tasks consider movements as a property of entities (e.g., people) and investigate the movement similarity or diversity of different groups of entities. Different combinations of the two conceptual views and the two general tasks can fulfil different analytical tasks, and require the proper application of the aggregation aspects (e.g., S, T and A aspects) (Andrienko and Andrienko, 2010). For instance, a situation-oriented space-centred approach allows the examination of space use and accessibility. A trajectory-oriented entity-centred approach is suitable for categorising entities into trajectory-similar groups. A trajectory-oriented space-centred approach, on the other hand, offers the capacity of investigating space connectivity, major flow and path-use of entities.

Drawing on the conceptual foundations outlined above, numerous studies have developed and applied spatial visualisation methods to big data to generate spatial-temporal movement patterns of people as well as other entities such as vehicles and animals. For some simple visualisation tasks, Kernel density method is a widely applied technique. Drawing on a Kernel function, the probability density of people visiting a certain location can be estimated and marked, reflecting the spatial hot spots of activity at a certain time point, e.g., Kwan (2000), Chu and Chapleau (2010). Other relatively simple methods such as constructing plots based on time intervals or k-mean clustering are useful to identify temporal patterns of travel behaviour, such as travel distance, departure or arrival time, e.g., Park et al (2008), Morency et al (2006). These methods are effective in providing important snapshots regarding spatial-temporal travel/movement patterns. However, due to the omission of essential information of actual movement path, they are mostly applied in the initial stage of investigating movement data.

More sophisticated methods focus on visualising travel trajectories that entail a series of locations to better capture the spatial features of movements. Clustering trajectories based on geometric similarity (e.g., vertex, angle and length) is among the commonly used approaches. Examples include the Douglas-Peucker algorithm (Douglas and Peucker, 1973), the Hausdorff distance (Brakatsoulas et al., 2005), the global and local feature description (Dodge et al., 2009) and the standardised space-time path method (Chen et al., 2011). Given the complexity of trajectories in many cases, these methods usually simplify trajectories by removing some movement information (e.g., certain intermediate points, transforming 3D space-time points into 2D points) before clustering them (Guo et al., 2010). To enhance the preservation of movement information, Lee et al (2007) developed an algorithm to first partition trajectories into segments (i.e., sub-trajectories) and then group sub-trajectories based on geometric characteristics to finally generate average trajectories. The strength of these methods resides in the capacity of grouping subjects based on movement characteristics and as such creating generalised movement path within the spatial context.

Another widely applied group of methods is distance-based methods, which seek to group trajectories based on spatial and/or temporal proximity. The results based on these methods usually illustrate major movement flows of high volumes and hide scattered and small volume flows. For example, Andrienko and Andrienko (2011) developed a multi-step methodology to group and separate vehicle movement points into clustered flows based on spatial proximity. Using point data of taxi-based trips, Guo et al (2012) grouped origins and destinations of the trips based on spatial proximity, and mapped out the OD matrix. Some researchers managed to apply distance-based methods in a 3D environment. Drawing on a historic migration dataset, Shaw et al (2008) developed a generalised space-time path approach that first clustered movement points at each cross-section to generate representative points and second, grouped representative times based on temporal proximity. Using a vessel movement dataset, Demšara & Virrantausb (2010) extended the 2D Kernel density method to the 3D space-time cube to generate space-time density of trajectories. Different from the geometric-based methods, the distance-based methods discard individual identities of movement entities and focus more on generating aggregated movement patterns. This can help highlight the spatial and/or temporal intersections among trajectories. However, the information regarding the interactions between generated movement patterns and the specific context (e.g., a road network) are usually reduced, since the aggregated trajectories are often somewhat detached from the specific context, e.g., Andrienko and Andrienko (2011; 2008), Shaw et al (2008). If the network context is not of particular interest, the distance-based approach can cause problems for interpretation of results.

Apart from the geometric-based and distance-based methods, some innovative methods derived from other scientific fields have been introduced to offer novel visualisations. Shoval and Isaacson (2007) introduced the sequence alignment from genetic studies as a tool to group tourists' trajectories based on the sequence of events. They argued it allows a more flexible comparison of trajectories than the conventional clustering methods. However, the reliability of this method needs to be further tested (Shoval and Isaacson, 2007). Another notable example is the graph-based method by Guo et al (2010). Drawing on the concept of 'modularity' in the Physics studies, they proposed a graph-based method that first constructs a hierarchy of clusters of representative movement points based on the level of connection measured by modularity (that is the difference between expected flow and actual flow volumes), and then partitions the hierarchy into self-contained areas (Guo, 2009; Guo et al., 2010). Their method is more useful in detecting place of interest and spatial structure embedded in a movement dataset.

Considering the detailed information stored by smart card records (e.g., boarding stop, service ID, vehicle ID), there are opportunities to capture the spatial-temporal dynamics of BRT usage with a level of detail previously impossible. Yet, instead of drawing on the aforementioned methods directly, it appears more appropriate to carefully develop a suitable methodology and apply it to smart card data to address the issue of interests here. This is due to two major reasons. First, the smart card data is significantly different from other types of movement data in previous studies (e.g., GPS data, migration data) in terms of information contained and data resolution. Second, while the above studies provided a diverse array of useful visual analytic tools to generate interpretable results from large movement data, each of these methods is inherently bonded with certain limitations, for example losing details of a transport network. Given this, the development of a suitable methodology for smart card data constitutes a major challenge for investigating the spatial-temporal dynamics of BRT usage in this thesis.

2.3 Understanding the attitudinal mechanisms of travel behaviour

Through reviewing the existing literature focusing on the spatial-temporal dynamics of travel behaviour and discussing potential challenges for investigating BRT usage, the focus of this section moves to the attitudinal mechanism of travel behaviour as another crucial component of this thesis.

2.3.1 Travel behaviour and attitudinal mechanisms

Apart from capturing the spatial-temporal behavioural characteristics, understanding the decision-making process (or attitudinal mechanisms) underpinning people's travel behaviour constitutes another key focus of travel demand analysis (Ben-Akiva and Lerman, 1985; Dobson et al., 1978; Golob, 2003). Conventionally, individual's travel behaviour (particularly mode choice behaviour) has been predominantly deemed as the function of monetary cost and time. The studies within this strand usually drew on a utility maximisation framework and assumed that people tend to minimise the monetary cost and time in choosing a transport mode for their trip-making (Ben-Akiva and Bierlaire, 1999; Ben-Akiva and Lerman, 1985). In addition to this viewpoint, people's travel behaviour decisions have been also considered to be influenced by contextual dimensions such as land-use density and diversity, that denser and more diverse land-use patterns encourage active and public transport while reducing the use of private motorised transport (Cervero and Kockelman, 1997; Ewing and Cervero, 2001).

Despite the prevalence of utility- and land-use-based perspectives in explaining travel behaviour, they appeared to have some conceptual and empirical limitations. For the utility-based approach, a major concern pertains to its overly rational and strict assumptions of people's mode choice behaviour, and that people rarely considers factors outside economic impacts (cost and time) of trip making (Schiefelbusch, 2010; Dijst et al., 2008; McNally and Rindt, 2008). The major drawback of such assumption is its over-simplification of people's travel experience. More empirical findings suggest that other less quantifiable aspects of using a transport mode (e.g., comfort, flexibility and safety) may also play important roles in shaping people's travel behaviour decisions (Hutchinson, 2009; Schiefelbusch, 2010; Steg, 2005; Steg, 2003). It has been also found that taking these more subjective dimensions (for example, convenience, preference) into account could significantly improve the performance of utility-based models in explaining mode choice behaviour, such as discrete choice model (Ben-Akiva and Bierlaire, 1999). In terms of the relationship between land-use and travel behaviour, more studies found that the effects of land-use characteristics (e.g., density, diversity) on travel behaviour were considerably alleviated after including such attitudinal factors as attitudes and preferences, suggesting the mediating role of the former between the attitude-behavioural relationship, e.g., Kitamura et al (1997), Van Wee et al (2002), Bhat and Guo (2007), Páez and Whalen (2010).

The identified limitations of the utility- and land-use-based studies indicate the need to undertake a more attitudinal approach to attain complementary insights into the decision process of people's travel behaviour (Dijst et al., 2008; Garling et al., 1998). An extensive search of the literature suggests that two bodies of theories, i.e., the attitudinal theories in the field of social and environmental psychology and concepts in service marketing studies, have received particular attentions in travel behaviour studies. Drawing on these two bodies of theories, a growing number of studies has found that significant relationships persist between people's attitudinal dimensions (e.g., perceptions about a transport mode, norms, environmental concerns and perceived control) and mode choice behaviour (Gardner and Abraham, 2008; Bamberg et al., 2007; Collins and Chambers, 2005; Harland et al., 1999; Cardozo, 1965; Jen et al., 2011; Lai and Chen, 2011). In addition, accumulating evidence suggests that understanding the attitude mechanisms related to people's behavioural intentions to use public transport also has the potential to critically inform transport policies aimed at changing travel behaviour towards a more sustainable direction, in particular, encouraging public transport use while reducing car use (Beale and Bonsall, 2007; Brög et al., 2009; Richter et al., 2011; Jen et al., 2011).

In this section, the key theories and concepts pertaining to the understanding of the attitudinal mechanisms of travel behaviour are introduced in Sections 2.3.2 and 2.3.3. Next, empirical travel behaviour studies drawing on these theories and concepts are reviewed in Sections 2.3.4 and 2.3.5. Their key findings and issues are highlighted, followed by the discussion of their implications for investigating the attitudinal mechanisms of BRT passengers.

2.3.2 Attitudinal theories

Two attitudinal theories in social and environmental psychology and the concept of 'habit' have been widely applied in travel behaviour studies that focused on investigating people's attitudinal mechanisms, each of which is introduced below.

The theory of planned behaviour (TPB)

The Theory of Planned Behaviour (or TPB) (Ajzen, 1988) is a widely applied theory for explaining and predicting general human behaviour (Armitage and Conner, 2001). As an extension of the theory of reasoned action (or TRA) (Fishbein and Ajzen, 1975), TPB assumes that behavioural intention (i.e., the perceived willingness for performing a given behaviour) serves as the central factor that determines whether the behaviour will be actually performed (Ajzen, 1991). In general, stronger intention for a given behaviour indicates higher likelihood of its performance.

A behavioural intention has three types of salient antecedents, i.e., attitude, social norm and perceived behavioural control. Attitude refers to one's perceptions of a given behaviour, for example, the performance of the behaviour is perceived as good or bad. Attitude towards a given behaviour is developed from one's beliefs (or expectations) concerning the results from performing the behaviour, that is, whether the results will be beneficial or not. Such beliefs can result from one's previous experience or information gained from others. As such, people tend to hold favourable (unfavourable) attitudes towards behaviours that are believed to be likely to generate positive (negative) results.

Social norm reflects the perceived support of important others (e.g., family members, friends) towards one certain behaviour. It originates from normative beliefs, which are the perceived likelihood that the important others will approve or disapprove of the conduct of the behaviour. Hence, positive normative beliefs will result in a positive social norm of performing the behaviour, and vice versa.

Perceived behavioural control (PBC) refers to perceived easiness (or difficulty) of performing a given behaviour. A person's perceived behavioural control originates from his or her control beliefs over a given behaviour, e.g., whether it is easy or hard to perform the behaviour given the actual resources or opportunities possessed by the person. Apparently, the more resources related to the behaviour one possesses, the higher the perceived behavioural control of the behaviour (e.g., less difficulty) will be. In addition, while attitude and social norm represent one's volitional control over behaviours, perceived behavioural control reflects the perceived environmental barriers or facilitators that are not subject to one's volition (Ajzen, 1991). As such, unlike attitude and social norm, perceived behavioural control has been argued to directly impact on the performance of the behaviour (Ajzen, 1991).

The norm-activation model (NAM)

The norm-activation model (or NAM) has been developed with a focus of explaining altruistic behaviour, such as helping others and recycling voluntarily (Schwartz and David, 1976; Schwartz, 1977). According to NAM, the behaviours of altruism are mainly driven by personal norms, which refer to a person's perceived responsibilities or obligations to behave in a certain altruistic manner (Schwartz, 1977). Different from social norms that reflect pressures from others such as friends, personal norms originate from one's own value system, which is embodied as a person's conviction that behaving in a certain way is morally right or wrong (Harland et al., 1999; Bamberg et al., 2007). As personal norms are activated under certain conditions, such as the realisation of negative results (e.g., problems experienced by others) of not being altruism, a person will act to avoid such potential negative results (Schwartz and David, 1976; Schwartz and Gottlieb, 1976).

In addition to altruistic behaviours, NAM has been widely applied in the investigation of pro-environmental behaviours that are considered beneficial for the well-being of others, such as energy conservation, recycling and, of course, the use of public transport for regular trips, e.g., Black et al (1985), Stern and Dietz (1994), Stern et al (1999), Harland et al (1999). The above studies have found that personal norms, measured as perceived responsibilities of behaving in an environmental-friendly manner, could significantly influence the performance of pro-environmental behaviours. These findings suggested that NAM provided suitable theoretical underpinnings to explain pro-environmental behaviours.

Habit

Both TPB and NAM assume that a person's behaviour is to a large extent determined by one's deliberate consideration concerning the behaviour. Both theories however suffer from an unstable (or even low) power of predicting the occurrence of an actual behaviour (Verplanken et al., 1994). With regards to this issue, it has been pointed out that a critical limitation embedded within these theories is the lack of the consideration of habits (Ronis et al., 1989).

In people's daily life, many behaviours (including the use of a transport mode such as car) are repeatedly carried out with little deliberate consideration (Ronis et al., 1989; Garling et al., 1998). This automatism of behaviour is considered as habit. As the execution of a given behaviour accumulates over time (for example, brushing teeth in the morning), any considerations preceding the behaviour become decreasingly active while certain environmental cues (for example, morning alarm) gradually gain more dominance in incurring the behaviour. As such, a habit is formed.

The inclusion of habits has largely altered the view of the attitude-behaviour relationship. While the effects of attitudes and habits on behaviour have been independently argued and investigated, it has also been suggested that an interactive relationship exists between attitudes and habits (Triandis, 1979; Verplanken et al., 1994). A strong habit will weaken the attitude-behaviour relationship, and a weak habit will be accompanied by a strong attitude-behaviour link. Given a strong habit, the prediction of behaviour will largely rely on the consideration of habitual behaviour. Additionally, in comparison to attitudes, it has been contended that habitual behaviour is more difficult to change, since little consideration is involved in the process (Garling et al., 1998).

The view of habitual behaviour as mere automatic repetition however has been questioned as well. Drawing on the viewpoints of philosophers including Félix Ravaisson and John Dewey, Schwanen et al (2012) argued that habits should be viewed as a strong collective tendency rather than an individual-based phenomenon. They further contended that instead of being pure automatic mechanisms, habits are more deeply entrenched in people’s lives, and from habits, attitudes are formed rather than the other way around. Taking the common cycling habits in the Netherlands as an example, Schwanen et al argued that a change of travel behaviour requires more long-term and extensive approaches than has previously been suggested, for example education of youngsters, or a change of policy environment. While this viewpoint appears to be somewhat contradictory, it might provide a potentially valid standpoint which has the capacity to explain why some intervention programs have failed to have long-term effects in reducing car use, e.g., Thøgersen and Møller (2008).

2.3.3 Customer loyalty and service experience

Apart from the aforementioned attitudinal theories, the concepts related to customer loyalty and service experience in service marketing studies constitute another significant theoretical foundation underpinning the understanding of attitudinal mechanisms of travel behaviour within the UPT context.

Customer loyalty has been defined as *‘a deeply held commitment to rebuy or repatronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having* *the potential to cause switching behavior'* (Oliver, 1999, p. 34). In service marketing studies, loyalty is commonly measured by customers' intentions or willingness to repurchase a service and to recommend the service to others, hence largely resembling the concept of 'behavioural intention' in the attitudinal theories in social psychology (Oliver, 1999). Notwithstanding such conceptual resemblance, it has been pointed out that compared to the studies drawing on attitudinal theories, service marketing studies seek to provide more detailed insights into the relationships between behavioural intentions of customers to repatronise a service and their self-interest considerations, in particular, their service experience (Liao et al., 2007; Olsen, 2007).

A number of empirical studies have investigated the relationship between service experience and customer loyalty (Boulding et al., 1993; Fornell, 1992; Lam et al., 2004; Olsen, 2007; Andreassen and Lindestad, 1998; Yang and Peterson, 2004; Zeithaml et al., 1996). By compiling extensive empirical studies, it has been found that across different service contexts, factors reflecting customers' evaluations of their service-experience have consistent and significant impacts on their loyalty, in particular, satisfaction, perceived service quality and perceived value (Cronin et al., 2000), each of which are briefly introduced below.

Satisfaction in service marketing studies has been referred to as an overall feeling a customer holds towards a service (Johnson and Fornell, 1991; Johnson et al., 1995). Earlier studies tended to view customer satisfaction as an encounter-specific concept, that a customer compares the perceived performance of a service to his or her expectations, and forms an attitude of satisfaction or dissatisfaction about the service right after consuming it (Anderson, 1973; Oliver, 1981; Yi, 1990). A critical weakness of this point of view is that it largely overlooks the cumulative process of customer satisfaction (Johnson et al., 1995; Johnson et al., 2001). It has been found that a cumulative satisfaction exists without the comparison process described above (yet usually in line with one's expectations about a service), and overrides the encounter-specific satisfaction in influencing customer loyalty (Johnson et al., 2001; Jones and Suh, 2000).

Perceived service quality has been referred to *'the consumer's judgment about an entity's overall excellence or superiority'* and *'similar in many ways to attitude'* (Parasuraman et al., 1988, p. 15-16). Perceived service quality has been argued to be similar to the concept of satisfaction, given that both originate from one's expectations about a service (Grönroos, 1984; Parasuraman et al., 1985). Yet, it has been pointed out that while satisfaction is largely affective-based (e.g., the experience of using a service being pleasant or unpleasant), perceived service quality is a cognitive-based concept (e.g., the delivery of a service being of high standard or low standard) (Cronin and Taylor, 1992; Cronin and Taylor, 1994). Hence the two constructs are to a degree distinguishable on a conceptual basis. To support this argument, some empirical studies have revealed that perceived service quality is a key antecedent of satisfaction, e.g., Boulding et al (1993), Spreng and Mackoy (1996).

Last, perceived value refers to the *'cognitive tradeoff between perceptions of quality and sacrifice'*, wherein sacrifice is usually considered as monetary and non-monetary costs, e.g. time and effort that consumers have to pay (Cronin et al., 1997; Zeithaml, 1988). Perceived value has been considered as a critical aspect of customers' evaluation of a service due to the fact that customers evaluate the costs of purchasing a service in relation to their gains. For example, a customer can be satisfied with a service of relatively low standard due to its associated low cost, while dissatisfied with a service of high standard given a considerably higher cost.

Having provided a theoretical basis for understanding the attitudinal mechanisms of UPT passenger travel behaviour, the following two sections review the empirical travel behaviour studies drawing on the attitudinal theories and concepts related to customer loyalty and service experience and their relations to the investigation of BRT passengers.

2.3.4 Empirical travel behaviour studies drawing on the attitudinal theories

Numerous studies have applied the theory of planned behaviour (TPB) to explain and predict the behaviour of private car use in order to identify possible ways of reducing car dependency, e.g., Garling et al (1998), Bamberg and Schmidt (1998), Kaiser and Gutscher (2003), Forward (2004), Yang-Wallentin et al (2004), Bamberg and Schmidt (2003). Drawing on cross-sectional survey data, the findings of these studies generally supported the TPB framework and that the three factors (i.e., attitude, social norm and PBC) influence people's intentions (not) to use private cars to fulfil their travel needs, which in turn influences their actual use of private cars (usually measured as retrospective use frequency). Cross-lagged studies have also been conducted to test the causal relationships of TPB concerning travel behaviour. For example, Bamberg et al (2003a) detected that the TPB framework substantially explained the car use between two time points interrupted by a six month time period. In another related study, Armitage et al (2011) managed to find that over a two month period, the change of attitudinal factors (i.e., attitudes, social norm and perceived control) significantly influenced people's car use in a rural community in the UK.

In addition to the TPB, some other studies have applied the Norm Activation Model (NAM) framework to explain travel behaviour from a pro-environmental perspective (Gardner and Abraham, 2008). Quite a few studies have found that personal norms resulting from environmental concerns related to travel behaviour (for example, the issues of air pollution and over-consumption of fossil fuels resulting from private car use) had the capacity to lead to the intentions of reducing private car use and increasing UPT use for certain trips (such as work trips), therefore incurring behavioural change, e.g., McKenzie-Mohr et al (1995), Nilsson and Küller (2000), Nordlund and Garvill (2003), Collins and Chambers (2005).

While the TPB and the NAM have individually provided applicable frameworks to explain people's travel behaviour, considerable room remains in enhancing the explanation and prediction powers for each of these theories. In addressing this issue, many researchers have sought to combine the strengths of different theories to model mode choice behaviour. Harland et al (1999), Heath and Gifford (2002), Bamberg and Schmidt (2003), Bamberg et al (2007), Wall et al (2007) found that models combining personal norms (the key construct of the NAM) with the TPB could explain more variances of both the intention and actual use of UPT (i.e., use frequency) in comparison to the use of the individual theories. Additionally, more recent studies have drawn on the combined theories to model travel behaviour and affirmed that people's use of private cars (or reducing car use) combines the impacts of both self-interest considerations as argued in the TPB and the moral aspect as suggested in the NAM, e.g., Abrahamse et al (2009), Klöckner and Matthies (2009), Mann and Abraham (2012).

While behavioural intention has been considered as the key factor that influences actual travel behaviour, it has been argued that for many people, mode choice behaviour as a form of repeated behaviour is more determined by habit than by deliberate considerations (Garling and Axhausen, 2003). In accordance with this argument, empirical evidence was provided, indicating that the inclusion of habit accounted for more variance of actual mode choice behaviour of people than otherwise, e.g., Verplanken et al (1994), Verplanken et al (1998), Bamberg and Schmidt (2003), Bamberg et al (2007), Thøgersen (2006). Therefore, changing travel behaviour (particularly reducing car use) can be very difficult, given that, in comparison to attitudes, people's habits (of car use) are much more difficult to change (Garling and Axhausen, 2003).

However, contradictory findings have also been found, indicating a weak influence of habits on mode choice behaviour (car use) as opposed to the dominant role of attitudinal factors, e.g., Bamberg et al (2003a), Bamberg et al (2003b). Also notably, through multi-group analysis, it has been found that stronger attitude-behaviour relationship were found among public transport users who did not own cars than among those who relied on private cars to fulfil their travel needs, suggesting that people's repeated use of UPT is more consistent with their attitudes rather than habits, e.g., Thøgersen (2006), Chen and Chao (2011).

The findings of previous studies investigating the attitudinal mechanisms of people's travel behaviour has raised some implications for policies that were aimed at reducing private car use in a more proactive manner. In particular, it has been highlighted that a core component of prompting travel behaviour change is to manage and change people's behavioural intentions regarding the use of non-car transport such as public transport through targeting their modifiable attitudinal dimensions (e.g., attitudes, norms, perceived control, habits) (Bamberg et al., 2011; Ampt, 2004; Brög et al., 2009; Richter et al., 2011). By carrying out information-based approaches (e.g., dispatching information brochures), changes in perceptions towards public transport, e.g., Garvill et al (2003), Ampt (2004), Brög et al (2009), Bamberg et al (2011), Beale and Bonsall (2007), Fujii and Taniguchi (2006) and personal responsibility of behaving in a pro-environmental manner, e.g., Matthies et al (2006), Eriksson et al (2008), could be incurred, which resulted in changes in behavioural intentions to use public transport instead of cars and consequentially, actual changes in travel behaviour.

Nonetheless, some studies cast questions on the effectiveness of such soft policy options in incurring travel behaviour change, e.g., Tertoolen et al (1998), Ker (2003). Based on a detailed examination of a travel behavioural modification program in Melbourne, Morton and Mees (2005) questioned the actual effectiveness of such intervention due to the potential 'artifacts' such as the expectancy effect (that is researchers' expectations of experiment outcomes may influence participants' behaviour), and nonresponse bias. To overcome such issues, Morton and Mees suggested that future intervention should be undertook in a more 'blind' manner, that observed and control groups are not pre-informed. Despite a somewhat mixed picture of practical results, it appears that from a theoretical perspective, attitudinal theories can help us better understand the psychological complexity concerning people's mode choice behaviour, which may provide evidence and caveats for transport policy-making if dealt with care (Hunecke et al., 2007; Van Acker et al., 2010).

While the existing studies predominantly focus on explaining people's car use, some researchers have also revealed that allied with the TPB and the NAM, people's use of public transport can be significantly driven by their behavioural intention, which summarises the impacts of attitudinal dimensions including perceptions, norms and perceived behavioural control, e.g., Heath and Gifford (2002), Bamberg et al (2007), Collins and Chambers (2005), Spears et al (2013), as well as their past behaviour or habit, e.g., Thøgersen (2006), Chen and Chao (2011). As such, the understanding of BRT passengers' attitudinal mechanisms should also pay attention to their behavioural intentions as well as the attitudinal dimensions highlighted in the above studies (e.g., attitudes, social norm, PBC).

An important yet less investigated issue related to people's consideration of alternative transport, however, exists in the aforementioned studies, and deserves particular attention in the current study as well. Through a meta-analysis drawing on the datasets of 23 empirical studies, Gardner and Abraham (2008) noted that behaviour and intention of car use are strongly related to the attitudinal dimensions concerning both car and non-car use (e.g., attitudes about non-car use, perceived control over non-car use). In a related study, Gardner and Abraham (2010) empirically re-affirmed that people's attitudinal factors related to non-car use (in particular, attitudes towards non-car use and perceived control and personal norm over non-car use) exhibited marked effects on their intention to drive. As such, they argued that reducing car dependency should focus mainly on enhancing the appeal of alternative transport modes to private cars (Gardner and Abraham, 2010). Similar findings and implications concerning people's intentions to switch from private car use to public transport for trips to city centre were found in a Dutch context study (Van Exel and Rietveld, 2009).

Based on the findings of Gardner and Abraham, a logical question can be brought up: to what extent UPT passengers' behavioural intentions will be subject to the influences from their considerations of alternative transport, in particular private cars, and should managing and securing passengers' transit use be assisted by targeting at these attitudinal dimensions? Some empirical studies have touched the edge of this issue. For example, Jensen (1999), Beirao and Sarsfield Cabral (2007) interviewed small samples (20-30) of public transport users about their reasons for using public transit in Denmark and Portugal respectively. In addition to the perceived good of using a transit service (e.g., convenience, avoiding congestion), participants in both studies cited lack of access to private cars as another common reason. Additionally, in a case study of promoting bus use in the UK, Beale and Bonsall (2007) found that information highlighting issues associated with private car use (e.g., environmental impacts and financial costs) and pointing out the benefits of bus use appeared to strengthen positive attitudes towards and actual use of bus services among current bus riders, while it reversely impacted on the attitude and behaviour of in-frequent or non-bus users.

The findings highlighted above point towards the possibility that UPT passengers' behaviour and intentions may to some extent relate to (e.g., negatively influenced by) their considerations (e.g., attitudes or perceived control) of private car use. However, an examination of the literature shows that very few empirical studies have examined the extent to which the attitudinal dimensions related to private car use have explanatory power concerning UPT passengers' behavioural intentions. In a study within a Swedish context, Nordlund and Westin (2013) found direct yet reverse influences of people's attitudes towards train and private cars on their intentions to use a new-established railway line. However, considering the prevailing car dependency as a major barrier for promoting UPT especially within highly motorised cities (Kenworthy and Laube, 1999; Steg, 2003), there is a compelling need to obtain more evidence to shed light on this issue in order to inform transport policies in terms of how to deal with passengers' attitudes concerning alternative modes (especially private cars) in an attempt to maintain and encourage UPT use.

2.3.5 Empirical studies examining UPT passenger loyalty and service experience

The management of a transit service has been conventionally concentrated on attracting new ridership (Schiefelbusch, 2010). However it has been highlighted that maintaining current ridership is a more economical strategy for the long-term survival of a transit service, given that retaining a passenger can be five times cheaper than attracting a new one (Miller et al., 1999; Foote et al., 2001; Figler et al., 2011; Lai and Chen, 2011). Hence apparently managing to maintain the transit use of current passengers is of necessity for establishing more sustainable urban transport. The key to achieving this involves the understanding and management of passengers' loyalty towards a transit service, which has received growing interest from transport researchers and practitioners over the past 15 years (Miller et al., 1999; Foote et al., 2001; Lai and Chen, 2011), and as such deserves particular attentions within the BRT context as well.

An examination of the existing literature concerning UPT passenger loyalty renders two groups of studies with distinguishable focuses. The first group of studies focuses on identifying secured and unsecured segments of UPT passengers. A prevailing approach in this area of studies is to segment the transport market based on captivity (i.e., with or without more than one modal option at their disposal) and regularity (i.e., use a transport mode on a regular or irregular basis) (Beimborn et al., 2003; Jacques et al., 2013). Drawing on this approach, a number of studies have provided insights into the differences between captive and choice travellers in terms of travel behaviour (e.g., travel time, trip purposes) and socio-demographic characteristics (e.g., gender, income), e.g., Wilson et al (1984), Polzin et al (2000), Giuliano (2005). In addition, some researchers included preference towards transport modes in the comparison of captive/choice and regular/irregular groups, e.g., Krizek and El-Geneidy (2007).

While this choice/captive approach provides a simplified method to segment UPT passengers, it is critically limited in capturing passengers' attitudinal loyalty and as such may provide misleading information for UPT services. Based on such an approach, passengers who regularly use a transit service, or have no access to alternative transport (particularly private cars) are commonly deemed as secured passengers, who presumably would keep using a transit service to fulfil their travel needs (Beimborn et al., 2003; Jacques et al., 2013). Based on this interpretation, a transit provider is inclined to direct its major strategy at attracting new passengers (e.g., establishing new routes and infrastructures) while paying limited attention to regular or 'captive' passengers. However, the passengers' repeated use of a transit service does not necessarily suggest that they are attitudinally loyal (i.e., willing to re-use) to a transit service (Miller et al., 1999). Some passengers who frequently use a transit service might still have the intention to defect to alternative transport, due to various reasons, including accumulating unpleasant experiences (e.g., receiving poor attitude from drivers) or the change of conditions (e.g., purchasing a car) (Miller et al., 1999; Jensen, 1999; Anable, 2005).

Due to the limitations of the conventional captive/choice approach, more researchers have focused on examining UPT passengers' attitudinal aspects (e.g., satisfaction, desired mobility) in order to achieve more detailed segments of UPT markets. For example, Diana (2012) conducted a correspondence analysis on a series of satisfaction measures concerning the performance of private cars and UPT services to segment multimodal travellers. He revealed that travellers' overall satisfaction of a transport mode did not significantly relate to the frequency of use. In another two related studies, by conducting a series of cluster analysis on three mobility measures (i.e., objective, subjective and desired mobility), Diana and Mokhtarian (2009a; 2009b) markedly found that mono-modal riders of UPT on average were more inclined to balance their use of multi-modes by increasing the use of private cars compared to multimodal users (i.e., public transport and car).

Some studies used the concept of loyalty to identify attitudinally secured and unsecured passengers for a UPT service. For example, Foote (2001) found that in a Chicago-based study, loyalty of rail passengers did not conform with their use frequency of the railway service, and choice passengers with access to private cars or voluntarily giving up car ownership showed higher loyalty compared to captive passengers. Jacques et al (2013) had similar findings in a case study in McGill, Canada. Drawing on a number of attitudinal aspects including perceptions towards car and UPT use, environmental concerns, perceived control over non-car use and habit, Anable (2005) identified two distinct segments of bus users in a UK-based study, i.e., ‘car-less crusaders’ who used transit services due to their favourable attitudes towards transit and pro-environmental responsibility, and ‘reluctant riders’ who used bus services due to situational restraints (e.g., financial and health conditions) and showed high willingness to shift to private car use.

Further to the above studies, the second group of studies has concentrated on the modelling and understanding of the relationships between passengers’ loyalty and their service experience within various UPT contexts, including intercity coach service (Wen et al., 2005; Jen et al., 2011), bus transit (Joewono et al., 2012; Jen and Hu, 2003; Minser and Webb, 2010; Friman et al., 2001), metro (Lai and Chen, 2011; Minser and Webb, 2010), paratransit (Joewono and Kubota, 2007a; 2007b) and the BRT (Joewono et al., 2012). Allied with the findings of service marketing studies, e.g., Bolton and Drew (1991), Cronin et al (2000), Yang and Peterson (2004), these studies have shown that satisfaction, perceived service quality and perceived value have important impacts on the levels of passenger loyalty. These findings confirmed that the attainment of passenger loyalty is largely based on achieving high levels of satisfaction, perceived service quality and perceived value of UPT passengers. Furthermore, some other service-related factors including corporate image of transit providers, e.g., Minser and Webb (2010), switching costs (e.g., time and monetary costs) passenger shifting to other transit providers, e.g., Wen et al (2005), attractiveness of alternatives that reflect the passengers’ attitudes towards alternative transit services, e.g., Jen et al (2011) and involvement that reflects the perceived interest or importance of a transit service to a passenger, e.g., Lai and Chen (2011) were also found to have significant influences on passenger loyalty, further contributing to the understanding of the service experience-loyalty relationship within the UPT context.

The aforementioned findings concerning UPT passenger loyalty have rendered important implications for transit providers mainly from three aspects. First, in line with the studies drawing on the attitudinal theories in social and environmental psychology, it is highlighted that the management of passengers' behavioural intention (or loyalty) is a key component for sustaining the long-term survival of a transit service (Foote et al., 2001; Miller et al., 1999). Second, through unveiling the disparity between UPT passengers' use frequency of a UPT service and loyalty, it has been highlighted that the understanding of UPT passenger market segments should draw on a more attitudinal-based approach (Jacques et al., 2013; Krizek and El-Geneidy, 2007; Miller et al., 1999). Third, passengers' evaluations of service experience, particularly perceived service quality, perceived value and satisfaction critically influence their level of loyalty to a UPT service. Hence transit providers should seek to enhance these attitudinal dimensions of UPT passengers to attain and reinforce their loyalty (Jen et al., 2011; Lai and Chen, 2011; Minser and Webb, 2010).

Despite the valuable information and implications obtained, the issue concerning the role of passengers' considerations of private car use in influencing their behavioural intentions is also largely unexplored in this group of studies. In addition, given the findings of some studies focusing on segmenting the transport market, e.g., Anable (2005), Diana and Mokhtarian (2009a; 2009b), another critical question can be raised: can loyalty fully capture the behavioural change tendency of UPT passengers' future mode choice? As highlighted by Anable (2005), Diana and Mokhtarian (2009a; 2009b), some transit passengers showed higher desires or intentions to shift to private car use than others. Moreover, it has be found that the passengers' desires to switch modal use were significantly associated with their both objective and subjective use of a transit service (e.g., measured by accumulated time) (Cao and Mokhtarian, 2005; Choo et al., 2005), whilst passenger loyalty was found to be less associated with their transit use frequency, e.g., Foote et al (2001). Taken together, the above findings point towards the possibility that loyalty, while capturing passengers' willingness to keep using a transit service, may not fully capture their change intentions in terms of future transit use and use of alternative transport, especially private cars.

Given these findings, there appears to be a need to investigate and understand UPT passengers' behavioural change intentions in addition to their loyalty, in particular the intention to shift to private car use and the intention to increase UPT use, in relation with their service experience and other potentially related attitudinal dimensions (such as the ones noted in the last section). This is due to that averting modal shift and increasing UPT use also relates to the establishment of more sustainable transport in the face of car dependency (Lai and Chen, 2011; Miller et al., 1999). Again, a scrutiny of literature shows that little empirical evidence exists to shed light on this issue.

2.4 Synthesis of knowledge gaps

2.4.1 Travel behaviour related to BRT

BRT has become an increasingly important component in the UPT networks across the world as a cost-effective way to promote UPT use against global car dependency. To capture BRT's impacts on travel behaviour and sustainable transport (such as increasing public transport use instead of cars) can be understood, a number of studies have examined the ridership change at the BRT corridor level, e.g., Hensher and Golob (2008), Deng and Nelson (2013), Currie and Delbosc (2010), Callaghan and Vincent (2007), as well as the service aspects that influence ridership level, e.g., Currie and Delbosc (2011), Hensher and Golob (2008). A careful examination of the literature, however, shows that the existing knowledge of BRT use is critically limited, which potentially hinders our ability to inform future BRT-related policy.

Three interlinked aspects of BRT passenger travel behaviour have received little attention but are worth particular attention here. First, the modal share patterns (in particular, the shares of private cars and public transport) of BRT catchments require examination to render additional evidence concerning the effects of BRT in shaping more sustainable travel behaviour of urban populations. Second, the spatial-temporal dynamics of current BRT usage across a UPT network are worth investigation in order to understand the role of BRT embedded within a UPT network in facilitating people's trip-making. Third, the attitudinal mechanisms related to BRT passengers' behavioural intentions also warrant investigation given their potentially critical role in influencing passengers' future use of BRT and private cars as a viable or potential alternative transport option. By addressing the three behavioural dimensions highlighted, it is expected that an enhanced understanding of travel behaviour related to BRT passengers can be obtained. This offers a more reliable evidence base to inform future BRT policy and planning as a means to help improve the sustainability of urban transport systems.

Apart from the knowledge gaps identified, it has been highlighted that critical methodological and theoretical issues related to the investigation of spatial-temporal dynamics (i.e., the use of smart card data) and attitudinal mechanisms (i.e., the understanding of behavioural intentions) persist in the current travel behaviour studies. These issues posit challenges to the understanding of travel behaviour related to BRT and should be dealt with in this study.

2.4.2 Smart card data

Conventionally the investigation of the spatial-temporal dynamics of travel behaviour largely relies on travel survey data as the principal data source. A number of critical drawbacks exist in association with travel survey data, including the generalisability of small sample size, high collection costs, low response rate and the accuracy of travel behaviour information recorded (Noland and Polak, 2002; Rickwood and Glazebrook, 2009; Chu and Chapleau, 2010). Each of these issues has the potential to compromise our understanding of the spatial-temporal patterns of people’s travel behaviour. Given this, there is a compelling need to consider alternative data sources that can provide more reliable information of travel behaviour.

With the growing prevalence of smart card systems as a mean to improve fare-collective efficiency for UPT networks, smart card data has been highlighted as an enhanced data source for investigating UPT passengers’ travel behaviour, due to its capacity to store large amount of detailed logs of UPT trips continuous in space and time (Bagchi and White, 2005; Pelletier et al., 2011; Utsunomiya et al., 2006). A growing body of studies has exploited the utility of smart card data in better understanding the spatial-temporal properties of UPT passengers, contributing to the evidence-based UPT planning and management (Hofmann and O'Mahony, 2005; Munizaga and Palma, 2012; Nassir et al., 2011; Morency et al., 2007). Given this, smart card data also provides new opportunities for understanding the spatial-temporal dynamics of BRT usage with potential to inform future BRT provision.

Despite its potential to help better understand BRT usage dynamics, smart card data posits critical methodological challenges to this study. First, given smart card data’s large quantities, applying the conventional statistical-mathematical methods may be limited in capturing the actual spatial-temporal patterns of travel behaviour due to their ‘aspatial’ nature and sensitivity to large sample size. By comparison, spatial visualisation appears to be a more appropriate analytic strategy, given its ability to reduce information redundancy and visualise quantifiable information of ‘big data’ (e.g., passenger volume, direction) in space and time (Andrienko and Andrienko, 2008; Andrienko and Andrienko, 2011; Kwan, 2000; Kwan and Lee, 2004). However, a geo-visualisation method to extract the travel patterns of BRT passengers from smart card data is still lacking and requires careful development. In achieving this, some of the limitations of smart card data (e.g., lack of geographic information) must be dealt with as well.

2.4.3 Behavioural intentions

Understanding the attitudinal mechanisms of people's behavioural intentions related to their mode choice has received growing interest in travel behaviour studies (Garling et al., 1998; Van Acker et al., 2010; Jen et al., 2011). Drawing on two bodies of theories, i.e., the attitudinal theories in the field of social and environmental psychology (particularly the TPB, the NAM and habit) and the concepts in the service marketing studies (in particular related to customer loyalty and service experience), studies have revealed that people's behavioural intention and use of public transport are critically influenced by various attitudinal dimensions that encompass self-interest (e.g., service experience) (Lai and Chen, 2011; Minser and Webb, 2010), moral (e.g., personal norm) (Bamberg et al., 2007; Collins and Chambers, 2005) and situational considerations (e.g., perceived control) (Bamberg et al., 2007). In accordance with these analyses, it has been reported that soft approaches targeted at these attitudinal dimensions have the capability to stimulate greener travel behaviour of people (e.g., increasing public transport use while reducing private car use) within different city contexts (Brög et al., 2009; Fujii and Taniguchi, 2006; Richter et al., 2011; Bamberg et al., 2011).

Despite the progress made in previous studies, the understanding of attitudinal mechanisms of UPT passengers' behavioural intentions remains to be further disentangled in regards to two interlinked issues: (1) the role of considerations of private car use in influencing one's intentions of public transport use; and (2) the potential limitation of loyalty in capturing UPT passengers' behavioural tendency concerning their future use of UPT and private cars as a viable (or potential) transport alternative. The findings of some studies highlight the possible relationships between considerations of private car use and the intentions of public transport use (Jensen, 1999; Beirao and Sarsfield Cabral, 2007; Beale and Bonsall, 2007) as well as the potential of including behavioural change intentions (in particular the intention to shift to private car use, and the intention to increase transit use, refer to Section 2.3.5) to fully capture people's behavioural tendency of their mode choice behaviour (Anable, 2005; Diana and Mokhtarian, 2009a; Diana and Mokhtarian, 2009b). However, little empirical evidence has been presented to clarify these possibilities and their implications for transport policy-making. Considering the persistent car dependency as a key barrier to promoting UPT use, these issues are worth explicit consideration in the investigations of BRT passengers' attitudinal mechanisms in order to identify possible means to maintain and promote BRT usage within highly motorised city contexts.

2.5 Research question

In summary, despite the growing popularity of BRT implementation globally as a cost-effective way to progress towards sustainable urban transport, little is known concerning the travel behaviour dynamics related to BRT worldwide. In order to address this deficit and render a more reliable evidence base to inform future BRT-related policy, this thesis proposes the following research question:

What are the travel behavioural dynamics of BRT passengers and how can our understanding of these dynamics enhance the understanding about BRT passengers' loyalty and change intentions?

Having proposed the core research question of this study, Chapter 3 continues to establish an overall conceptual framework and proposes research objectives related to the specific issues highlighted in the existing literature related to the investigation of BRT passenger travel behaviour (i.e., the change in modal share patterns, spatial-temporal dynamics and the understanding of attitudinal mechanisms), which serve to guide the operationalisation of the rest of the research.

Chapter 3 Conceptual framework

Through a critical review of literature in Chapter 2, it has been established that little is known about the travel behaviour dynamics related to Bus Rapid Transit (BRT) passengers. Hence this study poses the following research question: *What are the travel behavioural dynamics of BRT passengers and how can our understanding of these dynamics enhance the understanding about BRT passengers' loyalty and change intentions?* This chapter moves on to propose an overall conceptual framework that sums the knowledge gaps, critical issues to be tackled and contributions to be made in this study. Next, four research objectives are established to answer the overarching research question.

3.1 Conceptual framework

Figure 3.1 Conceptual framework

Based on the knowledge gaps, research challenges and issues identified in the critical review of the literature in Chapter 2, an overall conceptual framework is established to guide the remainder of the research (Figure 3.1). The Framework elaborates on the three behavioural dimensions, i.e., changes in travel patterns, spatial-temporal dynamics and attitudinal mechanisms of BRT passengers, as the major knowledge gaps identified concerning the understanding of travel behaviour dynamics related to BRT passengers. These behavioural dimensions form the main avenues based upon which the contributions of this study will be made.

First, while existing literature has conducted time-series analysis to examine the shift in modal share patterns in relation to the socio-demographic characteristics of passengers in order to understand the impacts of public transit services (e.g., rail transit) on people's travel behaviour, e.g., Norley (2010), Senior (2009), few have explicitly examined these issues within the BRT context (refer to Section 2.1.5). Clearly, the core concern of BRT's potential in advancing sustainable urban transport is underpinned by the extent to which its provision helps to encourage mode shift from private car use to public transport use. Therefore, this study focuses on the behavioural dimension within varying BRT catchments. It particularly pays attention to the changes in modal share patterns as one moves farther away from BRT stations.

Second, the analysis of travel behaviour dynamics in space and time constitutes a cornerstone for public transport planning in meeting passengers' travel needs (Ortuzar and Willumsen, 2001; Pelletier et al., 2011), yet is largely absent in the current BRT literature. A critical challenge concerning this issue relates to the use of alternative data sources of travel behaviour, given the limitations associated with the travel survey data. A review of the literature (refer to Section 2.2.4) highlights smart card data as an enhanced data source suited for addressing this aspect of travel behaviour; and spatial visualisation has been identified as the appropriate analytic strategy (refer to Section 2.2.5). However, a methodology has yet to be developed and applied to smart card data to investigate BRT usage dynamics in space and time. Given this, this study aims to redress this gap by developing a geo-visualisation-based method (the flow-comap) that enables the extraction and visualisation of the spatial-temporal trip patterns of BRT passengers previously unobserved.

Third, investigations of BRT passengers' behavioural intentions have been rather scarce in the existing literature, despite of their potentially critical role in influencing passengers' future use of a transit service (Bamberg et al., 2007; Jen et al., 2011). An examination of the literature shows that two bodies of theories, i.e., the attitudinal theories in social and environmental psychology and the concepts of customer loyalty and service experience in service marketing studies, provide the core theoretical foundations for understanding the attitudinal mechanisms of passengers' behavioural intentions. However, two critical issues, i.e., the considerations of alternative transport (especially private cars) and the limitations of loyalty in capturing behavioural change intentions of passengers, have received limited attention in the existing literature (refer to Section 2.3.4 and 2.3.5). By taking these two issues into account, this study finally seeks to model three behavioural intentions (i.e., loyalty, the intention to shift to private car use and the intention to increase BRT use) of BRT passengers in order to better understand their attitudinal mechanisms concerning their behavioural tendency of future mode choice (e.g., BRT versus private cars).

While aiming to capture complementary behavioural dynamics, the investigations of the three behavioural dimensions are also expected to deepen the understanding BRT passenger travel behaviour as one moves from one dimension to another (hence the arrows between the three empirical investigations in the conceptual framework). The examination of modal share patterns will initially provide insights into the aggregated changes in travel patterns of BRT catchments after BRT implementation. The investigation of the spatial-temporal dynamics of BRT usage seeks to render more detailed knowledge pertinent to the role of BRT in catering for passengers' travel needs at a UPT network level. And last, the modelling of behavioural intentions will shed light on the attitudinal mechanisms at the level of individual BRT passengers. Attaining this array of knowledge will provide a more holistic and multi-layered understanding of BRT dynamics. The practical value of this knowledge is expected to lie in enabling the development of more operatable and passenger-focused recommendations for future BRT policy and planning from both supply-oriented and demand-oriented perspectives, which transit agencies may draw upon to guide and strengthen BRT as a sustainable UPT option. While identified as a crucial component for BRT planning (among others including infrastructure design, land-use integration) (Wright, 2007), such behaviour-based recommendations exist only rarely in the current literature.

In summary, to answer the overall research question, four research objectives are proposed:

Objective 1: to examine the changes of modal share patterns and socio-demographic *characteristics of BRT catchments;*

Objective 2: to investigate the spatial-temporal dynamics of BRT usage of passengers;

Objective 3: to model the loyalty and behavioural change intentions of BRT passengers.

Objective 4: to develop recommendations for BRT policy and planning from the results of this study.

3.2 Research tasks

With the research objectives being established, this section further elaborates the specific questions and tasks underpinning the empirical investigations to be conducted in this research (i.e., Objectives 1 to 3).

3.2.1 To examine the changes of modal share patterns and socio-demographic characteristics of BRT catchments

Two questions are of interest in Objective 1:

(1) To what extent do the modal share patterns of BRT catchment areas change before and after BRT implementation?
(2) What are the relationships between travel patterns and socio-demographic characteristics for BRT's catchment areas?

The first question looks at the mode share patterns of the BRT catchments (i.e., the mode shares of public transport, private cars and other transport modes such as walking for people's trip making) before and after its implementation within the context of the study. Moreover, in order to provide a clear picture concerning the impacts of BRT over space, the examination of mode share patterns in this study distinguishes between different BRT catchment areas based on the access distance to the BRT, which is further detailed in Chapter 4.

Based on the examination of modal share patterns, the second question aims to reveal the socio-demographic groups that are more likely to be attracted to use BRT, and the groups that tend to remain dependent on private car use. Previous findings indicated that public transport often involves captive and more disadvantaged travellers characterised by low-income and lack of access to private cars, e.g., Giuliano (2005), Kitamura et al (1997). Yet it has also been argued that attracting less disadvantaged and choice passengers (e.g., with higher income and access to private cars) is another critical goal for both the survival and the achievement of more sustainable transport for a UPT service (Foote et al., 2001;

Jacques et al., 2013). Given this, it would be of value to examine the relationships between the modal share patterns and socio-demographic characteristics of BRT catchments to shed light on this issue.

3.2.2 To investigate the spatial-temporal dynamics of BRT usage of passengers

Three questions are of interest throughout the investigation of Objective 2:

(1) To what extent do the travel characteristics of BRT trips differ from the non-BRT trips across the UPT network?
(2) How and to what extent do the spatial-temporal dynamics of BRT trips differ from non-BRT trips across the UPT network?
(3) Within the BRT system (i.e., the BRT busway and related bus routes), is there notable spatial heterogeneity of passengers’ trips across the UPT network?

The first question seeks to reveal the extent to which enhanced mobility of UPT passengers can be achieved by the use of BRT across a UPT network. In accordance with previous studies examining people’s mobility patterns (Hanson and Huff, 1988; Pas and Sundar, 1995; Schlich et al., 2004; Dodson et al., 2010), a series of travel characteristics (including boarding time, trip distance, time and speed, and use frequency) concerning BRT trips (trips fully or partially running on the BRT busway) and non-BRT trips (UPT trips not involving the BRT busway) are compared to address the first question.

The second and the third questions aim to unveil more detailed BRT usage dynamics embedded in space and time by applying a series of geo-visualisation analytic techniques (detailed in Chapter 4). The second question compares the spatial-temporal dynamics of BRT and non-BRT trips to reveal the transport roles of BRT and the remainder of the UPT network within the study context; while the third question focuses solely on BRT-based trips to examine evidence of trip spatial heterogeneity, which refers to capturing the spatial diversity of passenger trip patterns using the BRT busway across the UPT network.

In addressing the latter two questions, research attention is paid to two groups of behavioural dimensions in order to generate a comprehensive picture concerning the spatial-temporal patterns of BRT usage, i.e., the stop-level behaviours and passenger flow patterns. The stop-level behaviours encompass the collective boarding and alighting, transfer behaviours of passengers, which has the potential to indicate the origin, destination and transfer patterns of passengers’ trip-making across the BRT and the remainder of a UPT network (Hofmann and O'Mahony, 2005; Nassir et al., 2011). The passenger flow patterns, on the other hand, aim to capture passengers' travel trajectories. The attainment and analysis of this information over space and time is also of crucial importance to BRT (and arguably other transit) providers, given that it has the capability to reveal passengers' actual path use between their travel origins and destinations, which serves as a critical component to underpin the spatial optimisation of transit services (Ortuzar and Willumsen, 2001; Pelletier et al., 2011; Tao et al., 2014a).

3.2.3 To model the loyalty and behavioural change intentions of BRT passengers

Two questions are of interest for Objective 3:

(1) How do BRT passengers' loyalty and behavioural change intentions vary across socio-demographic and behavioural characteristics?
(2) How do service experience, pro-environmental responsibility and considerations of private car use influence BRT passengers' loyalty and behavioural change intentions?

The first question seeks to elucidate to what extent behavioural change intentions and loyalty will vary systematically across the socio-demographic and behavioural characteristics of BRT passengers. It is expected that addressing this question will render evidence for the need of using loyalty coupled with behaviour change intentions to better capture the behavioural tendency of BRT passengers' future mode choice behaviours.

The second question is concentrated on modelling the three behavioural intentions in relation to a series of attitudinal dimensions of BRT passengers. While a broad spectrum of attitudinal variables may have influence on passengers' behavioural intentions, it is impossible to have an exhaustive examination of all the potential attitudinal antecedents. Based on the critical review of the literature, three groups of attitudinal variables are identified of particular interests here: passengers' service experience with BRT, pro-environmental responsibility and considerations of private car use.

First, in accordance with previous studies (Bamberg et al., 2007; Collins and Chambers, 2005; Jen et al., 2011), it is assumed that BRT passengers' behavioural intentions are primarily influenced by their self-interest (i.e., the benefits of using BRT) and moral considerations originated from pro-environmental concerns, which are captured by their evaluations of their evaluations of service experience and personal norm respectively. Based on the findings of previous studies, it is assumed that these variables will positively influence BRT passengers' intentions concerning BRT use (i.e., loyalty and the intention to increase BRT use) while negatively influence their intention to shift to private car use.

Next, in order to capture the considerations of private car use from different perspectives (e.g., attitudinal, social and situational considerations), the third group of attitudinal variables, considerations of private car use, are conceptualised into three variables drawing on the TPB framework, namely, attitudes towards private car use (or car attitudes), social norm and perceived behavioural control over private car use. Also based on previous studies (Beale and Bonsall, 2007; Beirao and Sarsfield Cabral, 2007; Jensen, 1999), it is assumed that these variables will positively influence BRT passengers' intention to shift to private car use, whilst negatively influence the other two intentions concerning BRT use.

Based on discussion above, a series of specific hypotheses concerning their relationships is proposed (detailed in Section 4.5.6, Chapter 4). The development and discussion of the recommendations for BRT planning and policy (i.e., Objective 4) is provided in Chapter 8.

Chapter 4 Data and methodology

In Chapter 3, an overall conceptual framework and three research objectives are established to guide the rest of the research. This chapter describes the data and methodology applied for addressing the research objectives. Section 4.1 introduces and justifies the case study context. Next, Section 4.2 identifies the suitable data sources for each of the research objectives. Sections 4.3 to 4.5 detail the research strategies (i.e., data preparation and analytic methods) for the research objectives.

4.1 Case study context

4.1.1 Selection of case study area

Australia provides a suitable context for selecting a case study area for the purpose of this particular study, largely due to its heavily car-oriented transport system across the metropolitan areas and as such, the challenges posited for promoting more sustainable urban transport (Cosgrove, 2011). To better comprehend such challenges, a brief overview of the historical background of Australian cities' car dependency is presented as follows.

Australia's car dependence began to take shape since the end of the Second World War (WWII), or 1945 (Cosgrove, 2011). A major immigration from Europe to Australia shortly after the WWII has been identified as the primary factor that triggered the development of car dependence within Australia (Frost and Dingle, 1995; Berry, 1999; Troy, 2004). Following the post-war immigration, there had been 38, 47 and 47 per cent population growth for Sydney, Melbourne and Adelaide respectively and to a lesser extent for other Australian cities between 1945 and 1961. Within the same time span, a 73 percent increase in national labour force was achieved, and falling to just under 50 per cent in the 1960s and 1970s (Frost and Dingle, 1995).

The drastic growth in population and labour force helped lay down an economic foundation that supported a low-density urbanisation process for years to come (Troy, 2004). As a result, many Australian cities had transformed from pre-war 'tightly knit layouts' surrounding transit nodes to a more dispersed urban form that remains essentially the same to date (Davison, 2006; Troy, 2004). This urbanisation process presented cars a much more ideal alternative to public transport, in particular tramways as a prevailing transit mode before the WWII, to fulfil people's daily travel needs (Newman et al., 1995; Cosgrove, 2011). Between 1945 and late 1960s, motor vehicle ownership had grown by 5 times, from one vehicle per 8.7 persons to one per 2.8 persons (Frost and Dingle, 1995). Under the pressure exerted by the growing motorisation, most cities (except Melbourne) closed their tramway networks between 1950s and 1960s to allocate more road space to personal motorised transport (Frost and Dingle, 1995). Despite a gradually ceasing trend of car ownership since the 1970s until today, irreversible has been the dominance of car as a transport mode across the major Australian cities (Cosgrove, 2011; Hensher, 1998).

Apart from a car-oriented base laid by the post-war population and urban growth, Australia’s transport policy has to some extent facilitated, if not encourage, the formation of its car dependence. Through comparing 43 dedicated transport strategies published for the five largest Australian cities (i.e., Sydney, Melbourne, Brisbane, Perth and Adelaide) between the first one (published in 1965 in Brisbane) and 2010, Bray et al (2011) identified similar evolving trajectories of transport policy across the five cities. The first discernible stage is between 1965 and 1974, wherein transport planning was made and implemented typically based on technical analysis and prediction of transport demand in adherence to the urban master plans. A continuing plunge of public transport mode share and increase of car share were observed across the same time span (Cosgrove, 2011). The second stage (roughly between 1980s and early 1990s) was characterised by a more ‘integrated’ approach, which placed more emphasis on the integration between land-use and transport planning. As a result the drastic changes of public transport and car shares appeared to cease (Cosgrove, 2011).

The last stage (from late 1980s and onwards) was marked by the prevailing notion of travel demand management in hopes of achieving tangible reduction of private car use and promotion of more sustainable urban transport. Notably, car parking levies have been introduced in several cities including Sydney, Melbourne and Perth (Bray et al., 2011). A number of voluntary behavioural change programs have also been initiated in certain selected suburbs of Adelaide, Perth and Brisbane (Freer et al., 2010; Taylor, 2007). With an apparent dedication to reversing the car-dependence of governments, a marginal increase of public transport share and decrease of private car use was achieved in the past five to ten years (Cosgrove, 2011). Nonetheless, considering the path dependence associated with Australia’s suburbia and car-oriented culture, the challenge of promoting public transport (including BRT) in Australian cities remains critical.

Currently, there are four existing BRT systems located in Adelaide, Brisbane, Melbourne and Sydney (Currie and Delbosc, 2010), from which a case study area can be selected to fulfil the research goal of this study. The selection of case study is based on the comparisons of the four Australian cities in terms of urban demographic (e.g., population and density) and transport context (e.g., car ownership, UPT system and usage) as well as the characteristics of existing BRT systems (e.g., infrastructure, service features).

Table 4.1 Selected travel and spatial features for Sydney, Melbourne, Adelaide and Brisbane

	Sydney	Melbourne	Adelaide	Brisbane
Overall population (in Millions)	4.07	3.99	1.20	2.04
Population density (persons/km2)	361.6	454.2	670.6	347.2
Employment density (number/km2)	169.9	218.9	315.7	169.9
Proportion of dwellings with motor vehicle(s) (%)	84.9	88	88	89.5
Major UPT modes	Bus & rail	Bus & rail	Bus & rail	Bus & rail
UPT modal share of all kilometres travelled (in %)	13.3	8.4	5.7	9.0
UPT modal share of all motorised commute trips (in %)	22.7	14.8	10.6	14.7

First, a comparison (Table 4.1) indicates that the four cities are generally comparable in terms of urban demographic and transport context (ABS, 2012; Cosgrove, 2011; BITRE, 2009). All four cities are state capitals with population size over one million. The population and employment densities of Sydney, Melbourne and Brisbane are at a similar level, whilst higher densities are observed in Adelaide. The vehicle ownership of the four cities is at a similar level as well (all above 85% except Sydney's indicator just below this level—84.9%). Furthermore, bus and railway serve as the backbone component of the UPT systems of the four cities, accounting for over 90% of all UPT trips made across the four cities (BITRE, 2009).

Comparing the UPT modal share in the four cities (i.e., by proportion of all kilometres travelled and by proportion of all motorised commute trips) (Cosgrove, 2011; BITRE, 2009), shows that Adelaide's, Brisbane's and Melbourne's figures fall below the national average levels (10.5% and 16.7% respectively) (Cosgrove, 2011; BITRE, 2009). In contrast, Sydney has higher UPT shares (13.3% and 22.7%). Thus, in comparison to Sydney, there is a more pressing need to prompt UPT use against car dependency within the other three cities.

Next, the BRT systems of the four cities are compared in terms of infrastructure and service features as another key consideration underpinning case study selection. The aim is to ensure that the selected area has a well-implemented BRT system that can be considered as a viable alternative to private cars. A scrutiny of existing literature (Levinson et al., 2003b; Levinson et al., 2003a; Currie, 2006; Currie and Delbosc, 2010; Hensher and Golob, 2008) illustrates that Melbourne's BRT (Smart Bus Routes) is less comparable to the BRTs of the other three cities, since its BRT only involves the implementation of bus priority signals with the on-street bus service (e.g., at cross-sections) (Table 4.2). By contrast, the other three cities have all implemented exclusive busways as a core component of BRT. Given this, Melbourne's BRT system is excluded from the selection process.

Last, some distinctions can be identified among the remaining BRTs as well. First, the BRT networks in Brisbane and Sydney are relatively more extensive (with total lengths of 49.1 and 31.4 kilometre respectively) compared to Adelaide's BRT network (12 kilometres). However, Sydney's BRT has a mixed design of the busway system, which means that its busway network has some on-street segments instead of providing continuously exclusive right-of-ways. Second, while Brisbane's and Sydney's BRTs employ intelligent transport systems that enable real time information display, Adelaide's BRT only uses guided buses. Third, Brisbane's and Adelaide's BRTs adopt an open design that allows on-street buses' access to the busway, whereas Sydney's BRT is operated as a trunkline service, by which on-street buses cannot access the busway and the BRT vehicles cannot run off the busway. Finally, Brisbane's BRT system involves a considerably larger number of bus services (over 170 bus routes) compared to Sydney (12 routes) and Adelaide (18 routes), suggesting Brisbane's BRT as a more integrated and important component within its UPT network. Based on the above comparisons, it appears that compared to the BRTs in Sydney, Melbourne and Adelaide, Brisbane's BRT is the more fully-fledged one that incorporates most characteristics of a typical BRT (Hoffman, 2008). Hence Brisbane is selected as the case study for this research.

Table 4.2 BRT system features of Sydney, Melbourne, Adelaide and Brisbane

	Sydney	Melbourne	Adelaide	Brisbane
Dedicated busway	X	_	X	X
Integration of intelligent transport system	X	X	_	X
Off vehicle fare collection	X	X	X	X
Service length (kilometres)	31	233	12	26.1
Number of busway stations	49.1	_	3	22
Direct service or trunk-only service	Trunk-only	Direct	Direct	Direct
Number of routes fully or partially operated in busway	12	_	20	187
Peak hour buses/hour (highest level)	55	4	78	259
Peak hour buses/hour (highest level)	25	4	18	48
Peak hour speed (kilometres/hour)	23	_	29	27

4.1.2 Brisbane's BRT system

With Brisbane selected as the case study area, this section continues to provide a bit more background concerning Brisbane's BRT. Before 2000, rail and bus transit constituted the backbone components of Brisbane's public transport network, which attracted similar levels of ridership of around 42 million trips on annual basis (Rathwell and Schijns, 2002). In particular, 4 rail transit lines radiating from the city centre served as the major corridors catering for Brisbane's commuters traveling between the CBD and other locales. Despite a reportedly well usage of the rail transit system, it has been noted that the rail patronage of Brisbane was restrained to the adjacent areas of rail stations, while limitedly coming from a wider catchment (Hoffman, 2008). In the mid-1990s, a bus operator's visit to Ottawa's BRT system, Canada inspired the back-then city mayor's decision to introduce exclusive busway in hopes of capturing the potential catchments that rail transit failed to attract hopefully within a relatively short period of time (Hoffman, 2008).

Based on an inspection of a series of potential corridors, Brisbane's first busway, the South East Busway (SEB) was constructed and opened in 2000. It is fair to say that Brisbane's BRT (or particularly, the SEB) was planned from an infrastructure-oriented rather than service-oriented perspective, that there has not been any articulate predication of ridership to guide service allocation (Hoffman, 2008). The actual impact of the SEB on bus ridership, however, appears to be rewarding: a 26% of increase of ridership along the busway corridor six months after its introduction and another 40% of ridership increase the year after (Hoffman, 2008). Such a rate of ridership increase urged the addition of more bus services to the busway, which also reinforced government's dedication to further expand BRT system. As such, an additional two sections of busways, the Northern Busway (NB) and the Eastern Busway (EB) were subsequently constructed. Along with the SEB, the three busway sections constitute the major infrastructure component of Brisbane's BRT network (Figure 4.1) (Department of Transport and Main Roads, 2013). The expansion of three busway sections (i.e., the SEB, the NB and the EB) is still on-going at the time of this research. This will result in a further 30 kilometres of busway within the near future.

Figure 4.1 Study context

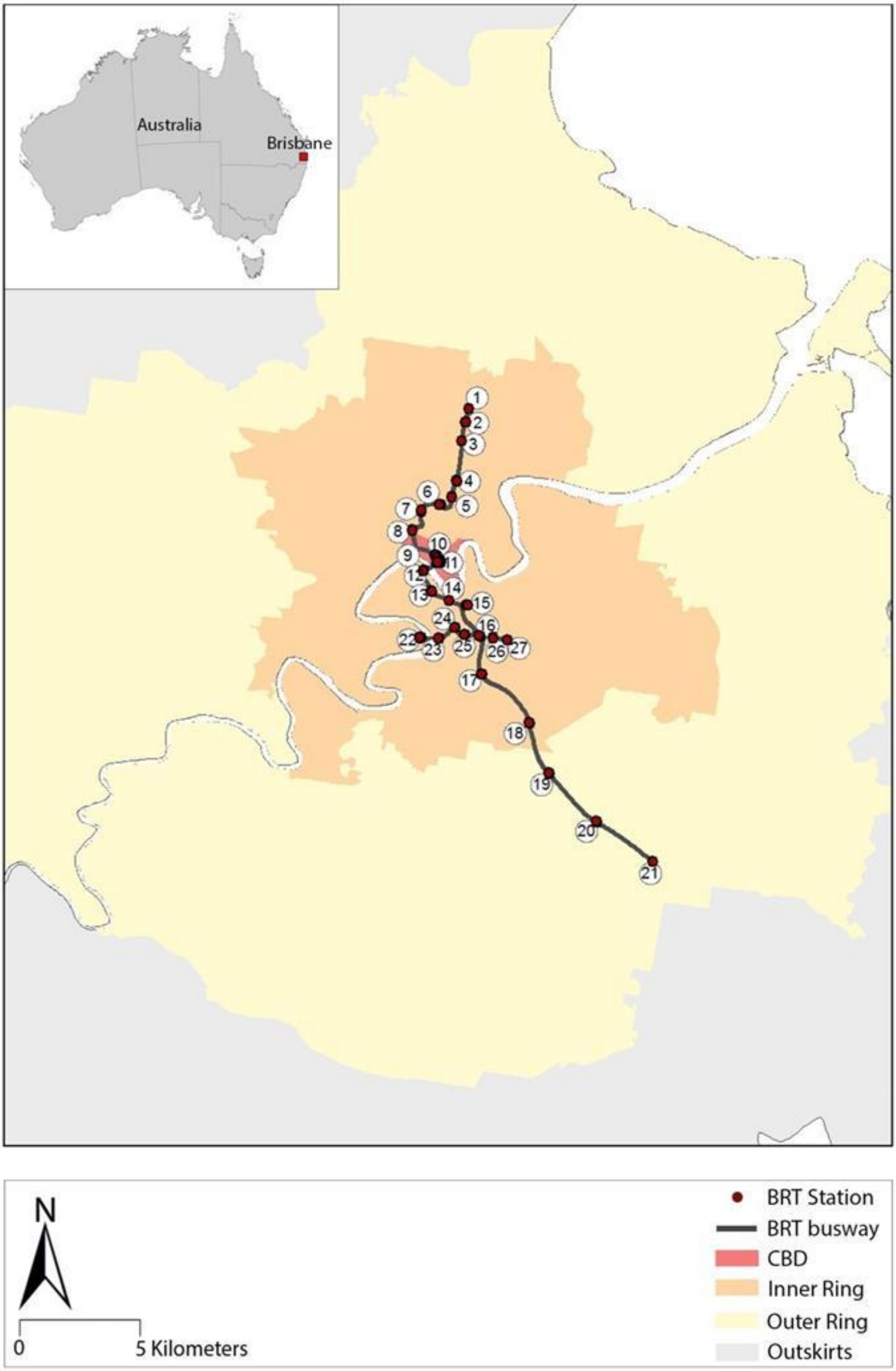


Table 4.3 Brisbane's BRT busway and stations, source: Department of Transport and Main Roads (2013a)

Busway Sections	Length (km)	Open year	No.	Stations	Stop type
Northern Busway (NB)	10.2	2004	1	Kedron Brook	Premium Stop
			2	Lutwyche	Premium Stop
			3	Truro Street	Intermediate Stop
			4	Federation Street	Intermediate Stop
			5	RBWH	Premium Stop
			6	RCH Herston	Premium Stop
			7	Kelvin Grove	Premium Stop
			8	Normanby	Premium Stop
			9	Roma Street	Premium Stop
			10	King George Square	Premium Stop
			11	Queen Street	Premium Stop
South East Busway (SEB)	16.5	2000	12	Cultural Centre	Premium Stop
			13	South Bank	Premium Stop
			14	Mater Hill	Premium Stop
			15	Wolloongabba	Premium Stop
			16	Buranda	Premium Stop
			17	Greenslopes	Premium Stop
			18	Holland Park West	Premium Stop
			19	Griffith University	Premium Stop
			20	Upper Mount Gravatt	Premium Stop
			21	Eight Mile Plains	Premium Stop
Eastern Busway (EB)	3.7	2009	22	UQ Lakes	Premium Stop
			23	Dutton Park	Intermediate Stop
			24	Boggo Road	Premium Stop
			25	PA Hospital	Premium Stop
			26	Stones Corner	Premium Stop
			27	Langlands Park	Premium Stop
Total	31.4				

A major difference between Brisbane’s BRT and its prototype—Ottawa’s BRT pertains to the integration between land-use and public transport. Compared to Ottawa’s stronger coordination between land-use (e.g., denser development) and BRT planning on a city level, Brisbane’s land-use development showed little response to its BRT possibly due to lack of both political and civilian support (Hoffman, 2008; Rathwell and Schijns, 2002). Given this, instead of attracting population and development to its surroundings to stimulate transit-oriented development, Brisbane’s BRT mainly functions as an enhanced transit service that reaches out to the suburbs around the city. Considering this, there emerges a compelling reason to urge the transformation of Brisbane’s BRT from an initially infrastructure-oriented project to a more service-based system that may better capture the travel needs of Brisbane’s population. The premise of achieving this goal then is to understand its usage pattern over space and time.

Table 4.3 summarises the open year and types of BRT stations for the busway sections. A total of 27 bus stops exclusively serve the busway network, among which 24 are Premium Stops and three are Intermediate Stops. According to the Public Transport Infrastructure Manual by Translink (Brisbane’ transit agency) (Translink, 2012), the Premium Stops are characterised with high passenger demand and highest standard of construction in terms of supporting components (e.g., shelter, seats), whilst the Intermediate Stops are associated with moderate levels of passenger demand and are more limited in terms of shelter and amenities. The stop-spacing of the BRT ranges from 670 metres to 1,650 metres; and real-time information systems are applied to all BRT stations (Currie and Delbosc, 2010). The fares of Brisbane’s BRT are not charged and managed separately from the rest of the bus network, which adopts a zone-based fare structure (Translink, 2015a). The base fare for an adult passenger is 3.35 Australian dollars when travelling during peak hours and 2.68 dollars during non-peak hours.

An open deign of the busway is adopted that enables on-road buses to freely enter and exit and therefore, capture the travel needs of a wide catchment areas (in particular the south and north suburbs) across Brisbane (Tao et al., 2014). With over 170 bus routes partially or fully operated on the busway network, Brisbane’s BRT involves about two thirds of all bus trips made across the city on both weekday and weekends (Tao et al., 2014). It has been reported that buses running on the busway can reach an average speed of over 50 kilometres per hour (Currie, 2006). During peak hours, the service frequency on the busway can reach a level of 259 buses per hour, coupled with 48 buses per hour off peak (Currie and Delbosc, 2010). A search of bus timetables shows that most of the bus services running on the busway are operated between 5:30am to midnight (Translink, 2015b). These service characteristics consequently yield a patronage of 70 million passenger-trips on an annual basis (Currie, 2006; Currie and Delbosc, 2010). The above figures surpass the performance of most BRT systems in Asia and North America (Hensher and Golob, 2008).

While the infrastructure and service characteristics of Brisbane’s BRT have received some attention, a search of literature indicates that the evidence concerning its financial performance in terms of costs and revenues has been limited. A previous evaluation of Brisbane's BRT reported a benefit-cost ratio of 0.35 for the SEB, and lower than 1 ratios for the NB and EB (Bitzios et al., 2009). These finding with doubt casted questions on the economic viability of Brisbane's BRT. It however has been also argued that other aspects such as improvement of road space use, environmental benefits and travel time savings should be included to provide more definitive evidence (Bitzios et al., 2009).

4.2 Data source selection and overall workflow

Having introduced the context for this study, it is now necessary to identify the suitable data sources for the research objectives and embedded questions proposed, which are summarised below:

Objective 1: to examine the changes of modal share patterns for work trips and socio-demographic characteristics of BRT catchments.

(1) To what extent do the modal share patterns of BRT catchment areas change before and after BRT implementation?

(2) What are the relationships between travel patterns and socio-demographic characteristics for BRT's catchment areas?

Objective 2: to investigate the spatial-temporal dynamics of BRT usage of passengers.

(1) To what extent do the trip characteristics of BRT trips differ from the non-BRT trips across the UPT network?

(2) How and to what extent do the spatial-temporal dynamics of BRT trips differ from non-BRT trips across the UPT network?

(3) Within the BRT system (i.e., the BRT busway and related bus routes), is there notable spatial heterogeneity of passengers' trips across the UPT network?

Objective 3: to model loyalty and behavioural change intentions of BRT passengers.

(1) How do BRT passengers' loyalty and behavioural change intentions vary across socio-demographic and behavioural characteristics?

(2) How do service experience, pro-environmental responsibility and considerations of private car use influence BRT passengers' loyalty and behavioural

change intentions?

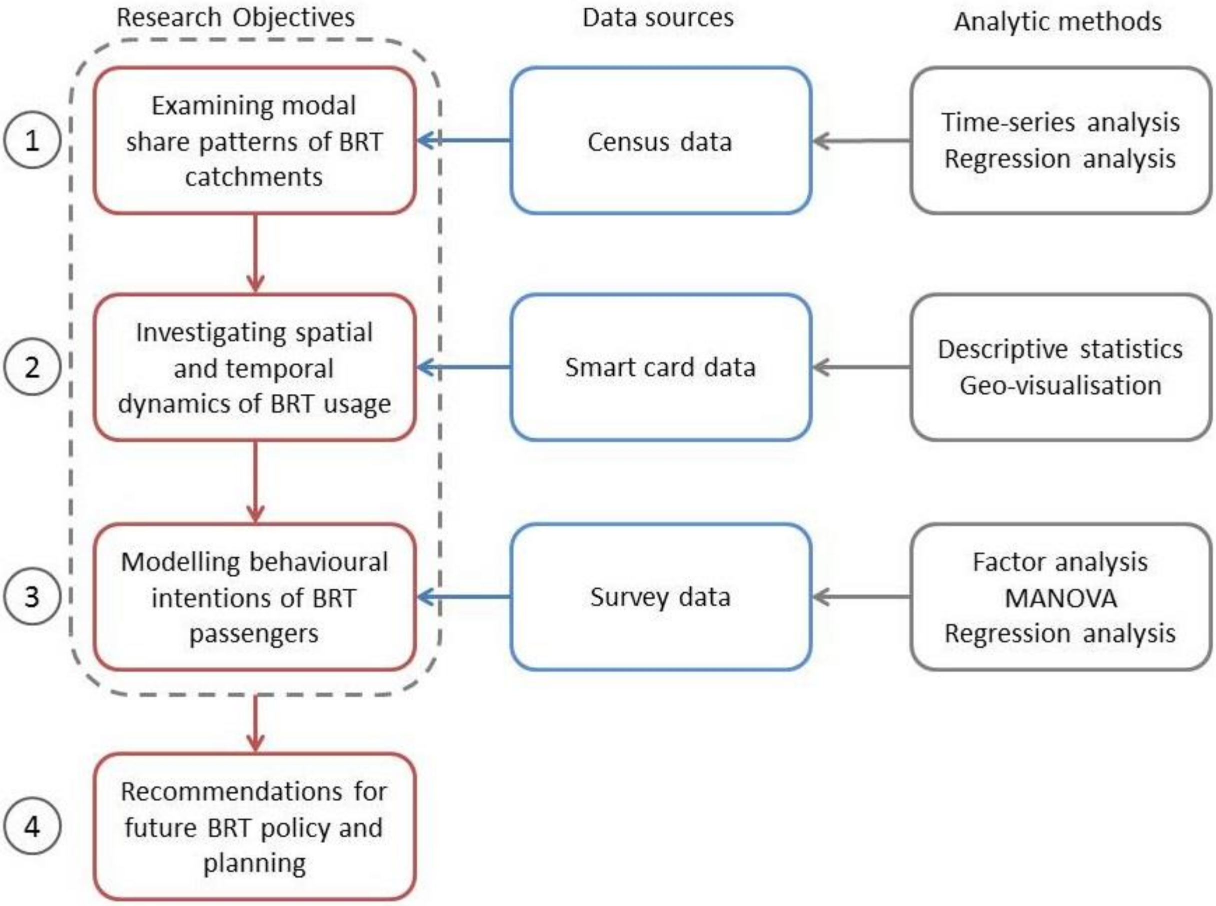
And *Objective 4: to draw on the results of Objectives 1, 2 and 3 to develop recommendations for future BRT policy and planning.*

As discussed in Chapter 2, smart card data has been highlighted as a relatively novel information source suited for the investigation of the spatial-temporal dynamics of UPT passenger travel behaviour. Hence it is selected as the data source for addressing Objective 2. While a detailed discussion concerning the strength and weakness of different travel behaviour data has been provided in Chapter 2 (Section 2.2.3) as well, the suitable data source for Objectives 1 and 3 has not been assigned so far. Based upon the discussion in Chapter 2, this issue is addressed below.

For Objective 1, census data of Australian Bureau of Statistics (ABS) appears to be the appropriate data source due to its two strengths as noted previously. First, census data contains comprehensive socio-demographic (United Nations, 2008) and modal share information for work-based trips of a population (Mees et al., 2008; Senior, 2009) of a country and the embedded regions (such as a city). Second, census data is commonly collected and released at a regular time interval (e.g., five years) in order to assist the ongoing administration of governments (United Nations, 2008). Given these characteristics, census data is suited for the time-series analysis of the modal share patterns and associated socio-demographic characteristics of BRT catchments. A limitation of the census data is that it lacks information for trips other than work-based trips. This however is to a degree considered justifiable given that commuting trips are of primary interest to governments and transport practitioners because of the traffic burdens generated during peak hours (Mees et al., 2008; Senior, 2009). Hence census data is drawn upon as the major data source for addressing Objective 1.

For Objective 3, travel survey data appears to be the preferred data source. While in Chapter 2 it has been argued that travel survey data is less effective in providing spatial and temporal information about travel behaviour, it allows direct interaction with participants (e.g., through face-to-face interview, or self-administrated questionnaire) and therefore offers an effective means to collect travellers' detailed attitudinal information related to transport modes (Stopher and Meyburg, 1979). By comparison, such information is usually not recorded by census or smart card data. Hence, survey data is selected as the main data source for addressing Objective 3.

Figure 4.2 Overall workflow



Through identifying the suited data source for the three objectives, an overall workflow chart can be established for guiding the empirical investigations of this study (Figure 4.2). Based on this flow chart, the following three sections (4.3 to 4.5) discuss the research strategies for each of the three research objectives targeting the different behavioural dimensions (Objectives 1-3) that entail data collection, preparation and analytic methods.

4.3 Research strategy for Objective 1

4.3.1 Compilation of Census data

The census data in Australia is readily purchasable from the Australian Bureau of Statistics (ABS). Given the research goal of Objective 1, the compilation of the census data involves the consideration of three major issues, namely, the year of census, data to be extracted and comparability of the data.

First, considering that Brisbane's BRT has been operated since the year 2000, census data before and after 2000 is apparently needed. A search of census years shows that census data of 1996, 2001, 2006 and 2011 are accessible and suitable to meet this cross-lagged consideration. For the second issue, in order to fulfil the examination of modal share patterns, for each census, the method for travel to work (MTW) data that stores the modal shares of various transport modes (e.g., private car, public transport and walk) for work trips are extracted. In addition, socio-demographic variables are also needed to model the relationships between modal share patterns and socio-demographic characteristics, which are available on the ABS website.

Compared to the first two issues, the third issue is the most challenging one due to the changes in the geographic unit systems between each of the censuses. Specifically, there have been some minor changes on the smallest census unit (i.e., Collection District or CD) boundaries between 1996, 2001 and 2006 censuses. For the 2011 census, there was a major shift from CD to Statistical Area 1 (SA1) as the smallest census unit. Such changes largely hinder the comparability between raw census data of different census years. To overcome this issue, census data need to be concorded to the same spatial units to enable the comparability between different censuses. Given the major shift in the 2011 census, its concordance with 1996, 2001 and 2006 census data (at the smallest spatial unit) is not possible. Therefore, concorded MTW data by place of enumeration of 1996, 2001 and 2006 on 2006 CD boundaries was purchased from the ABS. This constitutes the basis for the time-series analysis for the modal share patterns of BRT catchments of the study context.

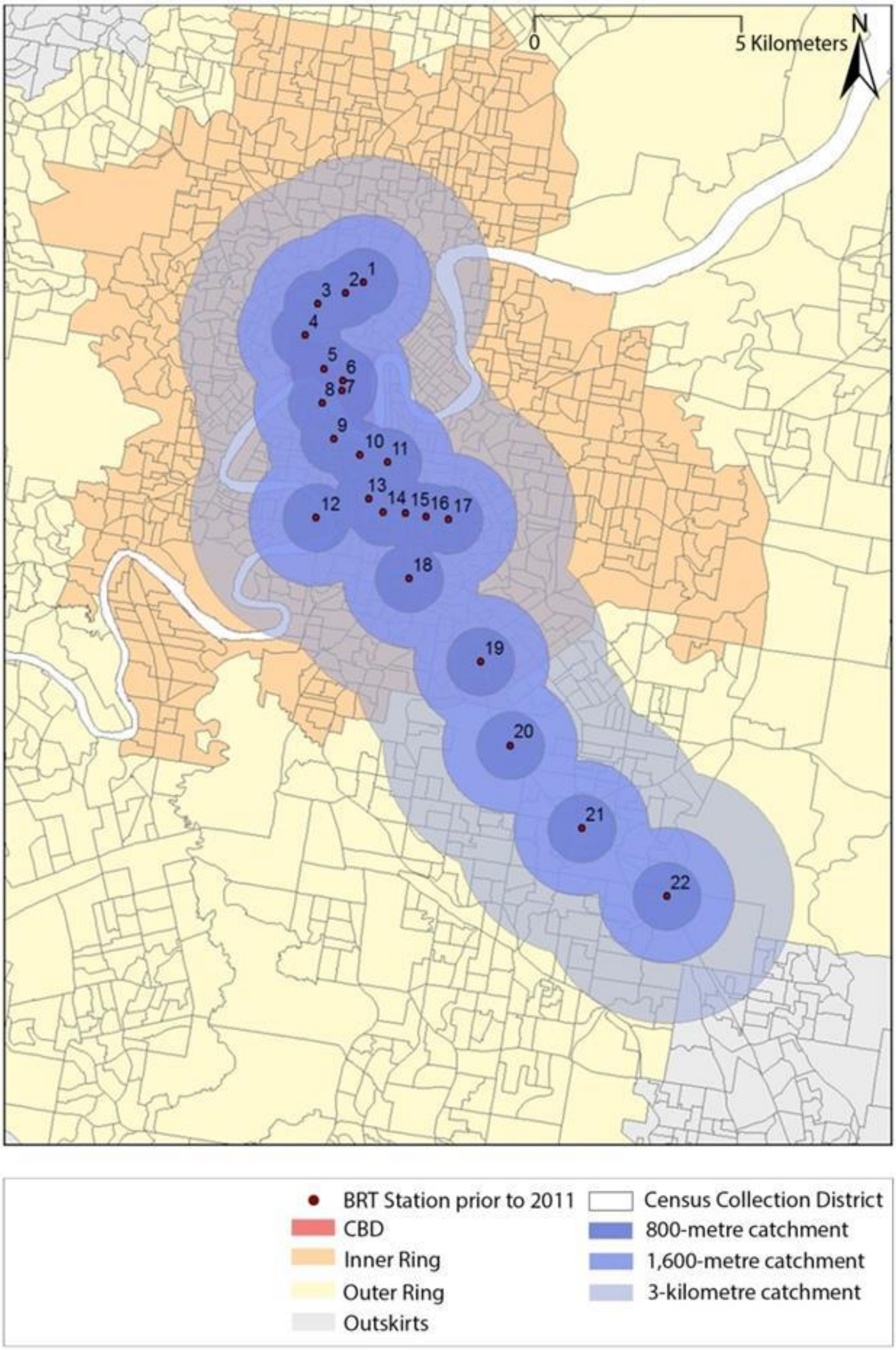
The 2011 census data was drawn separately from the Table Builder of the ABS as the basis for investigating the relationship between modal share patterns and socio-demographic characteristics of BRT catchments. Through reviewing previous literature examining public transport use and socio-demographic characteristics (Boarnet and Crane, 2001; Kitamura et al., 1997; Stead, 2001; Bagley and Mokhtarian, 2002), 20 variables were further extracted to reflect the key socio-demographic dimensions of commuters at the SA1 level (i.e., gender, age, income, education, household composition, education, motor vehicle ownership and population density), which is detailed in Chapter 5.

4.3.2 Defining BRT catchments

To assist the examination of modal share patterns of BRT catchments, three levels of catchment areas based on the access distance to the BRT stations are applied, i.e., 800-metre, 1,600-metre and 3-kilometre distance radiating from the BRT stations opened before year 2011 (Figure 4.3).

Common to many transport studies, an 800-metre radial distance from an identified UPT station is considered as the primary catchment area for a UPT service. The logic behind this is that for most people an 800-metre distance is the walkable distance to a transit station (Stringham, 1982; Guerra et al., 2012). Empirical evidence has been found to support this notion, that a large proportion of UPT passengers walk to their transit stations within 800-metre (Stringham, 1982; O'Sullivan and Morrall, 1996; Cervero, 2007), however it is noted that there have been some exceptions to this distance (Zhao et al., 2003). Given this, in addition to the 800-metre catchment, two additional distances (i.e., 1,600-metre and 3-kilometre) were also adopted here to investigate the change of travel patterns for work trips under the impacts of BRT (Figure 4.3). The 1,600-metre distance represents the maximum walking distance to transit service following previous studies, e.g., Zhao et al (2003), while the 3-kilometre distance is found to be a limit for drive-in/bus-in distance to a transit service (Norley, 2010). By comparing the travel patterns on these three bands, it is expected that a clearer picture of the impacts of BRT on travel behaviour of its catchments can be obtained.

Figure 4.3 Catchments of BRT stations prior to 2011



4.3.3 Analytical methods for census data

For Objective 1, the reported modal share patterns are mainly concentrated on the mode shares of train, bus, car (car driver, car passengers and total), walk and bicycle for work trips. Given that the mode shares of other methods including ferry, taxi, motorcycle and mixed methods were low individually at both CD and city-wide levels, they were added together as the ‘other’ group. Total number of people who made work trips excludes people who did not go to work, worked at home, or did not state their travel methods.

Two sets of analysis were carried out: (1) time-series analysis of modal share patterns for work trips before and after BRT implementation; and (2) regression analysis of socio-demographic characteristics and modal share patterns. For the first task, the MTW data of 1996, 2001 and 2006 are aggregated to calculate and compare the modal shares for the BRT catchments. Three catchment areas, i.e., 800-metre, 1,600-metre and 3-kilometre areas, are adopted to distinguish the changes in modal share patterns at different BRT catchments. Next, stepwise regression is applied to the 2011 census data at the SA1 level to model the relationship between modal shares (mainly focusing on the modal shares by bus and private cars) and socio-demographic characteristics. The detailed results are provided in Chapter 5.

4.4 Research strategy for Objective 2

4.4.1 Data extraction

Six months of smart card data (covering UPT trips in Brisbane from 1st October, 2012 to 30th April, 2013) was acquired from Translink, Brisbane’s transit agency. Instead of using the records of all UPT trips (i.e., bus, railway and ferry trips), only bus trip records are drawn upon for the following two reasons: (1) Brisbane’s BRT busway primarily serves as an integrated component of the bus transit network, with most of its patronage coming from the rest of the bus service (Currie, 2006; Currie and Delbosc, 2010); (2) the route information for train and ferry trips are not recorded in the current smart card data, which renders the inspection of travel trajectories and path use of these UPT services infeasible. The key information stored in the smart card data included the name of operator, route ID, date, direction (i.e., inbound trips moving towards the CBD or outbound trips moving away from the CBD), boarding and alighting stop and time, and smart card ID. A screenshot of the smart card data sample is provided in Appendix 1.

The six months of smart card data is a massive database, accounting for a total of 20 gigabytes (GB) of smart card records. Hence it is necessary to extract a smaller while sufficient dataset to fulfil the research tasks of Objective 2. For the investigation of travel characteristics and spatial-temporal dynamics of BRT usage, five days of smart card data in April was extracted due to the following three reasons.

First, previous studies have shown that people's travel demands for UPT services vary under different calendar events (e.g., a workday, a weekend, a public holiday), e.g., Schlich et al (2004), Lockwood et al (2005). In order to capture such variety of passengers' travel demands, BRT usage across different calendar events should be investigated. As such, drawing on the public calendar of Queensland (DETA, 2013), five days of smart card data in April was extracted, including a workday, a school holiday, a Saturday, a Sunday and a public holiday. Second, compared to the other months of the smart card data, April is a mild month with no extreme weathers such as high temperature (e.g., over 35°C), or rainstorm (Bureau of Meteorology, 2013). As such, using the data in April excludes the impacts of extreme weather conditions on travel behaviour. Third, in the application of a newly developed geo-visualisation-based method (detailed in Section 4.4.4), the smart card data needs to be processed in combination with another dataset that records the UPT service patterns of Brisbane (i.e., the General Transit Specification Feed or the GTFS data, detailed in Section 4.4.2) to reconstruct travel trajectories, given that such information is not provided in the smart card data. However, the available GTFS data was created at a later time (July, 2013) compared to the smart card data provided. Considering this elapsed time difference between the GTFS and smart card data, in order to retain as many smart card records as possible in the data pre-processing of the developed geo-visualisation-based method, it is more appropriate to use the latest month (i.e., April) of the smart card data. Table 4.4 summarises the date, corresponding calendar event, temperature, rainfall, number of records of the extracted smart card data.

Table 4.4 Summary of five days of smart card data

Date	Calendar event	Temperature		Rainfall (mm)	Number of records
		Min (°C)	Max (°C)		
4th, April, 2013	School holiday (Semester break)	17.6	26.8	2.4	209,205
16th, April, 2013	Workday	17.3	29.2	0	276,580
20th, April, 2013	Saturday	14.0	25.5	0	113,559
21st, April, 2013	Sunday	12.0	26.2	0	74,201
25th, April, 2013	Public holiday (ANZAC day)	16.0	28.6	0	68,015

Last, previous studies have suggested that to fully capture the regularity or habitual patterns of travel behaviour (e.g., use frequency over continuous days), at least a two-week dataset should be collected as a sufficient basis (Schlich and Axhausen, 2003; Susilo and Kitamura, 2005). Considering this, for the investigation of the use frequency related to BRT, four weeks of smart card data in March (from 1st to 28th March) was extracted and drawn upon. The smart card data of April is not applied for this research task, given that the first two weeks of April was school holidays within the study context, and therefore may considerably downplay the regular travel demand related to school-based commuting trips.

4.4.2 General Transit Feed Specification (GTFS)

In addition to the smart card data, General Transit Feed Specification (GTFS) is also drawn upon for fulfilling Objective 2. This is due to the fact that smart card data does not store the actual geographic (e.g., coordinates of boarding and alighting stops) as well as complete service information of the bus network in Brisbane (e.g., the stops served by a bus route). Hence, smart card data itself cannot offer adequate information for the visualisation of the mobility patterns of BRT passengers (in particular the travel trajectories that specify the actual paths taken by passengers) in space and time.

GTFS data is an open data format that specifies a series of files (e.g., shape, stop, route, trip files) in comma-delimited values, each of which contains detailed geographic information concerning one aspect of a transit service. For instance, a stop file details the name, ID and geographic coordinates of all UPT stops. Since 2006, GTFS data have been widely incorporated in the Google Maps applications to visualise public transport information (Google Developers, 2012). Researchers have previously applied smart card data in combination with GTFS data to investigate UPT passenger travel behaviour, e.g., Nassir et al (2011). In this study, GTFS data for the SEQ region were obtained from the Queensland Government (2013).

4.4.3 Conditional plotting and flow-mapping

As highlighted in Chapter 2, geo-visualisation has been increasingly applied to reveal the spatial-temporal patterns embedded within big data, due to its strong capacity of handling data redundancy and graphically displaying quantitative information (Andrienko and Andrienko, 2008; Andrienko and Andrienko, 2011; Kwan, 2000; Kwan and Lee, 2004). In this study, two geo-visual analytic techniques are applied to investigate the spatial-temporal dynamics of the stop-level behaviours and passenger flow patterns related to BRT, i.e., conditional plotting and conditional flow-mapping (or flow-comap).

Previous studies (Barry et al., 2002; Chu and Chapleau, 2010; Jang, 2010; Nassir et al.,

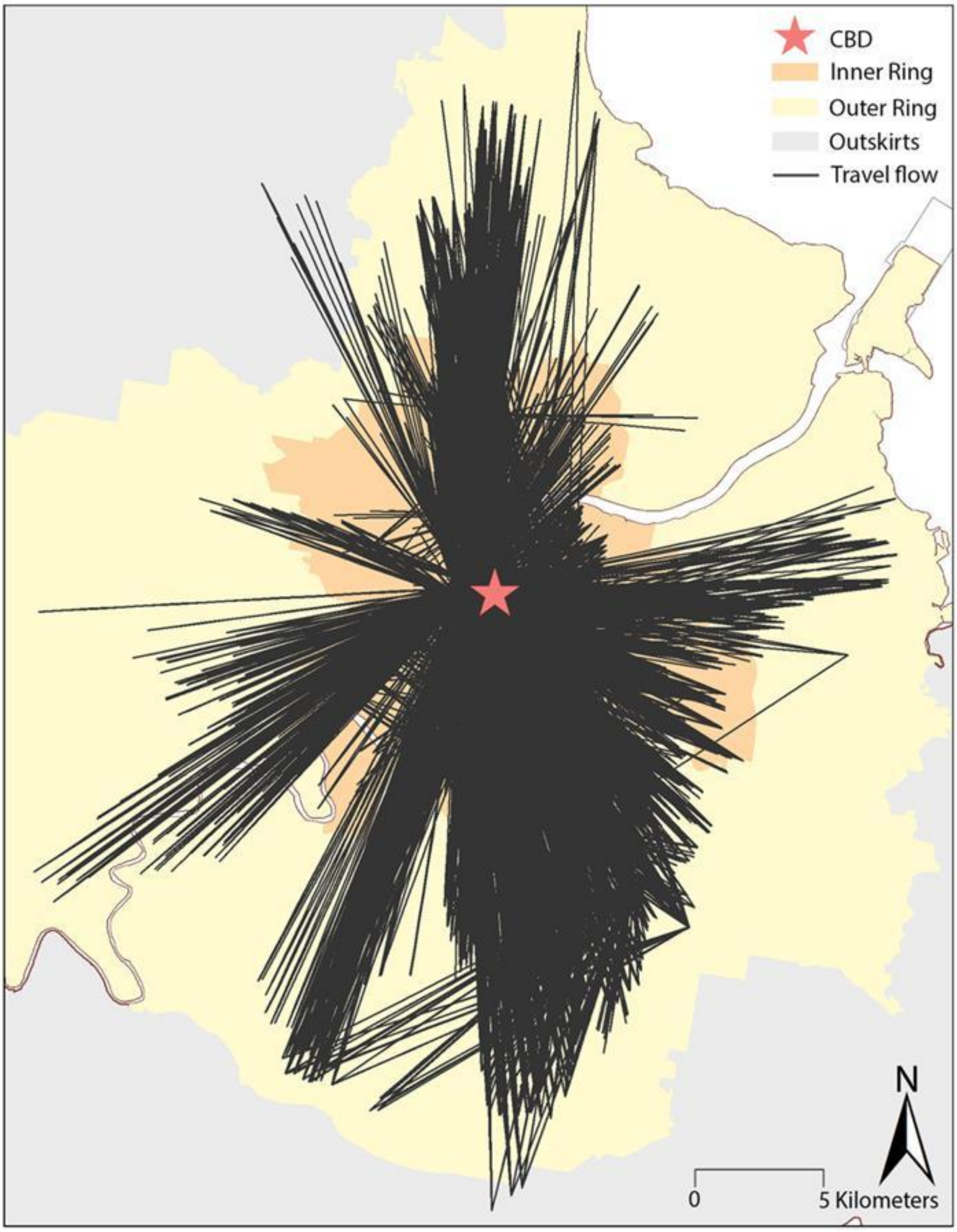
2011) indicated that the understanding of the spatial-temporal dynamics of stop-level behaviours of UPT passengers (i.e., boarding, alighting and transfer behaviours) using smart card data requires the aggregation of passengers' travel behaviours (e.g., boarding, alighting, transfer) based on the associated locations (e.g., the transit stops where passengers board, alight or transfer) at different time periods (e.g., morning versus noon). Such analysis is 'situation-oriented space-centred', which is effective for revealing the spatial positions of all moving entities at different time stamps (e.g., morning, evening periods) (Andrienko and Andrienko, 2008; 2010). Considering this, conditional plotting (or comap) (Brunsdon, 2001) is identified as the suitable analytic technique for investigating the stop-level behaviours of BRT usage in this study. The underpinning concept of this method is to classify the raw information of a geo-dataset into subsets based on the multivariable information contained (e.g., different dates, weather conditions). The subsets of data are then mapped out separately to reveal the potentially different patterns under differing conditions within the same spatial context.

In terms of passenger flow patterns, in accordance with the studies investigating travel behaviour using GPS data (Asakura and Hato, 2004; Guo et al., 2010), it is desirable to obtain such patterns from smart card data that capture the travel trajectories (i.e., a continuous line connecting a series of spatial points as movement stamps) of passengers across a UPT network, so that the actual paths taken by the passengers between trip origins and destinations can be observed. Capturing such path-use of moving entities at different time stamps is a 'trajectory-oriented space-centred' approach (Andrienko and Andrienko, 2010). However, there has been limited investigation of passenger flow patterns in the existing travel behaviour studies applying smart card data (Tao et al., 2014a). Hence there have not been techniques readily available for addressing this behavioural aspect of BRT usage. Given this, a visual analytic technique—conditional flow-mapping (or flow-comap)—is developed in this study to investigate the passenger flow patterns related to BRT usage.

The flow-comap is essentially a technique that combines the strength of conditional plotting and flow-mapping in order to capture the spatial-temporal patterns of passenger flows across a UPT network. Besides conditional plotting, flow-mapping is another widely applied technique for visualising spatial patterns of movements, (see for example, Tobler (1987), Thompson and Lavin (1996), Andrienko and Andrienko (2008)). In the utilisation of flow-mapping, the movements of people or vehicles are depicted as straight lines that connect origins with destinations, with direction of movement flows represented by arrows and flow volume captured by adjusting the width of line. As such, flow maps can provide an interpretable visual representation of spatial movement patterns. Integrating flow-mapping with the conditional plot therefore renders conditional flow-map (or flow-comap), which has the potential to capture the temporal change of flow patterns of UPT passengers.

Figure 4.4 provides an example of visualising the raw smart card records, where only the origin-destination information was known and a straight line was drawn between these points. Clearly, very little might be gleaned from such a representation which failed to account for the actual path taken by UPT passengers. In order to better capture the passenger flow patterns, additional steps are needed to reconstruct travel trajectories from smart card data as the input for creating flow-comaps, which are detailed in the next section. It is noted that this proposed method also constitutes a major methodological contribution of this study, and has been translated into a published manuscript, i.e., Tao et al (2014a).

Figure 4.4 A sample of visualising unprocessed smart card data



4.4.4 Data processing for geo-visualising smart card data

In order to compute conditional plots and flow-comaps to achieve the research goal of Objective 2, three components of data processing were conceptualised and carried out, including extracting bus service patterns, reconstructing travel trajectories and finally constructing flow matrices, each of which are explained as follows.

Extracting bus service patterns

First, GTFS data was processed to extract the service patterns, specifically, the sequence of bus stops for all bus routes across the Brisbane network. This provided the basis for reconstructing bus passengers travel trajectories such that the intermediate locations (i.e. the bus stops that are passed through) and time stamps (i.e. the times at which the passenger passed through each of the stops) between the boarding and alighting stops can be identified and added to each smart card record. This process contains the following three steps.

(1) Brisbane's bus service patterns were first extracted from a 'stop-times' file embedded within the GTFS data, in which the times each bus route arrives at and departs from the individual stops on daily basis are detailed (Google Developers, 2012). However, the resulting service patterns might not be sufficient for reconstructing travel trajectories of bus trips, due to the fact that this method does not identify the passed through stops for all the bus routes, particularly express lines that do not serve certain intermediate stops.

(2) To address the aforementioned issue, next, drawing on two GTFS files (i.e., stop file and shape files of bus routes), a distance of 20 metres was applied to spatially join stops with routes by using GIS-based techniques, given that 99.8% of stops were within this distance to their nearest routes. This procedure generated a list of bus stops that were geographically proximate and were assumed to be passed by a given bus route. To avoid the potential error of missing certain stops, this list (or the spatial-based routes) was examined against the stop-sequence patterns extracted from the stop-times file of GTFS (or stop-times-based routes).

(3) Finally, it was found that 119 inbound and 108 outbound routes had missing stops. A further examination of the spatial layout of these routes showed that six inbound and four outbound routes considerably deviated from the stop-times-based routes and therefore were excluded from the analysis (Table 4.5). This also resulted

in the removal of a rather small proportion (less than two per cent) of the original smart card records (summarised in table 4.6) for the five days, which is considered an acceptable level of inclusion of the original data.

Table 4.5 Summary of problematic routes

Route	Number of missing stops
Inbound	
204	6
320	4
321	3
338	3
397	2
690	8
Outbound	
303	16
338	4
353	9
416	2
S799	3

Table 4.6 Summary of removed records

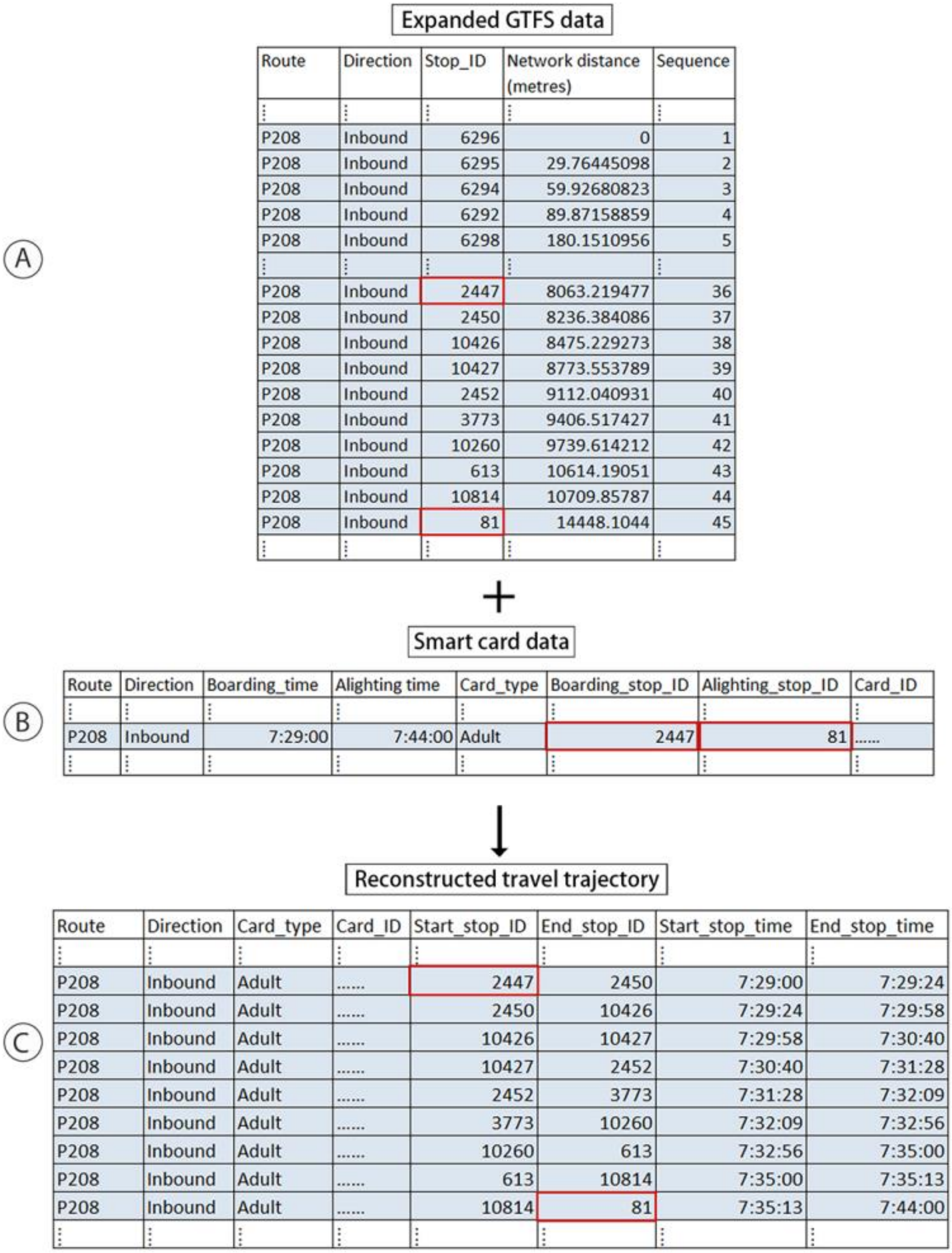
Date	Number of removed records	Proportion of total records (%)
April 4	2,956	1.4
April 16	3,501	1.2
April 20	1,165	1
April 21	843	1.1
April 25	646	0.9

Reconstructing travel trajectories

The process of reconstructing travel trajectories is depicted in Figure 4.5. Using the expanded GTFS data (Figure 4.5A) as the baseline, the passed-through stops for each passenger trip recorded by smart card data (Figure 4.5B) were identified and added. This was achieved by finding matching information in terms of route, direction, boarding and alighting stops between smart card data and the expanded GTFS data (Figure 4.5A). This step broke each of the original passenger trip records into a number of continuous stop-to-stop legs (or mini-trips), of which each added stop was denoted as the end point for one leg and the start point for the next one (Figure 4.5C).

Through adding the intermediate stops between boarding and alighting stops, integrating the intermediate time stamps across all mini-trips also became feasible. This was achieved by two simple steps: first, the network distance for each mini-trip was calculated; second, drawing on the time differences between boarding and alighting times of a single trip, the travel time for each mini-trip was estimated proportionally to the ratio of network distance to the total trip distance. Based on the estimated travel times for the mini-trips, the time stamps for passing through the intermediate stops were added. Through the addition of both passed-though stops and intermediate time stamps, the travel trajectories of bus passengers were reconstructed at the bus stop level. After this process, over five million mini-trips were attained. Due to some minor non-concurrences between the GTFS data and smart card data, not all bus trips were successfully reconstructed as mini-trips. This issue is examined in detail as part of the results in Chapter 6.

Figure 4.5 Data processing for smart card data, souce: Tao et al (2014a)



Ⓐ

Expanded GTFS data

Route	Direction	Stop_ID	Network distance (metres)	Sequence
⋮	⋮	⋮	⋮	⋮
P208	Inbound	6296	0	1
P208	Inbound	6295	29.76445098	2
P208	Inbound	6294	59.92680823	3
P208	Inbound	6292	89.87158859	4
P208	Inbound	6298	180.1510956	5
⋮	⋮	⋮	⋮	⋮
P208	Inbound	2447	8063.219477	36
P208	Inbound	2450	8236.384086	37
P208	Inbound	10426	8475.229273	38
P208	Inbound	10427	8773.553789	39
P208	Inbound	2452	9112.040931	40
P208	Inbound	3773	9406.517427	41
P208	Inbound	10260	9739.614212	42
P208	Inbound	613	10614.19051	43
P208	Inbound	10814	10709.85787	44
P208	Inbound	81	14448.1044	45
⋮	⋮	⋮	⋮	⋮

+

Smart card data

Ⓑ

Route	Direction	Boarding_time	Alighting time	Card_type	Boarding_stop_ID	Alighting_stop_ID	Card_ID
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
P208	Inbound	7:29:00	7:44:00	Adult	2447	81	......
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Reconstructed travel trajectory

Ⓒ

Route	Direction	Card_type	Card_ID	Start_stop_ID	End_stop_ID	Start_stop_time	End_stop_time
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
P208	Inbound	Adult	......	2447	2450	7:29:00	7:29:24
P208	Inbound	Adult	......	2450	10426	7:29:24	7:29:58
P208	Inbound	Adult	......	10426	10427	7:29:58	7:30:40
P208	Inbound	Adult	......	10427	2452	7:30:40	7:31:28
P208	Inbound	Adult	......	2452	3773	7:31:28	7:32:09
P208	Inbound	Adult	......	3773	10260	7:32:09	7:32:56
P208	Inbound	Adult	......	10260	613	7:32:56	7:35:00
P208	Inbound	Adult	......	613	10814	7:35:00	7:35:13
P208	Inbound	Adult	......	10814	81	7:35:13	7:44:00
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Constructing flow matrices

The reconstructed travel trajectories of bus passengers of the five calendar events were classified into two groups, i.e., BRT trips and non-BRT trips. The ‘trips’ here refer to linked trips that consider transfers between smart card records, which can be identified based on the ‘Trip-ID’ entry in the smart card data, i.e., linked records were given consecutive Trip-IDs, e.g., 1, 2, 3. Based on this definition, as long as a part of a bus trip operated on the BRT busway, it was considered a BRT trip; otherwise, it was classified as a non-BRT trip. This enabled the detection of spatial connections between the BRT busway and the remainder of the bus network in terms of travel demand (e.g., the trips feed into the busway from the rest of the bus network).

Following the identification of BRT and non-BRT trips, ten subsets of smart card data were attained (i.e., BRT, non-BRT trips for each of the five calendar events). Flow matrices that depicted the flow volumes between all the bus stops were then constructed for each of the ten subsets. Each of the flow matrices was further disaggregated into two directional series based on the ‘Direction’ entry of smart card data (i.e., inbound series reflecting flows moving towards the CBD, and outbound series reflecting flows moving away from the CBD). To capture the temporal change of travel patterns, each series was segmented into four sub-matrices that were on continuous time periods of the day (i.e., morning, noon, evening and night). This rendered a total of 80 flow matrices (i.e., 16 matrices for each day).

Drawing on the flow matrices constructed comaps of stop-level behaviours and flow-comaps of passenger flow patterns were generated using GIS. The detailed results are presented and discussed in Chapter 6.

4.5 Research strategy for Objective 3

4.5.1 Purposive sampling design

For Objective 3, a purposive sampling design is applied to collect primary data due to the following two reasons. First, due to lack of a sampling frame for the target population (i.e., a comprehensive list of BRT passengers), it is impossible to conduct a probability sampling approach. Second, there are over 170 bus routes which are partially or fully operated on the busway which covers an extremely extensive area and an enormous number of stations (Currie, 2006). As such, it is infeasible to survey the whole BRT service area. Given this, it is more appropriate to conduct a purposive sampling plan at the BRT stations. Purposive sampling design permits the researcher to approach a diverse range of sample without sampling the total target population (Dillman et al., 2008). This has been applied widely in UPT passenger travel behaviour studies (Stopher and Meyburg, 1979; Foote et al., 2001; Jen et al., 2011).

The purposive sampling plan of this study first involves selecting certain BRT stations as the survey venues. In order to approach a diverse range of passengers with different socio-demographic characteristics and travel patterns, a number of considerations are taken into account including land-use patterns (including major public facility) and ridership (number of boarding and alighting), coupled with the population-weighted score of Index of Relative Socio-economic Advantage and Disadvantage (IRSAD) of 2011. It is assumed that by doing so, serious bias can be avoided in the resulting sample.

Table 4.7 Selection of survey venues

Group	Stations	Land use patterns	Major Public Facilities	Ave. daily Boarding Number	Ave. daily Alighting Number	Population weighted IRSAD
1	Queen Street	Commercial	Queen Street Mall	10598	5882	1068.35
	King George Square	Commercial	Officeworks Brisbane CBD, Brisbane Town Hall, Museum of Brisbane	7310	6855	1076.41
	Cultural Centre	Commercial	Queensland Museum, Queensland Cultural Centre, South Bank Railway Station	5460	6024	1054.24
	Roma Street	Commercial	Roma Street Railway Station	4591	4142	1063.92
2	UQ Lakes	Education,	UQ	3752	3622	1034.13
	Griffith University	Education, Parkland	GU	2863	2596	1066.27
	Kelvin Grove	Education, Parkland	QUT	1930	1966	1033.48
3	Mater Hill	Hospital/Medical, Commercial	Mater Private Clinic, Hoca @ Mater, Mater Children's Hospital, Mater Adult Hospital	2868	2625	1045.03
	RBWH	Hospital/Medical, Commercial	Royal Brisbane and Women's Hospital, Children's Health Foundation	1816	2157	1040.79
	Greenslopes	Hospital/Medical, Residential, Parkland	Greenslopes Private Hospital	650	556	1044.25
	PA Hospital	Hospital/Medical, Residential, Industrial	PA Hospital	598	520	1025.23
	RCH Herston	Hospital/Medical, Parkland	Royal Children's Hospital	549	496	1024.31
4	Upper Mt Gravatt	Residential, Commercial	Westfield Garden City Shopping Centre	4786	4555	1021.64
	South Bank	Residential, Education	Southbank Institute of Technology	3221	2772	1039.6
	Buranda	Residential	Buranda Railway Station	1877	1698	1016.47
	Eight Mile Plains	Residential,	-	1628	1454	1050.05

		Commercial, Agricultural				
	Woolloongabba	Residential, Commercial	-	1604	1351	1044.51
	Holland Park West	Residential, Education	Holland Park State High School	935	753	1087.82
	Boggo Road	Residential, Parkland	-	838	753	1028.7
	Langlands Park	Residential, Parkland, Industrial	-	454	320	1046.32
	Normanby	Residential, Education, Parkland	Brisbane Grammar School	446	386	1050.06
	Stones Corner	Residential, Commercial, Parkland	-	216	56	1019.97
	Lutwyche	Residential	-	589	536	1056.61
	Kedron Brook	Residential	-	419	350	1057.52

🟥 Selected stations

In the selection process, three Intermediate Stops (i.e., Truro Street, Federation Street and Dutton Park—refer to Table 4.3) are not considered, given that these stops were designed with lower standards in terms of stop shelter and amenities and have catered for considerably lower passenger demand compared to the remaining 24 Premium Stops (Translink, 2012). As illustrated in Table 4.7, among these 24 Premium Stops, nine BRT stations (i.e., RBWH, King George Square, Cultural Centre, Mater Hill, UQ Lakes, Buranda, Langlands Park, Holland Park West, and Upper Mount Gravatt) are selected as the survey venues according to the following two steps.

First, four groups of stations with distinguishable land use patterns can be identified (refer to Table 4.7). Group 1 includes four stations located within or near the CBD areas, surrounded by commercial land use, i.e., Roma Street, King George Square, Queen Street and Cultural Centre. Group 2 has three stations that are serving for the major universities in Brisbane, including Kelvin Grove, UQ Lakes and Griffith University. Group 3 has five stations, which are located near the major hospital and medical institutes, including RBWH, RCH Herston, Mater Hill, Greenslopes and PA Hospitals. Last, Group 4 includes 12 stations that are serving for residential areas as well as the local centres such as TAFE, secondary schools and shopping centres, including Upper Mount Gravatt, South Bank, Buranda, Eight Mile Plains, Woolloongabba, Holland Park West, Boggo Road, Langlands Park, Normanby, Stones Corner, Lutwyche and Kedron Brook.

Next, based on the grouping of stations, a subset of stations is purposively and proportionally selected from each group to capture the varying ridership levels and IRSAD scores across the BRT busway network. From Group 1, King George Square and Cultural Centre are selected with high ridership (number of passengers boarding over 5,000 per day). From Group 2, UQ Lakes is selected, characterised with relatively high ridership (3,752 passengers boarding per day). From Group 3, RBWH and Mater Hill are selected to represent medium level ridership (on a daily basis, 1,816 and 2,868 passengers boarding respectively). From Group 4, Upper Mount Gravatt is selected to reflect high ridership stations in this group (4,786 passengers boarding per day); Buranda with the medium level ridership (1,877 passengers boarding per day); and Holland Park West and Normanby with low ridership (935 passengers and 454 passengers boarding per day respectively). In terms of population-weighted IRSAD scores, the selected stations cover a wide range from relatively high score (e.g., Holland Park West with population-weighted IRSAD score = 1087.82) to relatively low score (e.g., Buranda with population-weighted IRSAD score = 1016.47). Furthermore, the selected stations are also covering the spatial extent of the BRT network to capture passengers from different directions.

4.5.2 Target population and sample size

The target population is the BRT passengers in Brisbane, i.e., whoever rides the busway service during the time of survey. The desired sample size in this study is estimated by a sample size calculator that uses finite population correction factor (Israel, 1992) in the estimation process (Raosoft, 2004). This can be described as two steps:

$$n_0 = \frac{z^2 * p * (1 - p)}{e^2}$$

and

$$n = \frac{\mathrm{N} * n_0}{n_0 + (N - 1)}$$

Where:

n_0 represents the sample size calculated without considering finite population correction factor;

n represents the desired sample size;

e represents the acceptable margin of error (set at 5%);

t represents the desired confidence level (set at 95%);

p represents the response distribution of questions of interests (set at 0.5);

and N represents the population size.

Passenger count data of 2012 (i.e., the number of passengers boarding and alighting at the BRT stations) was acquired from Translink to calculate the required sample size (it is noted that by the time of this survey, smart card data was as yet inaccessible and not used for estimating sample size). For all BRT stations, the annual number of passengers boarding and alighting is calculated, which is pegged at 39,534,280. This number is then divided by 366 days to generate the average daily number of passengers boarding and alighting as an approximation of the total population of passengers riding the BRT service, which is pegged at 108,017. The sample error and confidence level are set at 5% and 95% respectively, given these standards are commonly considered statistically acceptable for a sample (Sarantakos, 2005; Stopher and Meyburg, 1979). Based on these standards, a sample size of 384 is estimated to be acceptable for this study. Considering the likelihood of missing data in the survey process, the aimed sample size is eventually set at 450.

4.5.3 Questionnaire design and pilot test

In order to fulfil the research tasks of Objective 3 (detailed in Chapter 3), the questionnaire should be able to collect information concerning the socio-demographic, (past) behavioural characteristics and attitudinal dimensions related to the behaviour intentions of BRT passengers. Given this, the questionnaire is designed to comprise two sections of questions: the first relates to the socio-demographic and behavioural characteristics, and the second concentrated on the attitudinal dimensions of BRT passengers.

The design of the first section draws on previous literature (Bagley and Mokhtarian, 2002; Boarnet and Crane, 2001; Kitamura et al., 1997; Stead, 2001) and a public transport survey of South East Queensland (TransLink, 2010). A series of socio-demographic characteristics is included and summarised in Table 4.8. In terms of the behavioural characteristics, eight items are included. The first three items seek to measure the past use of BRT, which to some extent reflects the habit of BRT passengers. The remaining four items are aimed to capture BRT passengers' access to the BRT service (i.e., the access distance and mode), as they may also relate to passengers' experience and attitudes of using BRT (Norley, 2010; Zhao et al., 2003).

Table 4.8 Socio-demographic and behavioural characteristics

Socio-demographic characteristics
Gender
Age
Level of education
Employment status
Marital status
Possession of a valid driver licence
Access to a private car
Weekly household income
Behavioural characteristics
Years of using BRT
Weekday use frequency of BRT
Weekend use frequency of BRT
Name of usual BRT station used
Access method to BRT station(s)
Main trip purpose on the survey day
Postcode of usual residence
Street name of usual residence

For the second section of the questionnaire, as discussed in Chapter 3, the attitudinal dimensions to be measured encompass three behaviour intentions (loyalty and two behavioural change intentions), service experience of BRT (satisfaction, perceived service quality and perceived value), personal norm concerning mode choice behaviour and considerations of private car use (car attitude, personal norm and social norm over private car use). The measurement of each attitudinal dimension is led by an overarching question that seeks to help the participants understand the aims of the more specific items (refer to Table 4.9).

In measuring the attitudinal variables, 44 items were developed based on the review of the existing literature (see Appendix 3 for the items). The items for measuring BRT passengers' loyalty (Items 33-34) and behavioural change intentions (Items 54-60) have drawn upon studies by Lai and Chen (2011), Bamberg et al (2007), Gardner and Abraham (2010). The measurement of perceived service experience (Items 17-32) draw upon Jen and Hu (2003), Jen et al (2011), Wen et al (2005). The items targeting BRT passengers' car attitudes (Items 43-50), social norm (Items 39-42) and perceived behavioural control (PBC) over private car use (Items 51-53), have referred to Steg (2005), Bamberg et al (2007) and Gardner and Abraham (2010). Finally, the measurement of personal norm (Items 35-38) has recourse to

Heath and Gifford (2002) and Bamberg et al (2007).

Table 4.9 Questionnaire design

Conceptualised dimensions	The overarching question (s)	No. of items	Referred studies
Loyalty (LO)	How committed are you to the busway service?	2	Lai and Chen (2011), Gardner and Abraham (2010), Bamberg et al (2007)
Intention to shift to private car use (IS)	In the near future, do you intend to use a private car instead of the busway service for more of your regular trips (such as travelling to or from work/study/shopping) in Brisbane?	4	
Intention to increase BRT use (II)	In the near future, do you intend to increase your use of the busway service for your regular trips (such as travelling to or from work/study/shopping) in Brisbane?	3	
Perceived service experience	How satisfied are you with the busway service? What do you think about the busway service? How valuable is the busway service to you?	16	Wen et al (2005), Jen and Hu (2003), Jen et al (2011)
Attitudes towards private car use (CA)	What do you think about private cars?	8	Steg (2005), Gardner and Abraham (2010), Bamberg et al (2007)
Social norm over private car use (SN)	Are your family and friends supportive of you in using a private car for regular trips (such as travelling to or from work/study/shopping) in Brisbane?	4	
Perceived control over private car use (PBC)	Is it easy for you to use a private car in Brisbane?	3	
Personal norm (PN)	Do environmental concerns encourage you to use the busway service?	4	Heath and Gifford (2002), Bamberg et al (2007)
Total		44	

In a number of previous studies (including the ones aforementioned), Likert scale, such as discrete points from 1-5 or 1-7, has been widely applied to measure UPT passengers' attitudes. Usually, the two extremes (e.g., one and five) of a measurement scale represent opposite opinions (e.g., strongly disagree versus strongly disagree) regarding the question being asked (e.g., I'm satisfied with the bus service). Additionally, in comparison to a 5-point scale, a 7-point scale was found to better capture the variability of responses, whilst fewer significant differences were found for higher scales, e.g., between a 7-point scale and a 9-point scale (Yüksel and Rimmington, 1998). Therefore, a 7-point Likert scale is applied for measuring participants' response to the attitudinal items in the questionnaires, with one being 'strongly disagree' and seven representing 'strongly agree'.

In addition to the design of questions, attention has been paid to other related issues, in particular the layout and length of questionnaire, as they may critically influence participants' response rate and quality as well. The design of layout sought to render a clear and logical organisation of questions, so that participants can easily follow the flow of questions. The issue of questionnaire length is also of concern, since overly lengthy questionnaires can incur fatigue of participants and potentially reduce response rate (Denscombe, 2007). Considering this only the questions of central interest to this study are included in the questionnaire.

After finalising the questionnaire design, a pilot test of the questionnaire was carried out during March, 2013. The aim is to assess the clarity of the questionnaire in terms of questions being asked and the format, as well as the length of questionnaire. In the pilot test, questionnaires were first dispatched purposively to 12 individuals within the School of Geography, Planning and Environmental Management, the University of Queensland, including four students, five professional staff and three lecturers. They were asked to fill in the questionnaire and at the same time, make detailed notes on the questions that were difficult to answers and reasons, as well as the completion time.

The major issues reported from the first round of the pilot test included the ambiguous wording of certain attitudinal items, as well as some socio-demographic and travel behaviour questions. The reported completion times of the questionnaire ranged from less than 10 minutes to 12 minutes, which was considered acceptable by the 12 persons. Based on the comments, the questionnaire has been revised and sent to two social scientists for a second round of review. After this, some final minor changes in terms of the wording of some questions were made before the formal survey.

4.5.4 Survey plan

Considering the commonly low response rate for questionnaire surveys (usually below 20%), it is expected to have a response rate between 14-16%, specifically 450 responses from handing out 2,700 copies of questionnaires. The author and one volunteer (or two volunteers at stations with higher level ridership, i.e., King George Square, Cultural Centre, Upper Mount Gravatt and UQ Lakes) handed out questionnaires coupled with postage-paid envelopes to passengers waiting at the platforms of each selected stations, meanwhile the passengers' verbal consent to participate in the survey was sought.

The formal survey (Table 4.10) for each station was scheduled and carried out based on the examination of average boarding and alighting patterns (calculated as average amounts of passengers boarding and alighting over the year 2012) across different time periods on weekdays and weekends (as shown in Tables 4.11 and 4.12 and discussed below). The numbers of questionnaires distributed were first estimated according to the ridership (number of boarding and alighting) at each station (the estimated number columns in Table 4.10). In practice, questionnaires were distributed based on the estimated number (the actual number columns in Table 4.10).

In terms of weekday boarding and alighting patterns (Table 4.11), three groups of stations can be identified. First group includes King George Square, Mater Hill, UQ Lakes, Cultural Centre and RBWH stations. For these stations, the boarding peak concentrates in the afternoon, while the alighting peak concentrates in the morning, suggesting them as commuting destinations. The second group of stations includes Upper Mount Gravatt, Holland Park West, and Langlands Park stations. These stations have boarding peaks in the morning and alighting peaks in the afternoon, suggesting them as commuting origins. The only remaining station, Buranda, has similar numbers of passengers boarding and alighting during morning and afternoon peaks.

Table 4.10 Survey plan

Station	Weekday	Est. No.	Actual No.	Weekend	Est. No.	Actual No.
Week 1 (15 April-21 April)						
RBWH	Friday (13:30-16:30)	134	200	Saturday (15:30-17:00)	30	30
Buranda				Saturday (13:20-15:00)	28	30
Week 2 (22 April-28 April)						
Mater Hill	Tuesday (13:30-16:30)	178	180	Saturday (13:20-15:00)	56	73
Buranda	Wednesday (7:30-10:30)	121	187			
King George Square				Saturday (15:30-17:00)	184	160
Week 3 (29 April-5 May)						
King George Square	Wednesday (13:30-16:30)	441	480			
Upper Mount Gravatt	Thursday (7:30-10:30)	294	300	Saturday (13:20-15:00)	114	130
Holland Park West				Saturday (11:30-13:00)	15	11
Week 4 (6 May-12 May)						
Cultural Centre	Wednesday (13:30-16:30)	339	380			
Holland Park West	Thursday (7:30-10:30)	56	100			
Week 5 (13 May-19 May)						
UQ Lakes	Tuesday (13:30-16:30)	264	300			
Langlands Park	Thursday (7:30-10:30)	25	60			
Week 6 (20 May-26 May)						
UQ Lakes				Saturday (13:00-14:30)	27	22
Langlands Park				Saturday (16:20-17:30)	8	8
Cultural Centre				Saturday (14:30-16:10)	186	165

Table 4.11 Weekday boarding and alighting patterns

Stations	Ridership	Morning 7:00-9:00	Noon 9:00-15:00	Afternoon 15:00-18:00	Evening 18:00-00:00
King George Square	Passengers boarding/h	331	369	1198	420
	Passengers alighting/h	1293	489	537	126
Cultural Centre	Passengers boarding/h	563	315	607	214
	Passengers alighting/h	899	399	506	171
Upper Mount Gravatt	Passengers boarding/h	759	342	499	106
	Passengers alighting/h	531	255	663	179
UQ Lakes	Passengers boarding/h	77	298	839	146
	Passengers alighting/h	893	459	164	17
Mater Hill	Passengers boarding/h	234	195	466	97
	Passengers alighting/h	522	196	203	58
Buranda	Passengers boarding/h	435	91	238	45
	Passengers alighting/h	361	77	238	46
Holland Park West	Passengers boarding/h	293	49	68	9
	Passengers alighting/h	33	28	169	42
RBWH	Passengers boarding/h	126	120	358	61
	Passengers alighting/h	551	148	129	71
Langlands Park	Passengers boarding/h	157	22	19	5
	Passengers alighting/h	11	10	68	21

In terms of weekend boarding and alighting patterns, three groups of stations can be identified as well (Table 4.12). The first group includes King George Square, Cultural Centre and UQ Lakes. These stations have alighting peaks in the morning and boarding peaks in the afternoon. The second group includes Buranda, Mater Hill, RBWH and Upper Mount Gravatt. The alighting patterns at these stations are relatively flat throughout the day, while their boarding peaks are in the afternoon. The last group includes Langlands Park and Holland Park West. These two stations have boarding peaks around noon and early afternoon and alighting peaks in the afternoon.

Table 4.12 Weekend boarding and alighting patterns

Stations	Ridership	Morning 7:00-9:00	Noon 9:00-15:00	Afternoon 15:00-18:00	Evening 18:00-00:00
King George Square	Passengers boarding/h	64	209	404	174
	Passengers alighting/h	174	306	236	102
Cultural Centre	Passengers boarding/h	130	210	323	167
	Passengers alighting/h	184	302	252	132
Upper Mount Gravatt	Passengers boarding/h	92	196	230	62
	Passengers alighting/h	81	151	178	65
UQ Lakes	Passengers boarding/h	6	40	74	11
	Passengers alighting/h	23	57	35	3
Mater Hill	Passengers boarding/h	45	83	101	47
	Passengers alighting/h	51	76	84	34
Buranda	Passengers boarding/h	36	46	44	16
	Passengers alighting/h	27	33	42	17
Holland Park West	Passengers boarding/h	18	28	19	9
	Passengers alighting/h	3	13	28	12
RBWH	Passengers boarding/h	22	47	53	24
	Passengers alighting/h	26	46	39	15
Langlands Park	Passengers boarding/h	12	17	11	6
	Passengers alighting/h	2	7	14	7

4.5.5 Data entry

550 questionnaires were returned by 31st, December, 2013. The overall response rate was 19.53% (550/2816). Table 4.13 presents the response rate for each of the survey stations. The response rates of the weekend survey at UQ Lakes and Langlands Park stations are relatively low, which can probably be attributed to the small number of patronage and consequently of questionnaires distributed. Overall, the response rates at different BRT stations across different dates are considered within an acceptable range (between 10-30%).

Table 4.13 Response rate

	Weekday		Weekend	
	Number	Response rate (%)	Number	Response rate (%)
RBWH	52	26	5	16.667
King George Square	98	20.42	41	25.625
Cultural Centre	73	19.21	17	10.3
Mater Hill	41	22.78	11	15.068
UQ Lakes	38	12.67	2	8.9
Buranda	52	27.807	11	36.667
Langlands Park	8	13.333	1	12.5
Holland Park West	25	25	1	9.091
Upper Mt Gravatt	62	20.67	12	9.23

With a reasonable response rate from the questionnaire survey, the next step is to identify and deal with missing data. Out of 550 returned questionnaires, 417 were completed, while the remaining 133 had varying degrees of missing data. In addition, out of 60 questions, 48 had missing points. Table 4.14 classifies the incomplete questionnaires based on number of missing points. It shows that the majority (85 out of 133) of the incomplete questionnaires had only one missing point, while 26 copies had more than two missing points.

Table 4.14 Number of missing points of questionnaires

Number of missing points	Number of questionnaires
1	85
2	22
3	9
4	7
5	3
7	2
8	1
10	2
12	1
25	1

To further examine the pattern of missing data, Table 4.15 highlights the questions with high numbers of missing points (large than three). The majority of missing points are concentrated within a limited number of questions: street name of usual residence with 77 missing points, followed by weekly household income with 22, postcode of usual residence with 17, the four measurements on social norm for private car use with 10 to 13 missing points. This detected pattern is plausible. First, although the participants have been assured that no personal information will ever be revealed, many might feel insecure about this issue, therefore rendering high numbers of missing points for the questions on street name of usual residence, weekly household income and postcode.

As to attitudinal questions, out of 16 respondents who did not complete the questions about social norm for private car use, nine are without access to a private car (Table 4.15). The possible explanation is that these participants might think questions about car use are irrelevant to them. Last, years of using BRT has nine missing points. This might be due to the fact that these participants cannot recall how long they have been using the BRT service.

An examination of missing data shows that the pattern for missing points is not randomly distributed throughout the sample, but that missing points are concentrated on a given number of questions as discussed above. Given this, it has been suggested that casewise or variable deletion should be the suitable strategy (Hair et al., 2006). To retain as many questionnaires as possible, the information about the street name of usual residence is not considered in the deletion process. Instead, for cases without this information, the residential location of a participant is assumed to be the central point of the postcode zone, if one is provided. For other missing points, casewise deletion is conducted. Furthermore, another problematic item related to the behavioural characteristics (i.e., ‘the name of the usual BRT station used’) has been identified. The aim of this item is to identify the BRT station from which the participants usually take the BRT service and as such to assist the calculation of their access distance to the BRT (coupled with their residence locations). Yet, nearly 40% of participants filled in an unrecognisable stop name (e.g., 100 Inala, Aspley Hypermarket). Hence this variable is removed from the later analysis. The access distance to BRT is estimated by calculating the distance between participants’ usual residential location and the nearest BRT station.

After this data entry process, 469 questionnaires were retained. Last, the questionnaires with reported residential locations outside the Brisbane Statistical Division (BSD) boundary were further removed, rendering a final sample size of 457.

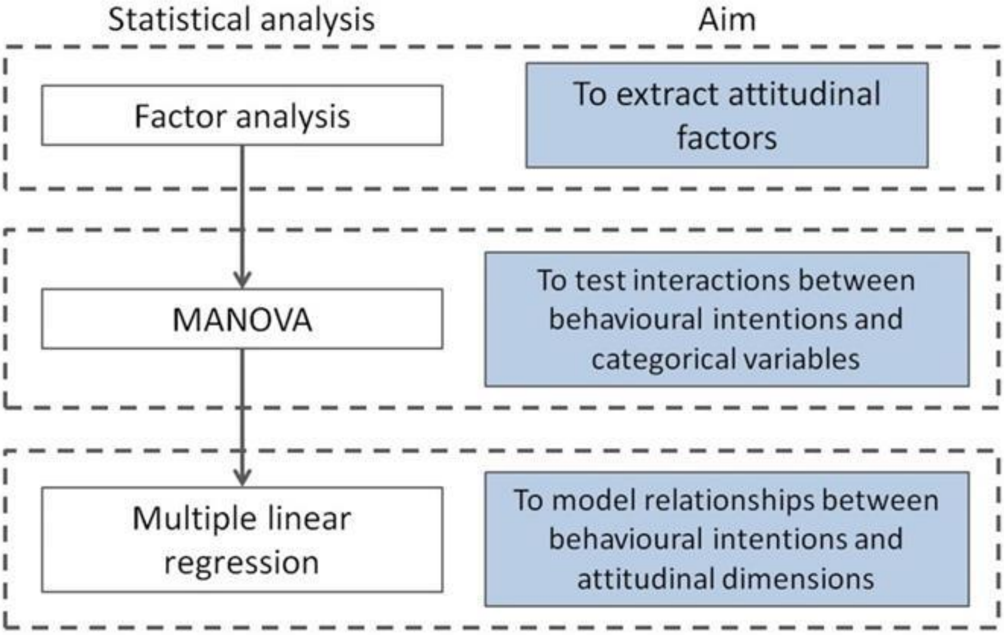
Table 4.15 Number of missing points by questions/items

Questions/items	Number of missing points
Weekly household income	22
Years of using BRT service	9
Postcode of usual residence	17
Street name of usual residence	77
Social norm on private car use	16
Social norm on private car use	16
Social norm on private car use	13
Social norm on private car use	10

4.5.6 Statistical analysis and hypotheses

A series of statistical techniques is applied to the collected primary data in order to fulfil the research tasks of Objective 3. Figure 4.6 depicts the flow charts of the statistical analysis conducted and associated aims.

Figure 4.6 Flow chart for analysing primary survey data



First, factor analysis is conducted to extract the conceptualised attitudinal factors measured in the designed questionnaire. Based on the results of factor analysis, problematic items (with factor loading smaller than 0.5) are eliminated from the analysis; and factor scores are calculated to represent the target (i.e., behavioural intentions) and the related attitudinal dimensions (i.e., evaluations of BRT service, personal norm and considerations of private car use).

Based on the results of factor analysis, Multivariate Analysis of Variance (MANOVA) is conducted to examine the interactions between the three behavioural intentions (i.e., loyalty, intention to shift to private car use and intention to increase BRT use) and socio-demographic and behavioural characteristics of BRT passengers. The aim is to detect whether the level of the behavioural intentions significantly and systematically varies across different socio-demographic and travel behaviour groups.

Finally, multiple linear regression is carried out to model the relationships between the behavioural intentions and the related attitudinal dimensions. Based on the discussion in Chapter 3 (Section 3.2.3), a series of hypotheses (Table 4.16) is proposed and tested in the regression analysis. The aim is to reveal the attitudinal dimensions that significantly influence BRT passengers’ behavioural intentions. The results are reported in Chapter 7.

Table 4.16 Hypotheses

Target variables	Hypothesis	
Loyalty (intention to continue BRT use)	1	BRT passengers' evaluations of service experience (i.e., satisfaction, perceived service quality and perceived value) will have positive effects on their loyalty.
	2	BRT passengers' personal norm will have positive effects on their loyalty.
	3	BRT passengers' considerations of private car use (i.e., car attitude, social norm and PBC over private car use) will have negative effects on their loyalty.
Intention to shift to private car use	4	BRT passengers' evaluations of service experience (i.e., satisfaction, perceived service quality and perceived value) will have negative effects on their intention to shift to private car use.
	5	BRT passengers' personal norm will have negative effects on their intention to shift to private car use.
	6	BRT passengers' considerations of private car use (i.e., car attitude, social norm and PBC over private car use) will have positive effects on their intention to shift to private car use.
Intention to increase BRT use	7	BRT passengers' evaluations of service experience (i.e., satisfaction, perceived service quality and perceived value) will have positive effects on their intention to increase BRT use.
	8	BRT passengers' personal norm will have positive effects on their intention to increase BRT use.
	9	BRT passengers' considerations of private car use (i.e., car attitude, social norm and PBC over private car use) will have negative effects on their intention to increase BRT use.

Chapter 5 Investigating modal use patterns for journey-to-work (JTW) trips using census data

5.1 Introduction

While BRT has attracted increasing popularity in both the Australasian region and the rest of the world, little knowledge exists concerning its impact on travel behaviour over time and as such to what extent BRT implementation helps achieve sustainable transport objectives such as the rebalancing of public transport and private car shares in fulfilling people's daily travel needs. This chapter seeks to fill this gap by analysing census journey to work data for the Brisbane BRT.

Having identified the data source and developed a methodological framework in Section 4.2, this Chapter aims to investigate the modal share patterns for journey-to-work (JTW) trips to reveal the changes of travel behaviour patterns before and after BRT implementation in the study context. Method for Travel to Work (MTW) data of four censuses (1996, 2001, 2006 and 2011) were used as the major data source as discussed in Chapter 4. The following two questions are of particular interest:

To what extent do the modal share patterns of BRT catchment areas change before and after BRT implementation?

What are the relationships between travel patterns and socio-demographic characteristics for BRT's catchment areas?

The first question aims to examine the extent to which urban population's modal share patterns have changed before and after BRT implementation. The second question seeks to model the links between socio-demographic characteristics and modal shares (particularly bus and private car shares for work trips). By addressing these two questions, this chapter fulfils the aim of capturing BRT's effects in shaping travel behaviour within the study context.

The remainder of the chapter is structured as follows. Section 5.2 provides the time-series analysis of modal share patterns before and after BRT implementation. Section 5.3 next reports the results of stepwise regression models to examine the relationships between modal share patterns (particularly bus and private car shares) and socio-demographic characteristics at geographically aggregate level. Finally, section 5.4 summarises the key findings of this chapter and discusses their implications.

5.2 The changes in modal share patterns for JTW trips

The concordance process of census data detailed in Chapter 4 resulted in a small proportion of CDs from 1996 and 2001 censuses without any data, due to the change of CD boundaries. To further validate the basis of comparison, only the CDs with census data for all three censuses were used. CDs within the three catchment areas (refer to Chapter 4) were extracted separately by using ArcGIS. For the 800-metre area, 152 CDs were extracted; 150 CDs extracted at the 1,600-metre area; and 294 CDs extracted at the 3-kilometre area. Mode shares for work trips at each of the catchment areas were calculated from the CD level data.

Table 5.1 summarises the mode share changes at four scales of areas, i.e., the Brisbane Statistical Division (BSD) as the metropolitan level, the 800-metre, 1,600-metre and 3-kilometre catchment areas. Figures 5.1 to 5.4 illustrate the change of travel patterns at the four areas.

Table 5.1 Mode share patterns for work trips before and after BRT implementation, 1996-2006

Year	**1996**		**2001**		**2006**	
Mode	**Number**	**%**	**Number**	**%**	**Number**	**%**
Mode share at BSD level						
Bus	25648	4.7	28353	4.7	39282	5.5
Train	25834	4.8	27217	4.5	33702	4.7
Car, as driver	382507	70.5	425048	70.2	499644	69.6
Car, as passenger	47820	8.8	48530	8.0	52658	7.3
Car (total)	430327	79.2	473578	78.2	552302	76.9
Walk	17212	3.2	18352	3.0	26257	3.7
Bicycle	5675	1.0	6705	1.1	7946	1.1
Other	38686	7.1	51669	8.5	58792	8.1

Overall	543382	100.0	605874	100.0	718281	100.0
Mode share at the 800-metre area						
Bus	2815	11.0	3026	11.0	4552	13.7
Train	662	2.6	785	2.8	921	2.8
Car, as driver	14527	56.6	15182	55.1	17185	51.8
Car, as passenger	2215	8.6	2175	7.9	2089	6.3
Car (total)	16742	65.2	17357	63.0	19274	58.1
Walk	2772	10.8	3328	12.1	4905	14.8
Bicycle	397	1.5	565	2.1	808	2.4
Other	2296	8.9	2471	9.0	2701	8.2
Overall	25684	100.0	27532	100.0	33161	100.0
Mode share at the 1,600-metre area						
Bus	2931	11.0	3219	11.4	4285	13.1
Train	1001	3.8	1088	3.8	1382	4.2
Car, as driver	16599	62.3	16876	59.6	18859	57.7
Car, as passenger	2305	8.7	2175	7.7	2106	6.4
Car (total)	18904	70.9	19051	67.3	20965	64.1
Walk	1491	5.6	1807	6.4	2611	8.0
Bicycle	373	1.4	627	2.2	828	2.5
Other	1948	7.3	2507	8.9	2636	10.3
Overall	26648	100.0	28299	100.0	32707	100.0
Mode share at the 3-kilometre area						
Bus	5586	10.1	5840	10.1	7560	11.7
Train	2604	4.7	3019	5.2	3438	5.3
Car, as driver	35653	64.6	36531	63.0	39836	61.5
Car, as passenger	4657	8.4	4514	7.8	4290	6.6
Car (total)	40310	73.0	41045	70.8	44126	68.1
Walk	2346	4.3	2521	4.4	3354	5.2
Bicycle	862	1.6	1087	1.9	1244	1.9
Other	3484	6.3	4440	7.6	5076	7.8
Overall	55192	100.0	57952	100.0	64798	100.0

Figure 5.1 Mode share for work trips, BSD level

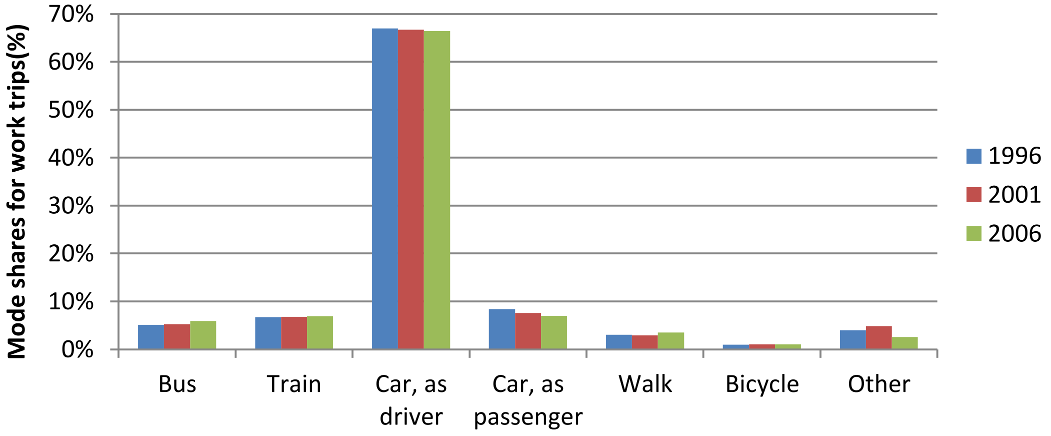


Figure 5.2 Mode share for work trips, 800-metre catchments

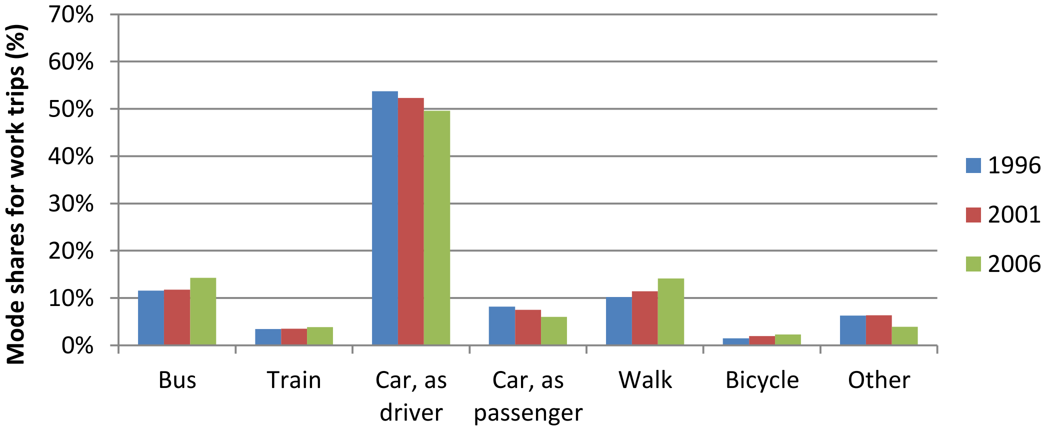


Figure 5.3 Mode share for work trips, the 1,600-metre catchments

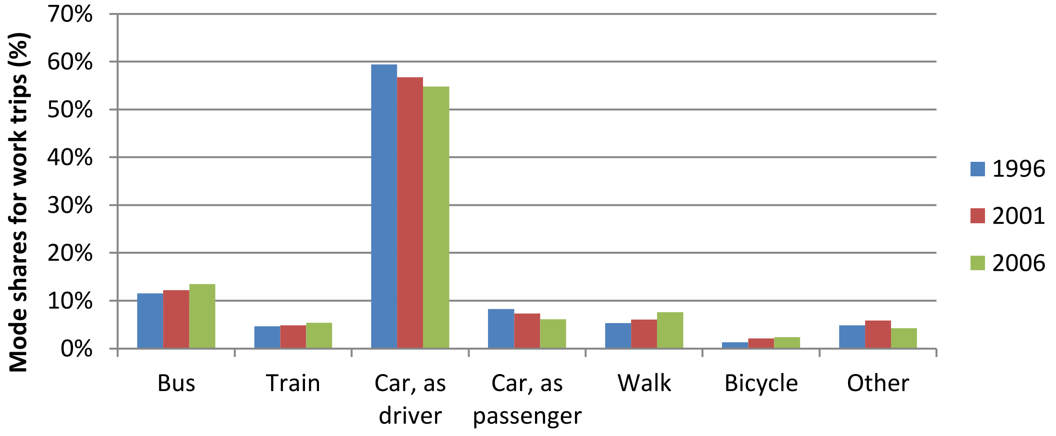
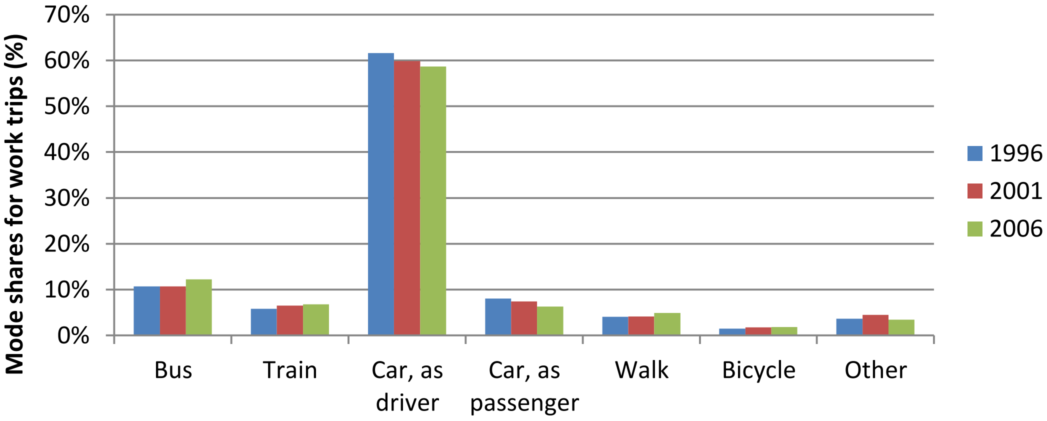


Figure 5.4 Mode share for work trips, 3-kilometre catchments



First of all, the travel pattern at the BSD level was examined as the baseline for the time-series analysis. At this level, 'car' (total) as expected dominated the share for work trips between 1996 and 2006 (79.2% to 76.9%). Small yet significant declines for share of 'car as driver (as passenger)' can be identified over the decade, from 70.5% (8.8%) to 69.6% (7.3%). Two major public transport modes, i.e., 'bus' and 'train', had similar mode shares for work trips. However, whereas train share was maintained at the same level (4.5% to 4.8%), there has been a more pronounced increase of bus share (4.7% to 5.5%). Last, bicycle share was maintained at a low level of around 1%, whereas walk share experienced an increase from 3% to 3.7%. The BSD level pattern identified here complies with the previous studies investigating travel patterns of Australia's major cities, e.g., Cosgrove (2011).

At the three catchment areas of BRT, car was the primary yet declining mode for work trips. However, compared to the BSD level, the car shares ('car as driver or passenger') were significantly lower over the decade. Meanwhile, the bus shares at the three areas (all above 10%) were considerably higher than at the BSD level (around 5%). Moreover, a significant rise of walk share can be observed for the three catchment areas. However, there was no notable enhancement of train share at any level. This might be attributed to a lack of investment in rail transit expansion and improvement in Brisbane (Mees et al., 2008).

Overall, prior to the opening of the BRT system, an environment that encouraged the use of sustainable transport modes already existed at the focused areas. Based on the current data, it appears that the BRT system has reinforced as well as enhanced this trend. Comparing the travel patterns at the three catchment areas further highlighted some localised patterns. Between 1996 and 2001, the bus shares at the 800-metre and 1,600-metre areas were maintained at the same level (around 11%), with a slightly lower bus share (around 10%) at the 3-kilometre area. Between 2001 and 2006, there was a considerable jump of bus share at the 800-metre area from 11% to 13.7%. Significant yet lower growths of bus share at the 1,600-metre and 3-kilometre areas were also achieved, from 11.4% to 13.1% and from 10.1% to 11.7% respectively.

There has been a strongly declining trend for car share at all three catchment areas over the decade. Between 1996 and 2001, the biggest decrease of car share occurred at the 1,600-metre area, from 62.3% (8.7%) to 59.6% (7.7%) for ‘car as driver (as passengers)’, compared to 56.6% (8.6%) to 55.1% (7.9%) at the 800-metre area and 64.6% (8.4%) to 63% (7.8%) at the 3-kilometre area. Between 2001 and 2006, the car shares at the 800-metre area declined to the largest extent, from 55.1% (7.9%) to 51.8% (6.3%) for car as driver (as passenger), significantly higher than the declines in the other two catchment areas, i.e., 59.6% (7.7%) to 57.7% (6.4%) at the 1,600-metre area and 63% (7.8%) to 61.5% (6.6%) at the 3-kilometre area. Last, the share of walking to work also had the biggest increase at the 800-metre area between 2001 and 2006, from 12.1% to 14.8%, compared to 6.4% to 8% at the 1,600-metre area and 4.4% to 5.2% at the 3-kilometre area.

Figure 5.5 (5.5a to 5.5f) visualises the change of bus and car shares (the total of ‘car as driver’ and ‘car as passenger’) at the three catchment areas. In accordance with the findings above, there presents a process of increase and concentration of CDs with higher bus share for work trips (over 15%) along the BRT network between 1996 and 2006. In contrast, a reversing trend can be identified for car share. However, it should be noted that the locales of the BRT stations within the central city, particularly King George Square, Queen Street and Cultural Centre, did not experience pronounced changes in terms of bus and car shares. This might be attributed to the fact that active transport modes such as walking and cycling were the main means for work trips within these areas.

Figure 5.5(a-f) Bus and car shares for work trips within BRT catchments, 1996-2006

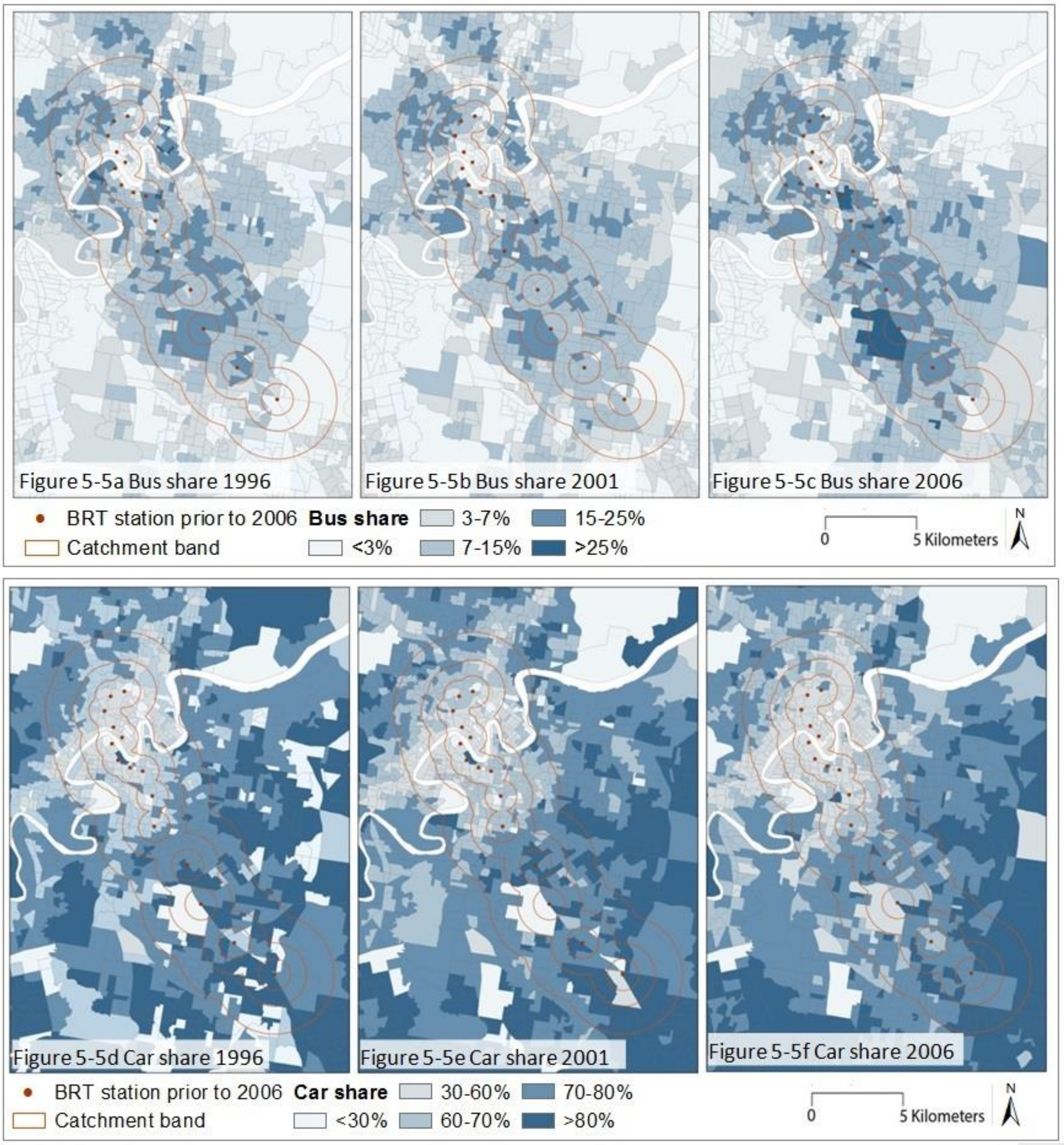


Figure 5-5a Bus share 1996

Figure 5-5b Bus share 2001

Figure 5-5c Bus share 2006

Figure 5-5d Car share 1996

Figure 5-5e Car share 2001

Figure 5-5f Car share 2006

In line with previous studies, e.g., O'Sullivan and Morrall (1996), Cervero (2007), the 800-metre area was revealed to be the primary catchment area under the impacts of BRT, backed up with the highest level of increase in bus share compared to farther catchment areas. Although to a lesser extent, an important increase for bus shares at the 1,600-metre and the 3-kilometre areas over the decade suggests that the implementation of BRT also significantly influenced catchment areas beyond the-800 metre distance. In addition, the declining role of car for work trips suggests that the BRT has importantly incurred the mode shift from car to more sustainable modes of public transport for work trips. Furthermore, considerable growth of walk share for work trips at the three catchment areas is highlighted. Previous studies found that transit-oriented locales such as transit stations coupled with pedestrian-friendly design significantly encouraged pedestrian activity, e.g., Rodríguez et al (2009). However, further investigation regarding urban form and travel behaviour at the focused areas is needed to have more conclusive explanations on this finding.

With the identification of the 800-metre area as the primary BRT catchment area in Brisbane, the next section moves on to analyse the associations between socio-demographic characteristics and travel patterns using 2011 census data and regression method. This provides an initial basis for profiling the current commuters (specifically bus users and car users) at the 800-metre catchment area.

5.3 The mode share patterns and socio-demographic characteristics

From the time-series analysis of the last section, this section moves on to conduct a regression approach to the 2011 Census data to better understand the characteristics of commuters at the 800-metre area. Except for other data being extracted from ‘Table Builder’ of the ABS, equivalised household income that takes household members’ relationships into account was required as part of customised data. This allows more accurate socio-economic indicators to be acquired. SA1 instead of CD was used as the unit for the regression analysis. All 22 BRT stations in Table 1 were used to identify the 800-metre catchment areas. 221 SA1s that were within or intercepting with the 800-metre circles were initially selected. After excluding eight SA1s with low population, i.e., less than 20 persons, 213 SA1s remained as the final sample.

Before the regression analysis, the travel patterns at the three catchment areas were examined. The 800-metre area still had the highest bus share (17% compared to 14.8% at the 1600-metre area and 13% at the 3-kilometre area), highest walk share (17% compared to 9.3% and 5.1%) and the lowest car share (overall 52.8% compared to 60.7% and 66%). The travel patterns of 2011 generally continued the trends identified in the time-series analysis.

5.3.1 Overview of variables

Table 5.3 provides the means and standard deviations of the variables. Two variables, 'mode share by bus' and 'mode share by car' (total of 'car as driver' and 'car as passenger') were constructed as dependent variables in the same way as in the time-series analysis. Through reviewing previous literature (Boarnet and Crane, 2001; Kitamura et al., 1997; Stead, 2001; Bagley and Mokhtarian, 2002), 20 variables were further constructed from census data to reflect the key socio-demographic dimensions of commuters at SA1 level (i.e., gender, age, income, education, household composition, education, vehicle ownership and population density).

Close scrutiny of each table and frequency plot showed that most variables did not have highly skewed distributions or problematic kurtosis. Yet, two variables, i.e., 'population density' and 'proportion of persons 15-24 years old', raised some concerns. Examination highlighted that these two variables were strongly skewed (both positively) and had overly concentrated distributions. Therefore transformation of these two variables was conducted before the modelling exercise. However, this did not improve the overall modelling results. Thus the original variables were used here.

Table 5.2 Description of dependent and independent variables

		Mean	Standard Deviation
Dependent variables			
Mode share of bus (%)		16.91	6.63
Mode share of car (%)		54.02	15.74
Independent variables			
1.Gender	Proportion of female (%)	49.16	4.25
2.Density	Population density (persons/ha)	38.98	38.03
3.Age	Proportion of persons 15-24 years old (%)	19.91	10.13
	Proportion of persons 25-34 years old (%)	24.89	9.49
	Proportion of persons 35-44 years old (%)	14.28	3.61
	Proportion of persons 45-54 years old (%)	10.93	3.48
	Proportion of persons 55-69 years old (%)	11.18	4.3

4.Household income	Proportion of households with equivalised weekly income $0-$399 (%)	14.36	7.32
	Proportion of households with equivalised weekly income $400-$999 (%)	29.69	7.84
	Proportion of households with equivalised weekly income $1000 or above (%)	42.32	12.5
5.Household composition	Proportion of couple family with no children (%)	47.2	13.03
	Proportion of couple family with dependent children (%)	23.71	9.48
	Proportion of couple family with no dependent children (%)	9.43	6.46
	Proportion of one parent family (%)	12.94	6.15
	Proportion of lone person household (%)	26.79	10.55
6.Education	Proportion of persons with bachelor degree or above (%)	50.73	9.8
	Proportion of persons with advanced diploma (%)	12.7	3.26
	Proportion of persons with certificate level of degree (%)	18.45	6.36
	Proportion of persons finishing school year 11 or less (%)	22.23	8.22
7.Vehicle ownership	Proportion of dwellings with motor vehicle(s) (%)	73.39	16.8

5.3.2 Modelling results

Two stepwise regression models were conducted to investigate the socio-demographic characteristics associated with bus share and car share. The inclusion standard was set at a significance threshold of 95% and removal standard was set at a significance level of 90%. The same modelling procedure was also applied to the 1,600-metre and the 3-kilometre areas. However, considerably lower model fit and explanation power was achieved particularly for the bus share model. This suggests that BRT might have attracted a certain transit-preferred population to the 800-metre area. At farther catchment areas, the use of bus appeared less related to socio-demographic aspects at the SA1 level.

Since aggregate geographic units (i.e., SA1) instead of actual commuters were used to conduct the regression analysis, it is noted that the regression results are tentative and that there is a need to further explore and explain the nature of the relationships.

Table 5.3 Results of the bus share model

Model Fit		
Adjusted R^2	0.381	
F	27.15	
Durbin-Watson value	1.6	
Variables	**β**	**t**
Proportion of persons 45-54 years old	-0.392	-6.74
Proportion of female	0.208	3.209
Proportion of households with equivalised weekly income $1,000 or above	-0.31	-5.437
Proportion of lone person households	0.242	4.069
Proportion of dwellings with motor vehicle(s)	0.315	4.435

Table 5.3 summarises the results of the bus share model. A statistically significant model was achieved, with adjusted $R^2 = 0.381$, $F (5, 207) = 27.15$, $p < 0.0001$. The P-P plot of standardised residuals showed a straight diagonal line. The relatively low Durbin-Watson value of 1.6 raised some concerns. Examining the residual plot however did not reveal highly serious problems such as residual autocorrelation. Given this, it is assumed that the omission of certain important variables such as service features (including speed, service frequency) as found in previous studies, e.g., Currie and Delbosc (2011) might be the major reason in this case. Overall, it is considered that the model result is acceptable for preliminary investigation.

A total of five independent variables remained in the final model, explaining 38.1% of variance of bus share at the SA1 level. There was no Variance Inflation Factor (VIF) value over the cut-off value of 10, indicating no collinearity issue. 'Proportion of persons between 45-54 years old' and 'proportion of household with equivalised weekly income $1,000 or above' were negatively associated with bus share (β = -0.392 and -0.31 respectively). 'Proportion of female', 'proportion of lone person households' and 'proportion of dwellings with motor vehicles', were positively related to bus share (β = 0.208, 0.242 and 0.315 respectively).

Table 5.4 Results of the car share model

Model Fit		
Adjusted R^2	0.786	
F	98.04	
Durbin-Watson value	1.93	
Variables	**β**	**t**
Proportion of dwellings with motor vehicles	0.398	7.31
Proportion of couple family with no children	-0.214	-4.58
Proportion of persons with bachelor degree or above	-0.177	-3.79
Proportion of persons 15-24 years old	-0.303	-7.81
Proportion of female	0.129	3.31
Proportion of persons with certificate level degree	0.197	3.87
Proportion of household with equivalised weekly income $1,000 or above	-0.177	-3.73
Proportion of lone person households	-0.124	-2.99

Table 5.4 summarises the results of car share model. A fairly good model fit was achieved, with adjusted $R^2 = 0.786$, F (8,205) = 98.04, $p < 0.0001$, Durbin-Watson value = 1.93. The examination of the P-P plot did not incur any serious concerns either.

Eight important independent variables were identified, accounting for 78.6% of car share variance. Again, none of the VIF values indicated collinearity issues. There were strong to moderate associations between car share and 'proportion of dwellings with motor vehicles' (β = 0.398), 'proportion of persons 15-24 years old' (β = -3.03) and 'proportion of couple family with no children' (β = -0.214). The remaining variables had relatively weak relationships with car share.

Based on the modelling results, it appears that within the 800-metre area, female commuters and lone-person (persons who live alone) commuters might rely more on the BRT service for work trips, while commuters in the middle age group between 45 and 54 years old and higher income commuters (proportion of household with equivalised weekly income $1,000 or above) are less likely to use the BRT service. A positive Pearson Correlation between ‘proportion of persons 45-54 years old’ and car share ($r = 0.33$) was found, suggesting the likelihood of preference of car over BRT for work trips. However, there is no evidence of higher income commuters related to high car use ($\beta = -0.177$). Vehicle ownership (‘proportion of dwellings with motor vehicle(s)’) not surprisingly, turned out to be the strongest contributor to car share. Young commuters between 15 and 24 years old and commuters from couple families without dependent children are less likely to use car to drive to work, given their negative relationships with car share.

What appears interesting is that in addition to car share, vehicle ownership was also positively related to bus share ($\beta = 0.315$) in this study, whereas the reverse relationships was often found in previous studies, e.g., Kitamura et al (1997), Bagley and Mokhtarian (2002), Simma and Axhausen (2001). Given this, BRT might have attracted passengers who have access to private vehicles (such as car) but still choose to ride BRT service. In previous studies, in comparison to captive passengers, passengers with access to private vehicles have been deemed as choice passengers, e.g., Foote et al (2001), Figler et al (2011). In addition, vehicle ownership has often been found to be linked with other socio-demographic aspects such as income and household composition (Stead and Marshall, 2001). Therefore it appears also necessary to examine the Pearson Correlations between vehicle ownership and the important independent variables in the models to further reveal the characteristics of possible captive and choice passengers of BRT as well as non-BRT passengers.

Vehicle ownership was found to be strongly related to a number of independent variables, most notably with ‘proportion of couple family with dependent children’ ($r = 0.628$) and ‘proportion of female’ ($r = 0.483$). The positive relationship between vehicle ownership and the presence of children in couple families is quite interpretable, that it might be more convenient for them to use car rather than bus to drop off (or pick up) their child/children at school before driving to (or from) work. The positive relationships found among ‘proportion of female’, vehicle ownership and bus share suggest that some female commuters could be choice BRT passengers. However, it is noted that for couples with cars, females usually have less access to cars than their male partners. Vehicle ownership was found to be negatively related to ‘proportion of persons 15- 24 years old’ (r = -0.395) and ‘proportion of lone person household’ (r = -0.399). As such, BRT riders from these two groups are more likely to be captive passengers than other groups.

Although not identified as important independent variables, ‘proportion of household with equivalised income $400-999’ and ‘proportion of persons with advanced diploma’ were positively related to vehicle ownership (r = 0.33 and 0.325 respectively) as well as bus share (r = 0.261 and 0.249 respectively). This indicates the possibility of choice passengers among these groups as well.

Considering the less statistically sound results of the bus share model compared to the car share model, we conducted three commonly applied tests, i.e., Mahalanobis Distance, Cook’s Distance and Leverage (Chatterjee and Hadi, 2006) to detect outlier cases with undue effects. None of the cases had a Cook’s Distance over the cut-off value of one. However, eight cases were found with a fairly large Mahalanobis Distance (over the cut-off value of 15) and Leverage value (over three times the average Leverage value of bus share model (0.282)). Re-running the bus share model without the outlier cases resulted in a slightly improved model, with adjusted $R^2 = 0.402$, $F (5, 199) = 28.477$ ($p < 0.0001$) (Table 5.5). The Durbin-Watson Value (= 1.666) was notably enhanced. The same five independent variables as in the original model remained in this model, with similar patterns of regression weights. This reinforces the findings in the original model.

Table 5.5 Results of re-running bus share model

Model Fit		
Adjusted R^2	0.402	
F	28.477	
Durbin-Watson value	1.666	
Variables	**β**	**t**
Proportion of persons 45-54 years old	-0.378	-6.608
Proportion of female	0.17	2.581
Proportion of households with equivalised weekly income $1,000 or above	-0.261	-4.611
Proportion of lone person households	0.361	5.236
Proportion of dwellings with motor vehicle(s)	0.439	5.515

5.4 Summary

This section has examined the change of travel patterns for work trips associated with Brisbane's BRT over the period 1996 to 2006, before modelling the associations between socio-demographic characteristics and bus and car shares in 2011. A number of localised changes in travel patterns and characteristics of commuters in the BRT context were revealed.

The key findings include:

- A radial distance of 800 metres from the BRT network was highlighted as the primary catchment area. At this distance, the greatest impacts of BRT on travel behaviour were identified, with the most notable increase of bus share and decrease in car share following the BRT implementation.
- BRT had important yet smaller impacts on adjacent areas beyond the 800-metre distance (up to three kilometres in distance in this study), in encouraging mode shift from car to UPT service.
- The introduction of the BRT encouraged pedestrian walking behaviour (an increase in walk to work in this study) in its adjacent areas (up to three kilometres in this study).

- The BRT has attracted more female and lone-person commuters, while car use was more related to the presence of children in a couple family.
- BRT has offered an attractive alternative to certain commuters with access to private car(s), therefore generating choice passengers who have a preference towards BRT service.
- Commuters from the middle aged group and couple families with dependent children were more likely to prefer car to BRT than other groups.

Chapter 6 Examining spatial-temporal dynamics of BRT usage of passengers using smart card data

6.1 Introduction

As highlighted in Chapter 2, public transport planning and provision requires a reliable understanding of people's travel behaviour in space and time. Attaining such information has the potential to inform local UPT management in better response to urban population's travel needs as a key aspect of establishing sustainable transport. Drawing on the MTW data of four censuses, Chapter 5 has investigated the changes in modal share patterns for work trips before and after BRT implementation, as well as provided insights into the socio-demographic information of BRT catchments. However, only geographically aggregate and work-trip related travel behaviour information is provided in the MTW data. As such, alternative data sources are needed to enable more detailed investigation regarding the spatial-temporal patterns of BRT usage within a UPT context.

As discussed in Chapter 2, the emergence of smart card data offers opportunities to investigate the spatial-temporal patterns of UPT passengers with an unprecedented level of detail. It has also been recognised that the potential of smart card data has yet to be fully exploited in investigating UPT dynamics. In addressing this issue, a geo-visualisation-based method is developed in Chapter 4. To further test the utility of this method and reveal detailed patterns of BRT usage, this chapter applies the developed method to a large smart card dataset and reveals passenger flow patterns at a stop-to-stop level. The following three questions are of particular interest:

To what extent do the trip characteristics of BRT trips differ from non-BRT trips across the UPT network?

How and to what extent do the spatial-temporal dynamics of BRT trips differ from non-BRT trips across the UPT network?

Within the BRT system (i.e., the BRT busway and related bus routes), is there notable *spatial heterogeneity of passengers' trips across the UPT network?*

By examining the trip characteristics, the first question looks at the basic temporal and spatial mobility patterns of BRT against non-BRT trips. The second question compares the spatial-temporal dynamics of BRT and non-BRT trips to unveil their roles in catering for passengers' travel needs. The third question is concentrated on the potential spatial-temporal differences of BRT trips across the urban space to offer more insightful information regarding BRT usage of passengers. Based on the responses to these three questions, important implications are expected to be attained to inform evidence-based BRT policies, including service management and infrastructure provision as they critically relate to the travel needs of passengers.

The remainder of the chapter is structured as follows. As noted in Chapter 4, a small proportion of records failed to be reconstructed as travel trajectories in the data processing for geo-visualisation and was excluded from the analysis. Hence, in order to detect whether serious bias is induced in this process, Section 6.2 first examines these missing data against the retained data in terms of temporal and spatial patterns. Section 6.3 examines the travel characteristics (i.e., temporal boarding patterns, travel time, distance, average speed and use frequency) of BRT and non-BRT trips. Based on the contextualisation of Section 6.4, Sections 6.5 and 6.6 offer more detailed investigation of the spatial-temporal dynamics of BRT and non-BRT trips in terms of stop-level behaviours (i.e., boarding, alighting and transfer) and passenger flow patterns through a series of geo-visualisation techniques (i.e., comap, flow-comap and weighted flow-comap). Finally, Section 6.7 summarises the key findings of this chapter.

6.2 An examination of missing data

As described in Chapter 4, one of the major components of the methods of processing smart card data is to reconstruct travel trajectories of passengers on a stop-to-stop basis. In this case, this process involves using the bus service patterns of Brisbane (extracted from the GTFS data) to insert the passed through stops between the boarding and alighting stops for each smart card record. While the majority of the records have been successfully processed, a number of records failed to be reconstructed as travel trajectories. This can be due to two reasons: (1) the non-concurrence between the smart card data and the GTFS data; and (2) errors in the smart card data such as recording stops with mismatched routes. These records have to be removed for the later analytical tasks (e.g., flow-comap) since they cannot be represented as travel trajectories (Tao et al., 2014a). Given this, it is necessary to first examine whether serious bias will be induced by removing these smart card records.

6.2.1 Enumeration of the missing and retained data

Table 6.1 enumerates the numbers of the missing (i.e., data that fail to be reconstructed as travel trajectories) and the retained data (i.e., data that are reconstructed as travel trajectories). For each of the five typical calendar events, over 87 per cent of the smart card records were retained.

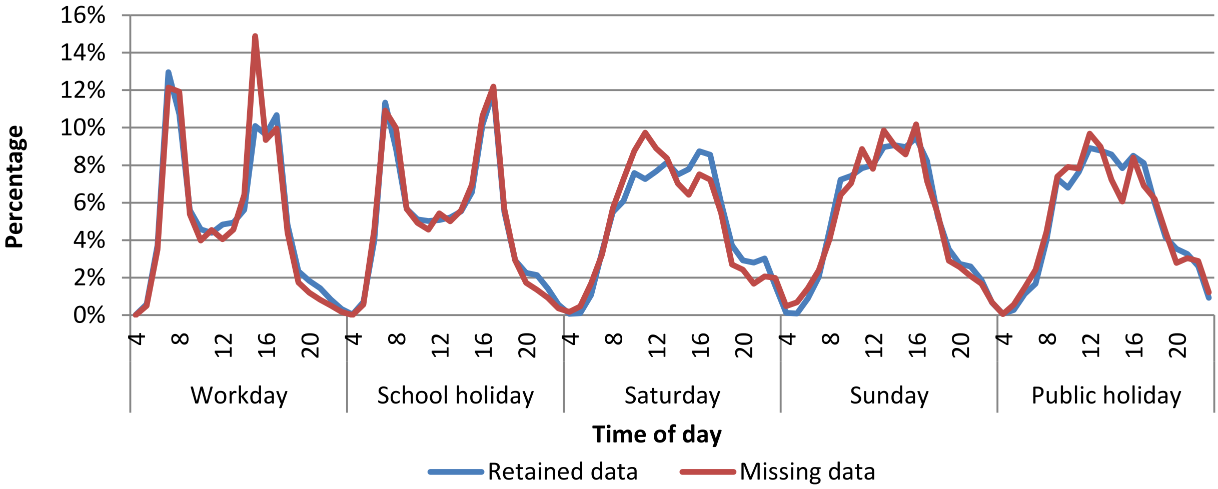
Table 6.1 Enumeration of the missing and retained data

Date	Calendar events	Number of missing records	Number of retained records	Percentage of retained records (%)
4, April	School holiday	24,319	181,930	88.2
16, April	Workday	34,727	238,352	87.28
20, April	Saturday	13,550	98,844	87.94
21, April	Sunday	7,887	65,471	89.24
25, April	Public holiday (ANZAC day)	6,856	60,511	89.82

6.2.2 Temporal boarding patterns

Figure 6.1 compares the temporal boarding patterns of the missing and retained data across the five dates. Both groups of data show peak-hour patterns during the workday and school holiday and non-peak hour patterns across the weekend and public holiday. It however can be identified that on the workday, the missing data have a more pronounced peak between 3:00 and 4:00 pm than the retained data. Additionally, on the Saturday, the boarding behaviour of the missing data appears to concentrate slightly more within the period between 10:00 am and 1:00 pm, while the retained data have a small boarding peak between 4:00 and 6:00 pm. Despite these two notable differences, the general boarding patterns of the missing and retained data are largely comparable.

Figure 6.1 Temporal boarding patterns of the retained and missing data



6.2.3 Spatial patterns

Using kernel density estimation, Figures 6.2 to 6.6 examine the spatial patterns of trip density between the missing and retained data. Given that the passed through stops for the records of the missing data were not added, the trips of the two data groups were represented as straight lines between the boarding and alighting stops. Across the five calendar events, both the missing inbound and outbound trips show higher density between the city centre and some locales in the south of Brisbane. These spatial patterns again largely concur with the retained data. It however can be observed that during the workday and school holiday, the missing data contain slightly more spatially-dispersed trips across the northern and southern borders of Brisbane.

Overall, through the above examinations, it appears that no systematic serious bias is induced by removing the unmatched records. Hence, it is assumed that reasonable results for analysing the retained data can be drawn.

Figure 6.2 Spatial patterns of the retained and missing data, workday

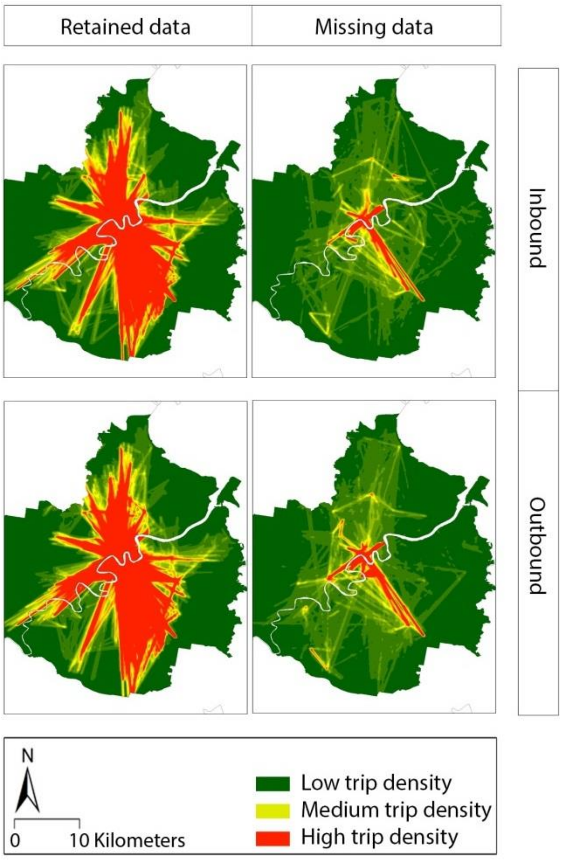


Figure 6.3 Spatial patterns of the retained and missing data, school holiday

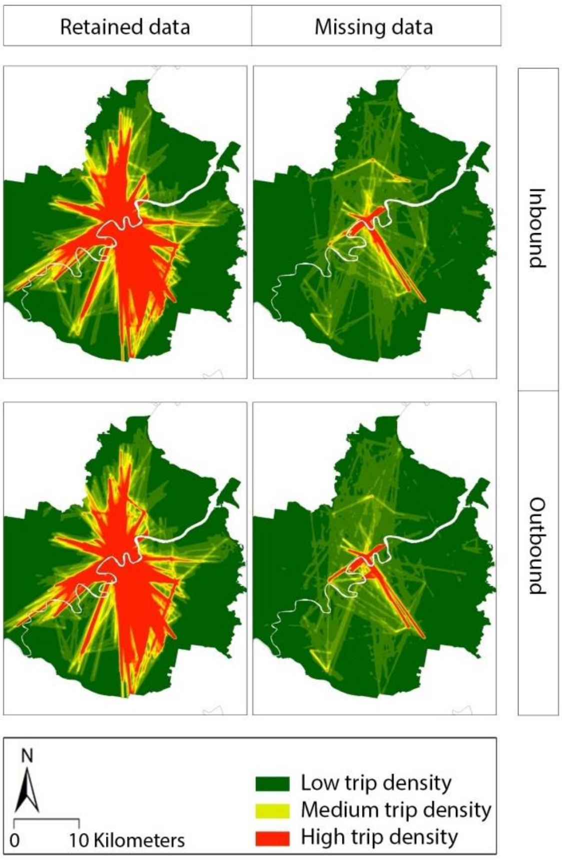


Figure 6.4 Spatial patterns of the retained and missing data, Saturday

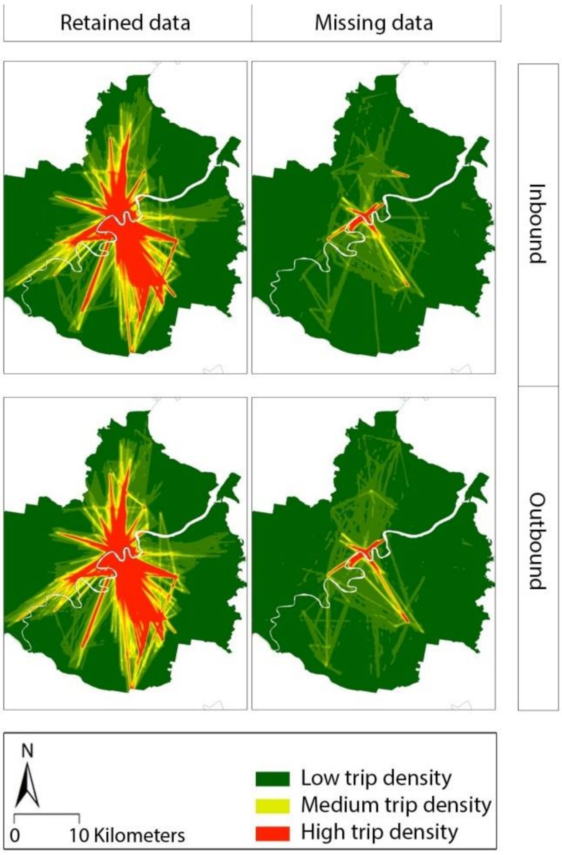


Figure 6.5 Spatial patterns of the retained and missing data, Sunday

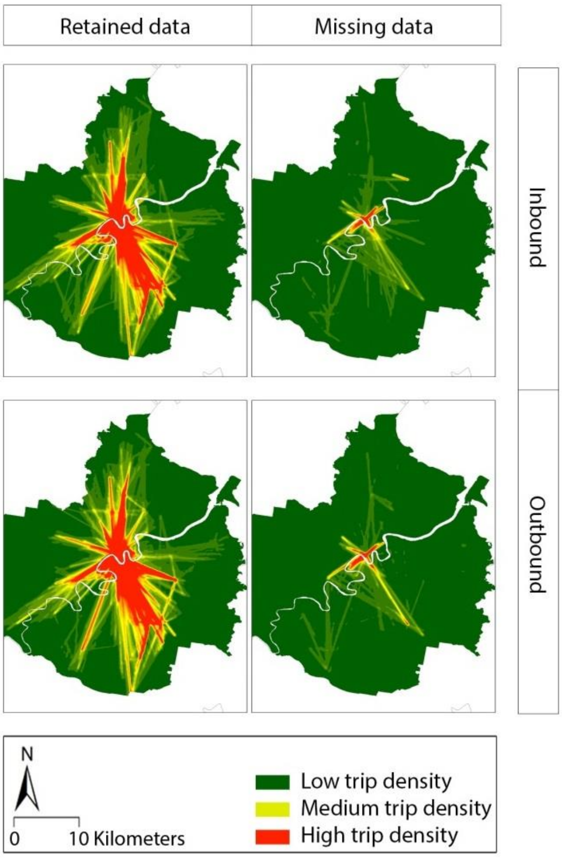
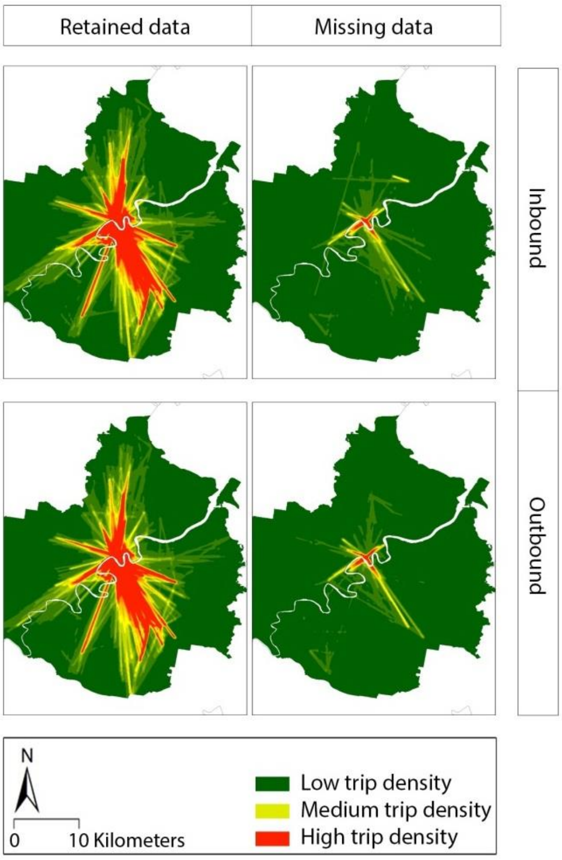


Figure 6.6 Spatial patterns of the retained and missing data, public holiday



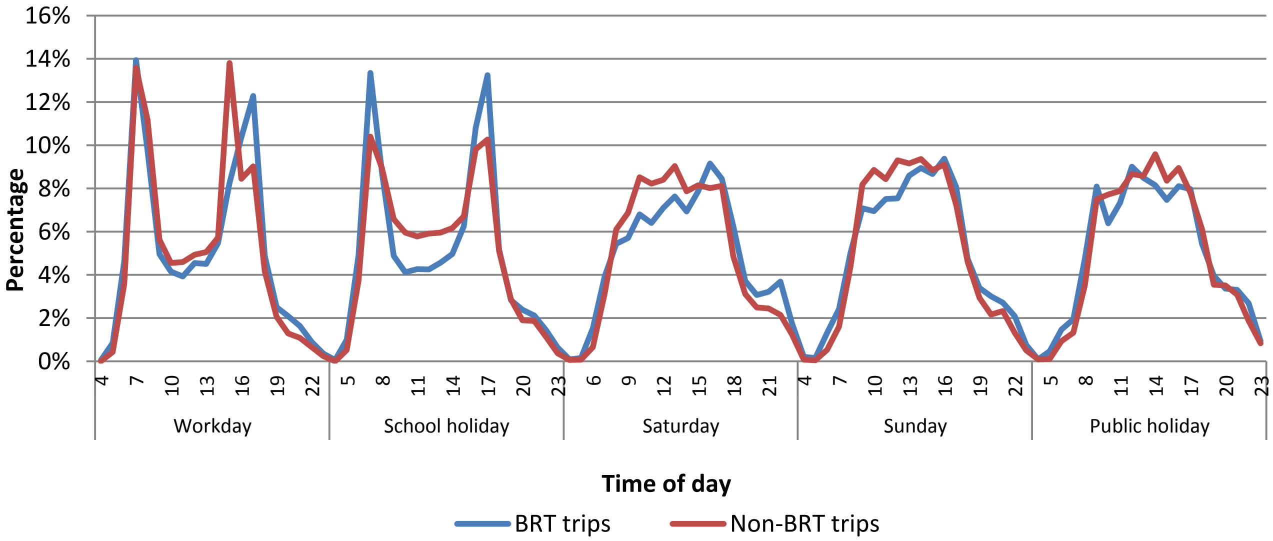
6.3 Descriptive analyses of travel characteristics

Based on an examination of the missing data, the section moves on to explore the temporal and spatial dynamics of BRT against non-BRT trips. Drawing on the journey ID information, many smart card records can be identified as intermediate segments that constitute part of linked bus trips in order to get to the final destination. Given this, in order to capture the accurate travel patterns of bus passengers, the trips here refer to the linked bus trips that include bus-to-BRT or bus-to-bus transfers.

6.3.1 Temporal boarding patterns

Figure 6.7 compares the temporal boarding patterns between BRT and non-BRT trips on the five calendar events. Generally, BRT and non-BRT trips have similar temporal boarding patterns across the five dates, both showing notable peak hour patterns during the workday and school holiday, and non-peak hour patterns during the weekend (Saturday and Sunday) and the public holiday.

Figure 6.7 Temporal boarding patterns of BRT and non-BRT trips



On the workday afternoon (2:00 to 6:00 pm), non-BRT trips reached a peak from 3:00 to 4:00 pm, while the peak hours of BRT trips concentrated in a later time period between 4:00 and 6:00 pm. On the school holiday, BRT trips appear to have pronounced boarding peaks during morning (7:00 to 8:00 am) and afternoon (4:00 to 6:00 pm), and drastic decrease of boarding between 9:00 am to 3:00 pm. By comparison, for non-BRT trips, the difference in the number of boardings between the peak hours and the time in between is less pronounced.

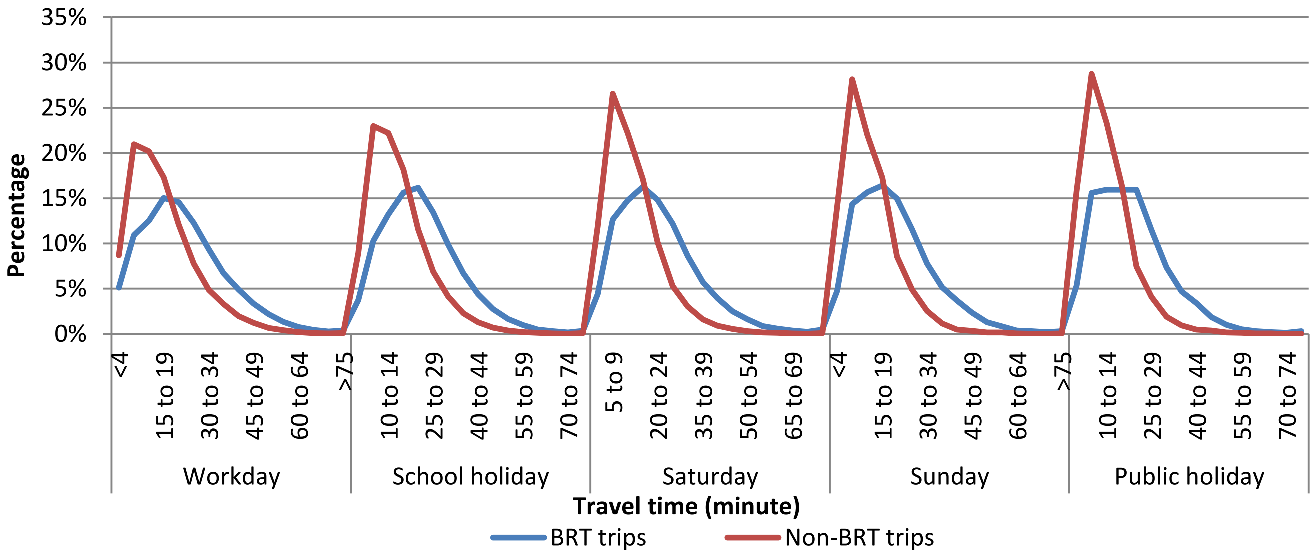
For the Saturday and the Sunday, both BRT and non-BRT trips showed non-peak hour boarding patterns. Observably, however, passenger boarding for non-BRT trips appears to be more evenly distributed between 9:00 am and 6:00 pm, whilst the boarding patterns for the BRT trips have a slight peak from 4:00 to 5:00 pm for the two dates. Finally, on the public holiday, the boarding patterns for both BRT and non-BRT trips are rather dispersed across the day.

6.3.2 Travel time

According to previous studies, e.g., Jang (2010), trips that are recorded with overly long durability (i.e., 120 minutes and over) are removed from the analysis, since these trips are more likely associated with coding errors of smart card systems.

Figure 6.8 depicts the travel time patterns for BRT and non-BRT trips. Most BRT and non-BRT trips are within 50 minutes of durability. While separately, BRT and non-BRT trips have demonstrated similarly positively skewed patterns across the five dates, some notable differences can be observed between the two sectors.

Figure 6.8 Travel time of BRT and non-BRT trips



Across the five dates, over half of the non-BRT trips are concentrated within three travel time bins, i.e., 5-9, 10-14 and 15-19 minutes, while the number of trips drastically diminishes as travel time increases from 20 minutes. Additionally, there is a considerably larger proportion of non-BRT trips with five to nine minutes of travel time on the Saturday, Sunday and public holiday compared to the other two dates.

The distribution of BRT trips, on the other hand, is more dispersed between less than four minutes and 35-40 minutes of travel time, with observable peaks within the bins of 15-19 and 20-24 minutes, except for the public holiday which was without any peaks.

Table 6.2 compares the median values of travel time between the BRT and non-BRT trips. In line with the above observations, the BRT sector saw more trips with longer travel times compared to the non-BRT sector.

Table 6.2 Median travel time of BRT and non-BRT trips

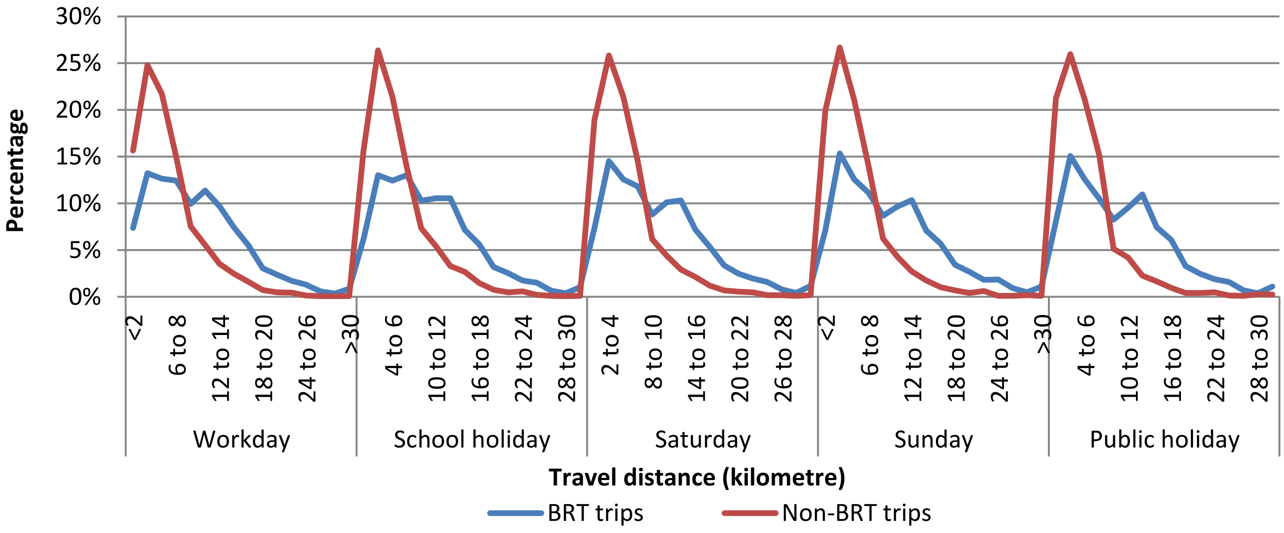
Calendar event	BRT trips (minutes)	non-BRT trips (minutes)
Workday	22	15
School holiday	22	14
Saturday	20	12
Sunday	19	11
Public holiday	19	11

6.3.3 Travel distance

Trips with travel distance of 100 kilometres and over are removed from this analysis. This is again due to the possible errors associated with these trips, given that the potentially longest trip within Brisbane (approximately 42 kilometres between the North and South borders, and around 50 kilometres between the Eastern and Western borders) might not exceed a 100 kilometre distance.

Most BRT and non-BRT trips are shorter than a 30 kilometre distance. Similar to the travel time patterns, while both BRT and non-BRT trips showed positively skewed patterns of travel distance, the differences are more perceptible between the two sectors than within the individual sectors across the five dates (Figure 6.9).

Figure 6.9 Travel distance of BRT and non-BRT trips



Over the five calendar events, over 70 per cent of non-BRT trips have travel distances within the bins of less than two, two to four, four to six and six to eight kilometres. Considerable increases of non-BRT trips with distances of 2-kilometres or less can be observed for the Saturday, Sunday and public holiday compared to the other two dates.

BRT trips, again, are more evenly distributed across the travel distance bins, from less than two kilometres to 16-18 kilometres. A comparison of the median values (Table 6.3) indicates that BRT trips are more associated with longer travel distance than the non-BRT trips.

Table 6.3 Median travel distance of BRT and non-BRT trips

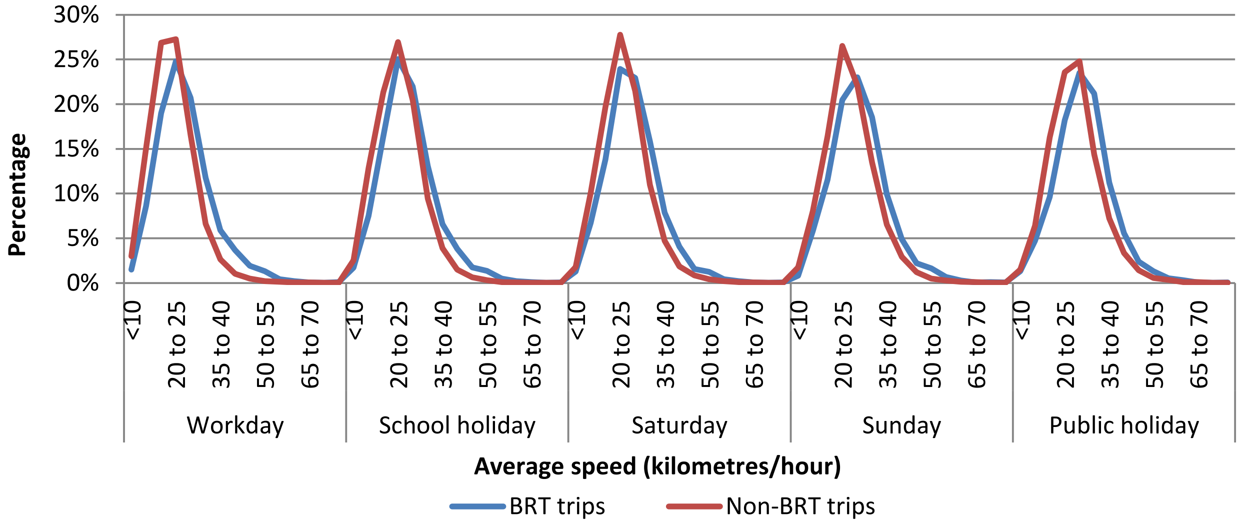
Calendar event	BRT trips (kilometres)	non-BRT trips (kilometres)
Workday	8.853	4.886
School holiday	8.989	4.756
Saturday	8.77	4.54
Sunday	8.835	4.399
Public holiday	8.859	4.323

6.3.4 Average travel speed

Based on the above investigation of the basic temporal and spatial dynamics of BRT and non-BRT usage, this section investigates the composite indicator of the two, the average speed of trips, since it relates with the travel experience of passengers and is also considered as a key aspect of BRT performance (Currie and Delbosc, 2011; Hensher and Golob, 2008). Trips with abnormally high average speed, in this case exceeding 80 kilometres per hour based on Currie and Delbosc (2010), were excluded from the analysis.

An examination of the average travel speed patterns for BRT and non-BRT trips again renders positively skewed patterns across the five dates (Figure 6.10). From the workday to the rest of the dates, there is a shift of trip distribution from lower to higher speed bins for both BRT and non-BRT trips. This is rather explainable due to the decrease of commute trips for the weekend, school and public holidays.

Figure 6.10 Average travel speed of BRT and non-BRT trips



Across the five dates, over 60 per cent of non-BRT trips are concentrated within the bins of 15-20, 20-30, 30-35 kilometres per hour, while the proportion of trips with higher speed considerably diminishes beyond the level of 35 kilometres per hour (Table 6.4). Similar patterns can also be identified for the BRT trips. Nonetheless, based on the percentage value, more BRT trips were operated at the higher speed bins, that include 35 kilometres per hour and above. This suggests that compared to non-BRT trips, slightly higher average speed is more likely to be achieved for BRT trips, although such improvement might mostly occur on the exclusive busway. A comparison of the median values of the average travel speed again complies with this observation.

Another notable observation is that a top speed of 80 kilometres has rarely been achieved for BRT as well as non-BRT trips. This suggests that while a busway system is usually designed to enhance the service speed of buses, such high speed might be hardly achievable in practice, at least not without additional infrastructure design such as guided vehicles (Currie and Delbosc, 2010).

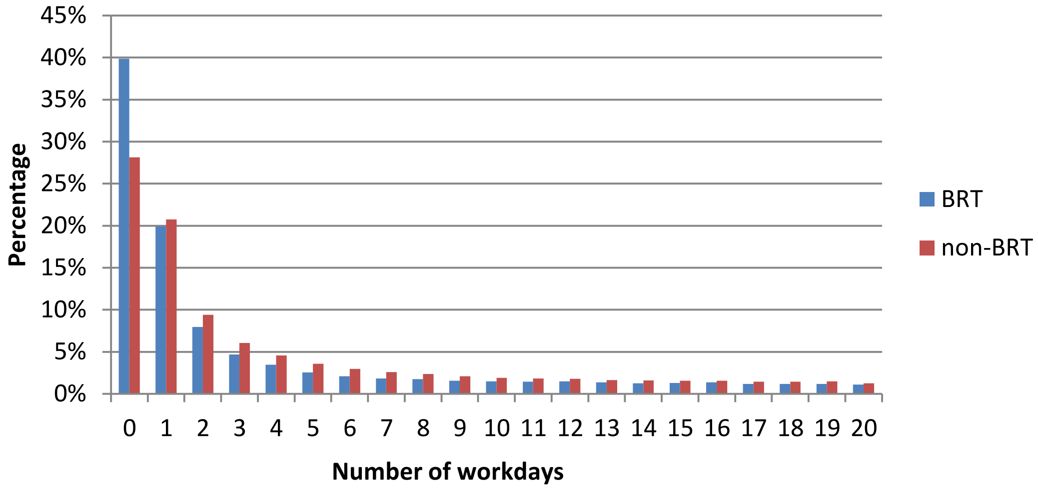
Table 6.4 Median average travel speed of BRT and non-BRT trips

Calendar event	BRT trips (kilometres/hour)	non-BRT trips (kilometres/hour)
Workday	24.184	20.864
School holiday	24.874	22.485
Saturday	25.925	23.313
Sunday	27.42	24.407
Public holiday	28.546	25.335

6.3.5 Use frequency over continuous days

From the above descriptive analyses of individual calendar events, this section examines the frequency of BRT and non-BRT usage of passengers over continuous days. The use frequency commonly refers to the enumeration of the number of days of an individual passenger repeatedly riding a transit service. It has been deemed as a key indicator reflecting the degree to which passengers are habitual or behaviourally loyal customers of a transit service (Miller et al., 1999; Trépanier et al., 2012). Considering that the first two weeks of April were school holidays, four weeks of March (1st to 28th March) were used for this analysis. Each unique smart card ID is deemed as an individual passenger, which is the basis for enumerating use frequency here. For the four week period, a total of 417,611 unique smart card IDs were detected.

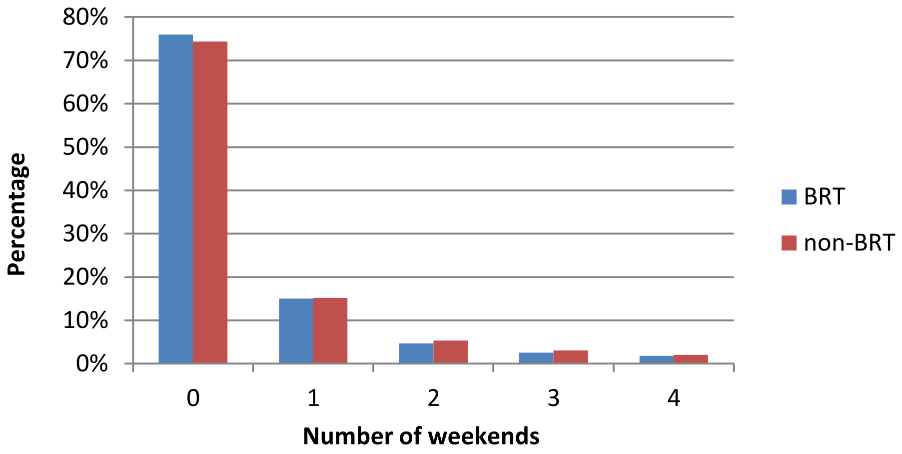
Figure 6.11 Use frequency of BRT and non-BRT on workdays



Over workdays, the distribution of use frequency of passengers was very similar between the BRT and non-BRT sectors (Figure 6.11). Within the two groups, the use frequency of a majority of the passengers (75 percent for BRT and 68 percent for non-BRT) was pegged at four workdays or less over the four weeks (or on average one work day or less per week), the rest of the passengers were spread over the higher bins of use frequency. Only just over 10 per cent of passengers use the BRT and/or non-BRT on a relatively frequent basis, i.e., 12 days over the four weeks or on average over three workdays per week.

Over the weekends (Figure 6.12), the majority of passengers did not use BRT or non-BRT (76 percent for BRT trips and 73 percent for non-BRT trips) at all. Within each group, 15 per cent of passengers used the service for one weekend; and for the remaining three bins, each accounts for two to five per cent of passengers.

Figure 6.12 Use frequency of BRT and non-BRT on weekends



An examination of the use frequency of passengers shows generally similar patterns between the BRT and non-BRT sectors, within both of which, the majority of passengers demonstrated rather low use frequency. In addition, within the BRT group, more passengers showed low use frequency for both workdays and weekends than the non-BRT group.

To further examine the observed patterns, these results are compared against the latest public transport survey of South East Queensland in 2010 (TransLink, 2010). This comparison reveals a serious disparity between the two in terms of passenger use frequency especially for workdays, in that the survey results indicate that over 70 per cent of passengers use public transport on a regular basis, i.e., three weekdays per week or above.

Such difference is plausible for two potential reasons. First, the number of unique smart cards over-counts the actual number of individual passengers, and some passengers may have two or more smart cards, some of these cards are rarely used. Based on the latest investigation of modal share patterns in Australian major cities (Cosgrove, 2011), the average level of modal shares by bus is around 5% for all trips made in Australia. Assuming the number of each trip to be made by different individuals, which is already an over-count, the number of bus passengers in Brisbane would be around 100,000. However, this over-counted number is still much lower than the total number of smart card IDs identified here (417,611), hence skewing the pattern of use frequency by adding more numbers to low use frequency bins. The second reason is that from a probability perspective, the frequent BRT or non-BRT users are more likely to be surveyed and also complete the survey than the infrequent users, hence the overrepresentation of frequent users in the survey results.

Based on the above two reasons, the use frequency observed based on both smart card records and survey should be taken with a caveat, given that the results might be skewed to a degree for both.

6.4 Contextualisation for spatial-temporal analyses

Before proceeding with the spatial-temporal analyses of BRT and non-BRT usage, it is first necessary to provide more details concerning the context of analyses.

Based on the results of Kernel density estimation of passengers' boarding and alighting counts (as presented in Section 6.4.1), 30 important locales were identified to facilitate the interpretation of spatial-temporal dynamics of travel behaviour (Figure 6.13), including four locales within and surrounding the CBD areas (locations 10, 11, 12, 13), seven shopping centres (locations 4, 5, 15, 16, 21, 23, 24), three major universities (locations 8, 17, 22), two hospitals (locations 9, 14), two transfer/park-and-ride hubs (locations 18, 25) and twelve residential suburbs (locations 1, 2, 3, 6, 7, 19, 20, 26, 27, 28, 29, 30).

Figure 6.13 Case study area

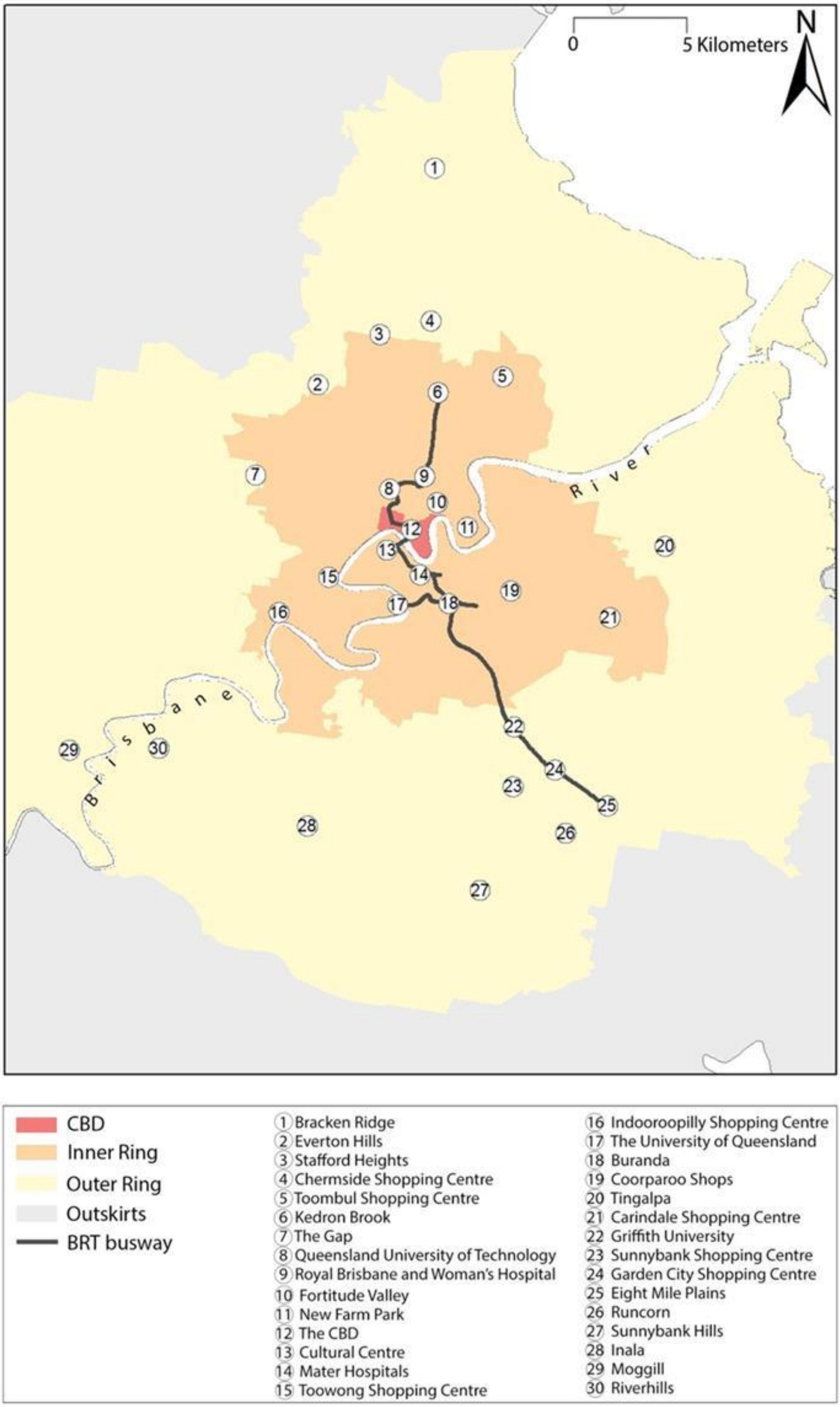
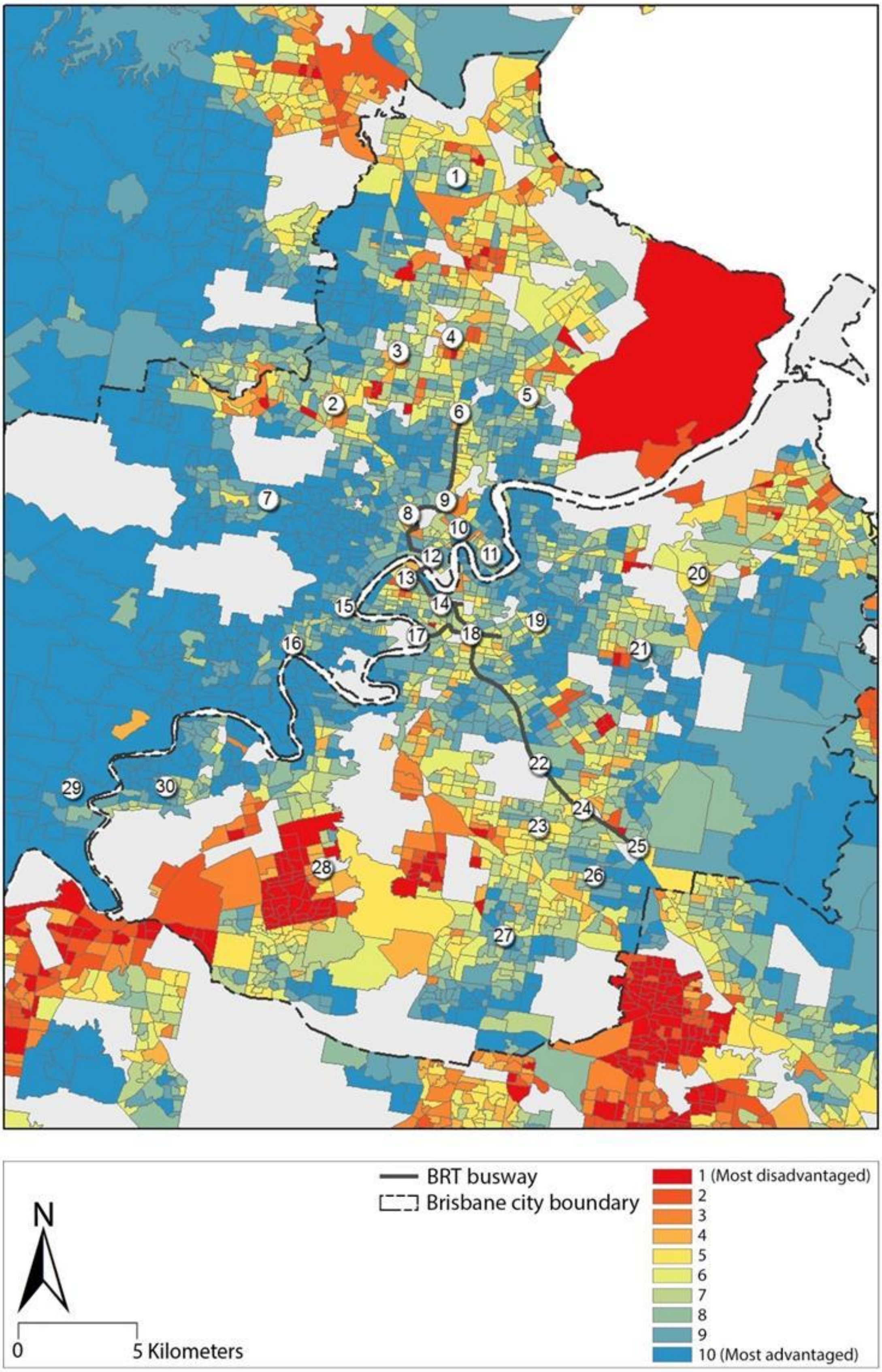


Figure 6.14 IRSAD pattern of Brisbane



As identified in previous studies, e.g., Bagchi and White (2005), Pelletier et al (2011), the socio-demographic characteristics (e.g., income, gender, household) of card users are not provided in smart card data. To further contextualise the findings of this paper, the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) of the latest Australian Census data (ABS, 2011a) was also mapped across the study area (Figure 6.14).

The IRSAD is one of the four the Socio-Economic Indexes for Areas (SEIFA), which are calculated as composite scores by applying Principal Component Analysis on a series of census data entries. Among the four indexes, the IRSAD is the most exhaustive one in accounting for a number of socio-demographic and economic indicators, including income level, household composition, employment status, dwelling types and education (ABS, 2011a). The resulting scores aim to capture the level of ‘people’s access to material and social resources, and their ability to participate in society’ at census geographic units (ABS, 2011a, pg.6). The smallest census unit of Statistical Level 1 (SA1) was applied here to map the IRSAD pattern of Brisbane (ABS, 2011b). Due to the low populations in certain areas (e.g., universities, open space), a small proportion of SA1s do not have IRSAD values. For the rest of the SA1s, IRSAD values were binned into deciles, with ten indicating the most socio-economic advantaged areas, and one being the most disadvantaged areas.

6.5 Stop-level behaviours

This section looks at the stop-level behaviours of passengers (i.e., boarding and alighting, and transfer behaviours) to provide initial insights into the spatial-temporal dynamics of BRT trips as well as non-BRT trips.

Co-maps (i.e., conditional maps) were created to achieve this goal. Along the horizontal direction, maps are classified into BRT and non-BRT trip groups, as discussed in Chapter 4. Along the vertical direction are the four map windows covering the course of the day (i.e., morning, 6:00 to 10:30 am; noon, 10:00 am to 2:30 pm; afternoon, 2:00 to 6:30 pm; and evening, 6:00 to 10:30 pm).

6.5.1. Boarding and alighting behaviours

Figures 6.15 to 6.19 depict boarding and alighting patterns across the five dates. The patterns on the workday (Figure 6.15) and school holiday (Figure 6.16) are rather alike. This can be due to the fact that the adult passengers constitute the dominant market segment of Brisbane’s public transport system. For BRT trips, the boarding and alighting behaviours of passengers show strongly city-centric patterns. During the morning period, the major boarding locations (or trip origins) were spread across Brisbane (particularly the Inner Ring, outer north and south of Brisbane), while the CBD and the inner Brisbane locales (including Fortitude Valley, Cultural Centre, South Bank, Mater Hospitals and the University of Queensland, refer to Figure 6.13) were the major alighting locations (or trip destinations). For the afternoon period, a reverse pattern of boarding and alighting can be identified for BRT trips.

For non-BRT trips of the workday and school holiday, the CBD and the nearby locales (the University of Queensland) can also be identified as the major alighting locations during the morning and the major boarding locations during the afternoon. By contrast, the morning boarding and the afternoon alighting patterns appear to be spatially scattered without highly notable hotspots.

Comparing the boarding and alighting patterns of BRT and non-BRT trips with the IRSAD pattern (Figure 6.14), it appears that the BRT system played an important role in catering for the travel needs of the catchments in north and south Brisbane, where more suburbs with medium and lower IRSADs can be observed. On the other hand, it appears difficult to identify the major catchment spots of non-BRT services based on the spatially-scattered boarding patterns.

On the Saturday (Figure 6.17), Sunday (Figure 6.18) and public holiday (Figure 6.19), unsurprisingly the boarding and alighting behaviours for BRT and non-BRT trips were less active compared to the previous two dates. For BRT trips, it is observable that the major boarding and alighting locations were concentrated within and near the CBD as well as South Brisbane (particularly Eight Mile Plains), possibly suggesting major trips occurring between these locales. For non-BRT trips, the major hotspots for boarding and alighting, again, were much less identifiable.

Figure 6.15 Comap of boarding and alighting patterns on workday (by time of day)

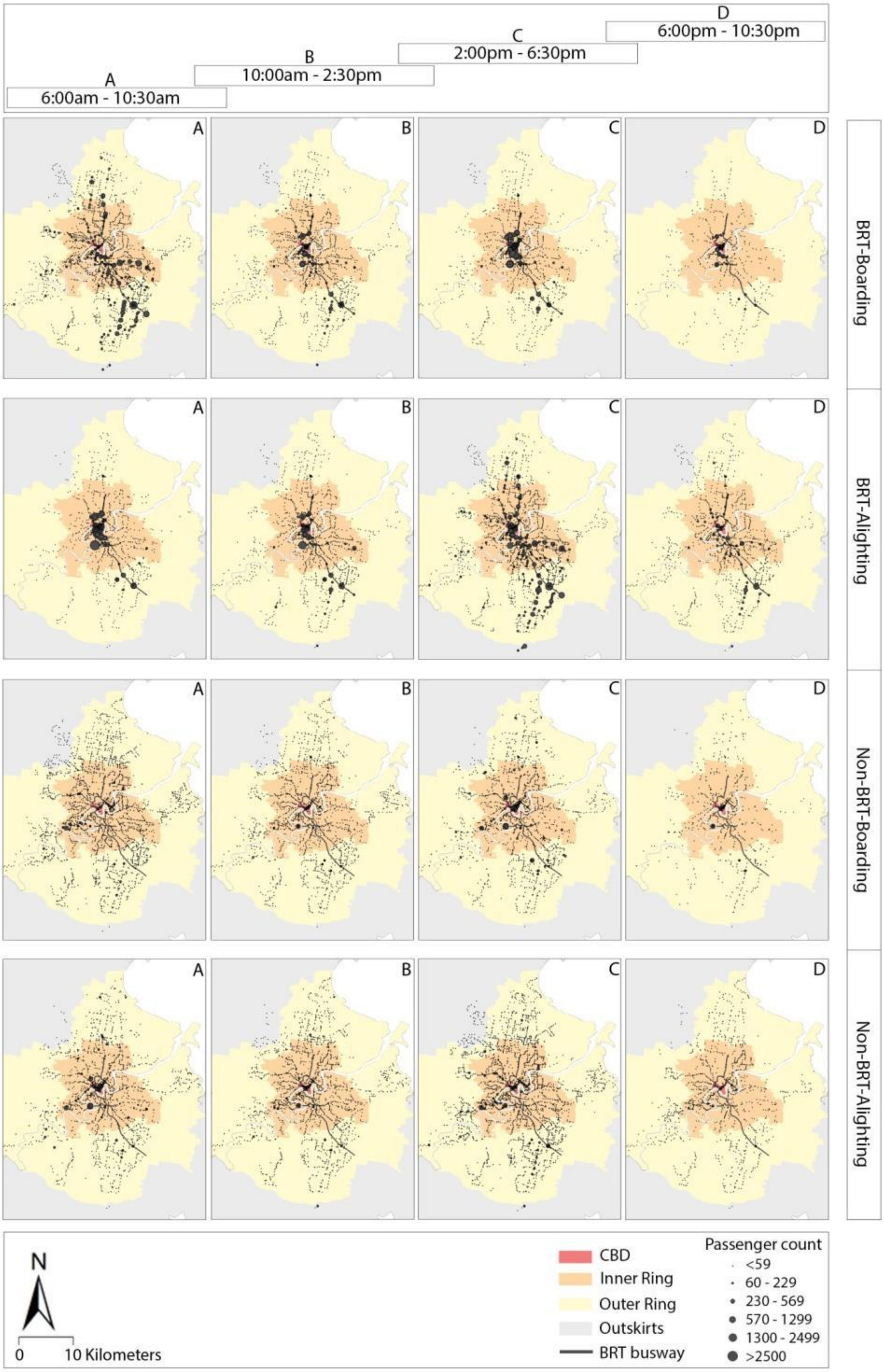


Figure 6.16 Comap of boarding and alighting patterns on school holiday (by time of day)

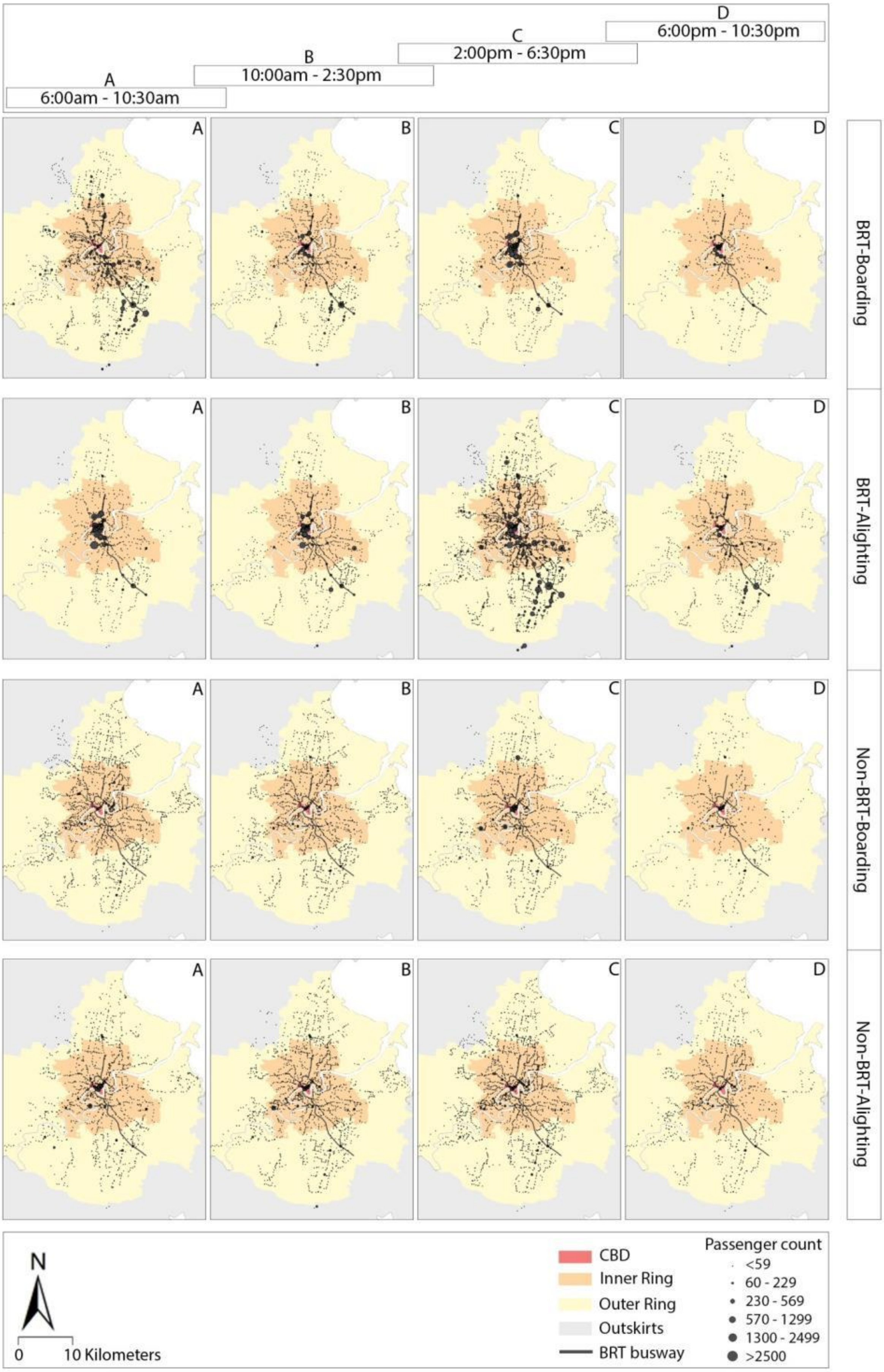


Figure 6.17 Comap of boarding and alighting patterns on Saturday (by time of day)

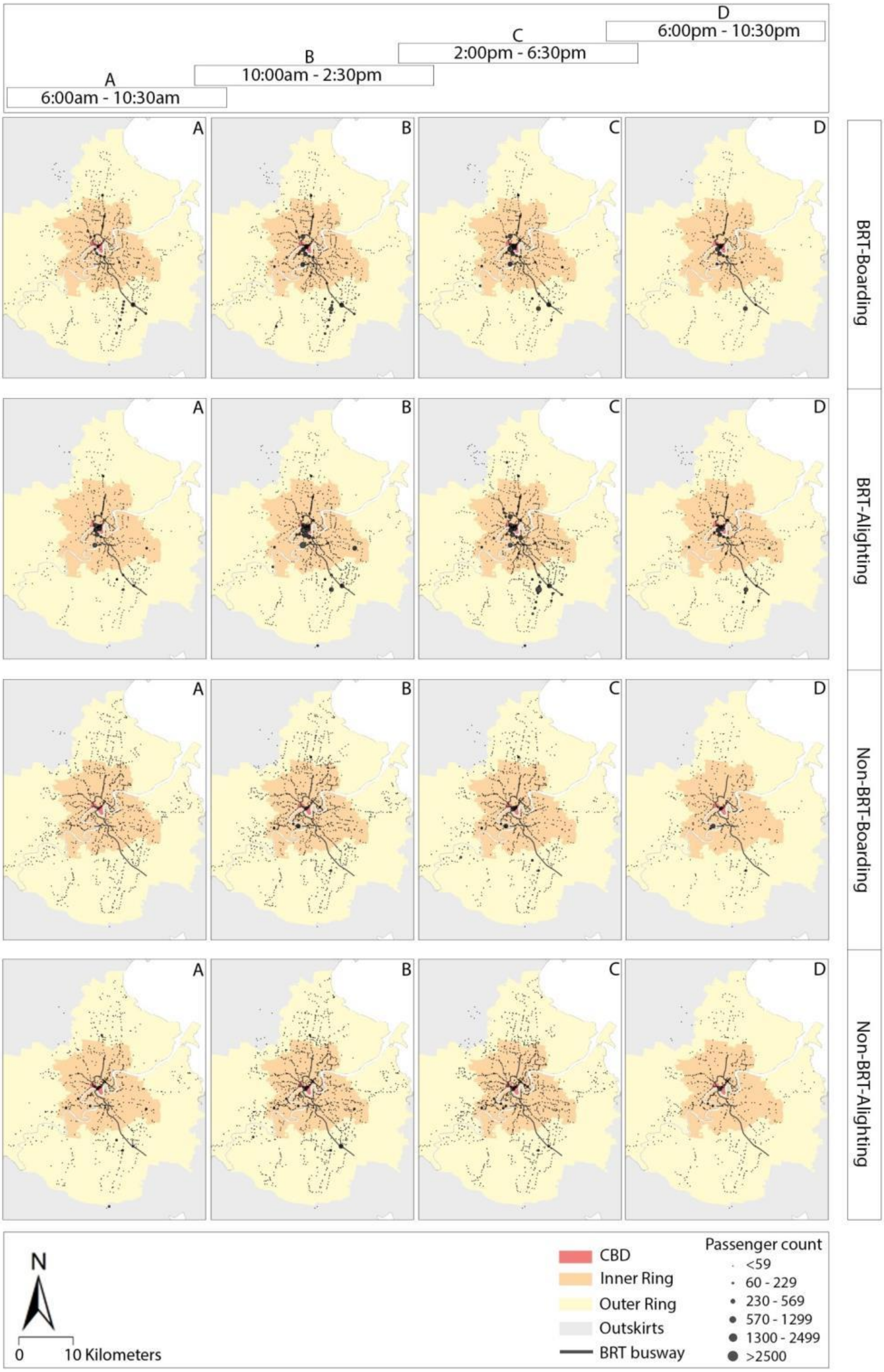


Figure 6.18 Comap of boarding and alighting patterns on Sunday (by time of day)

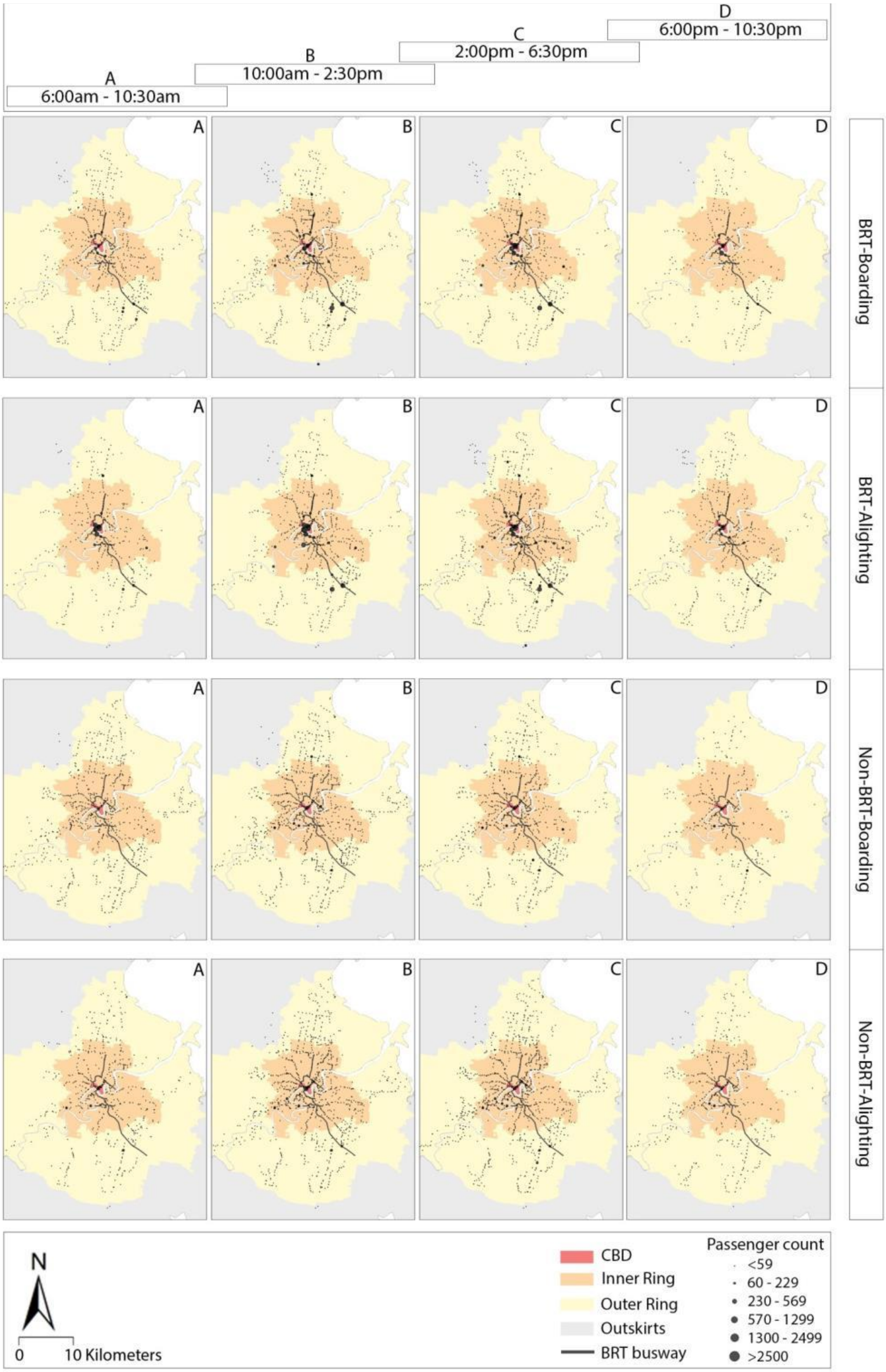
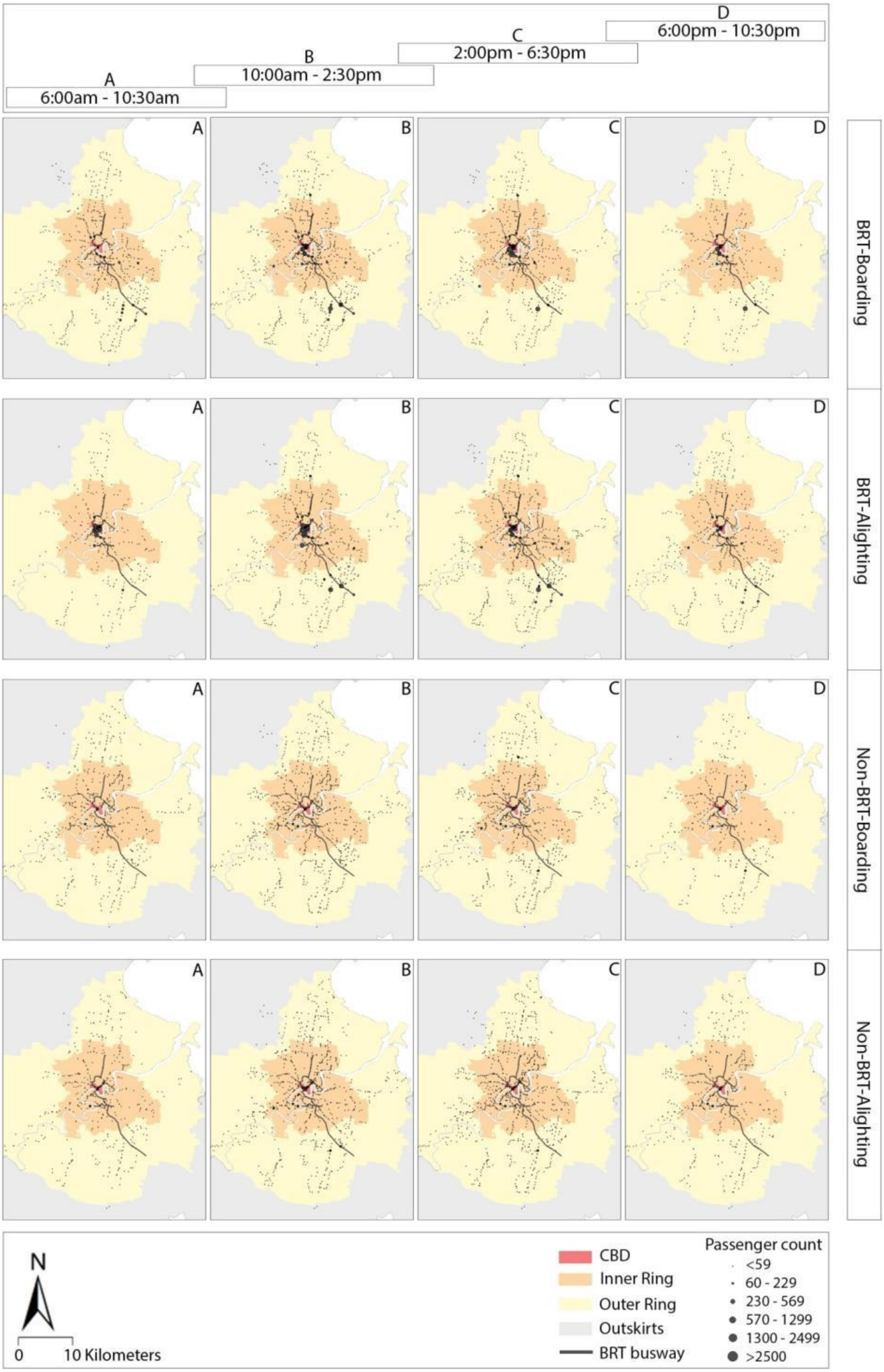


Figure 6.19 Comap of boarding and alighting patterns on public holiday (by time of day)



6.5.2 Transfer behaviour

Figures 6.20 to 6.24 illustrate the transfer patterns for BRT and non-BRT trips. Across the five dates, while bus-to-BRT transfer was explicitly considered for BRT trips, the major transfer locations of this group of trips appear to largely concentrate on the busway, particularly the BRT stations near the CBD and the ones in the southern section of the busway (e.g., Upper Mount Gravatt, Eight Mile Plains). A further examination of the transfer patterns show that for non-BRT trips, Indooroopilly Shopping Centre can be identified as a key transfer location outside the CBD on the workday and school holiday, suggesting the role of transit hubs. During the rest three dates, the transfer behaviours of non-BRT trips were again quite dispersed with no particularly prominent hotspots.

Figure 6.20 Comap of transfer patterns on workday (by time of day)

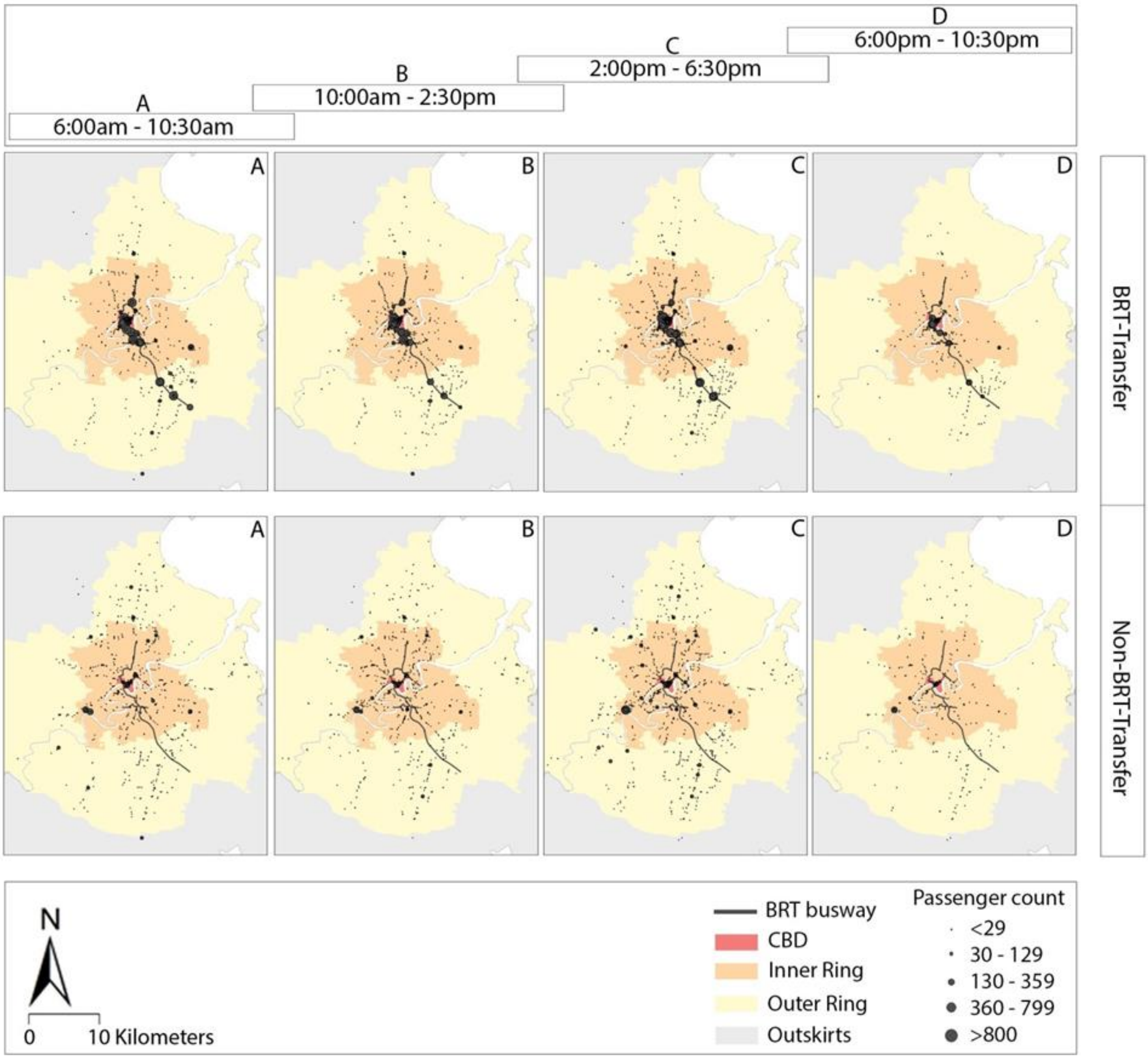


Figure 6.21 Comap of transfer patterns on school holiday (by time of day)

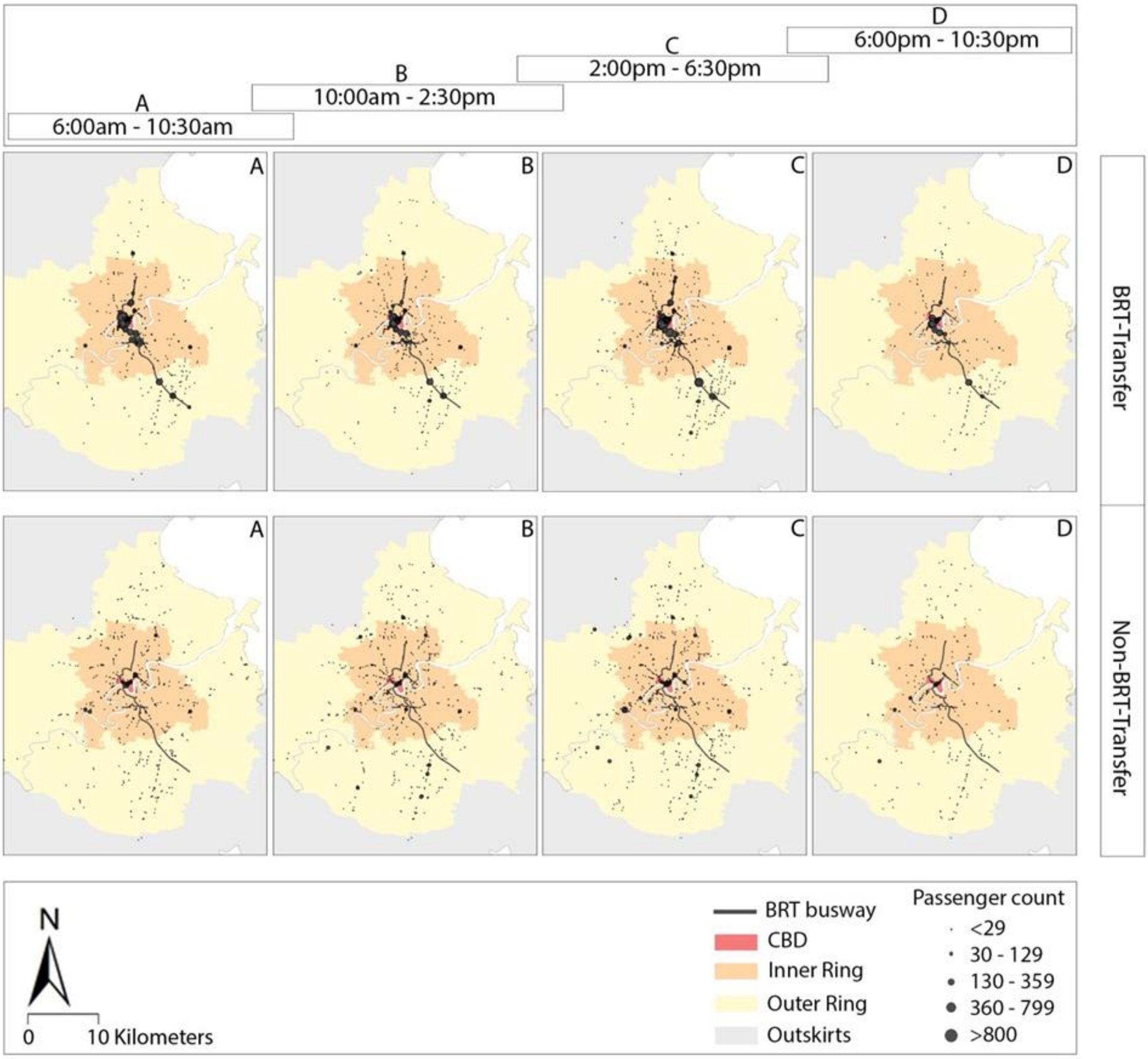


Figure 6.22 Comap of transfer patterns on Saturday (by time of day)

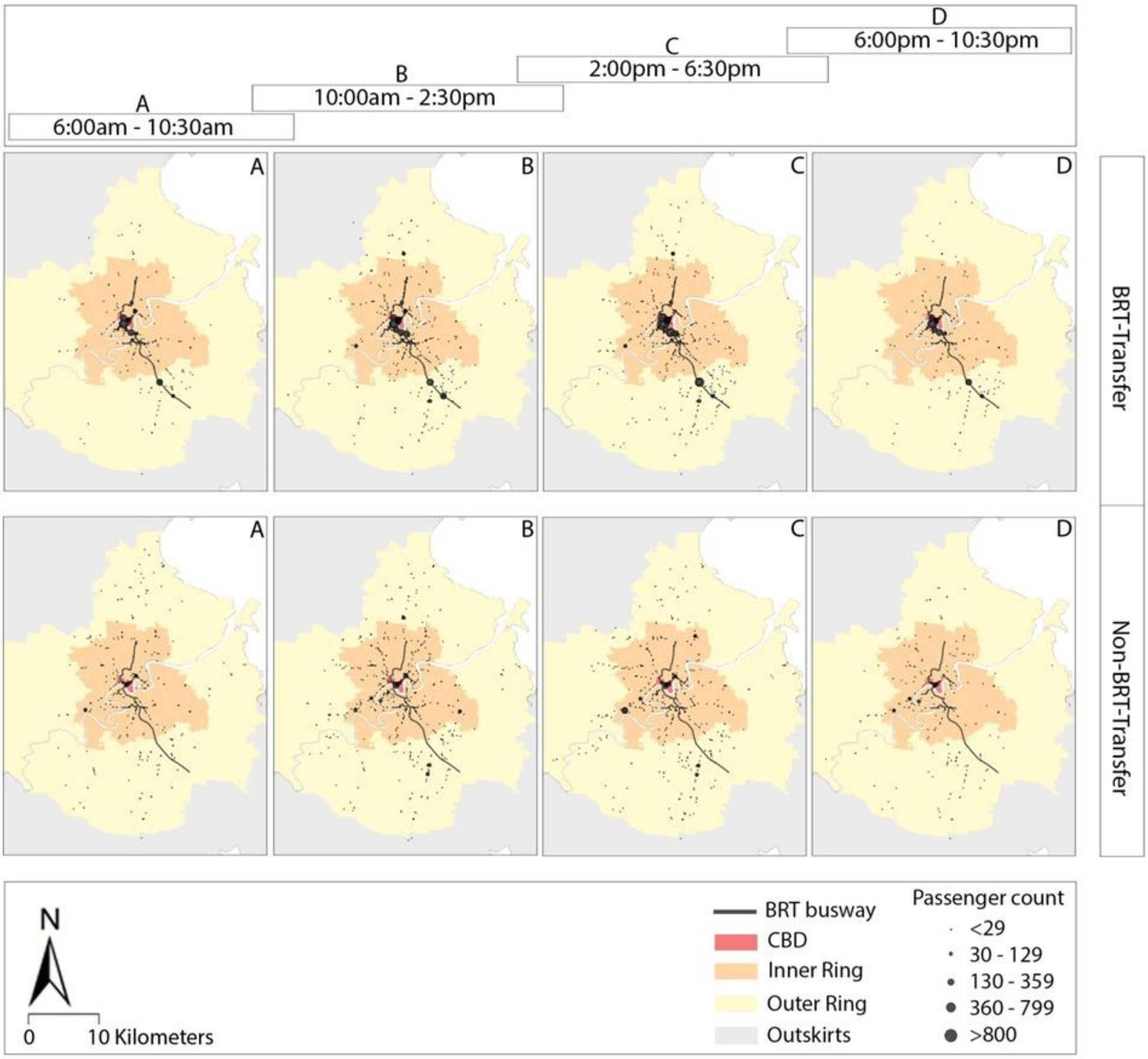


Figure 6.23 Comap of transfer patterns on Sunday (by time of day)

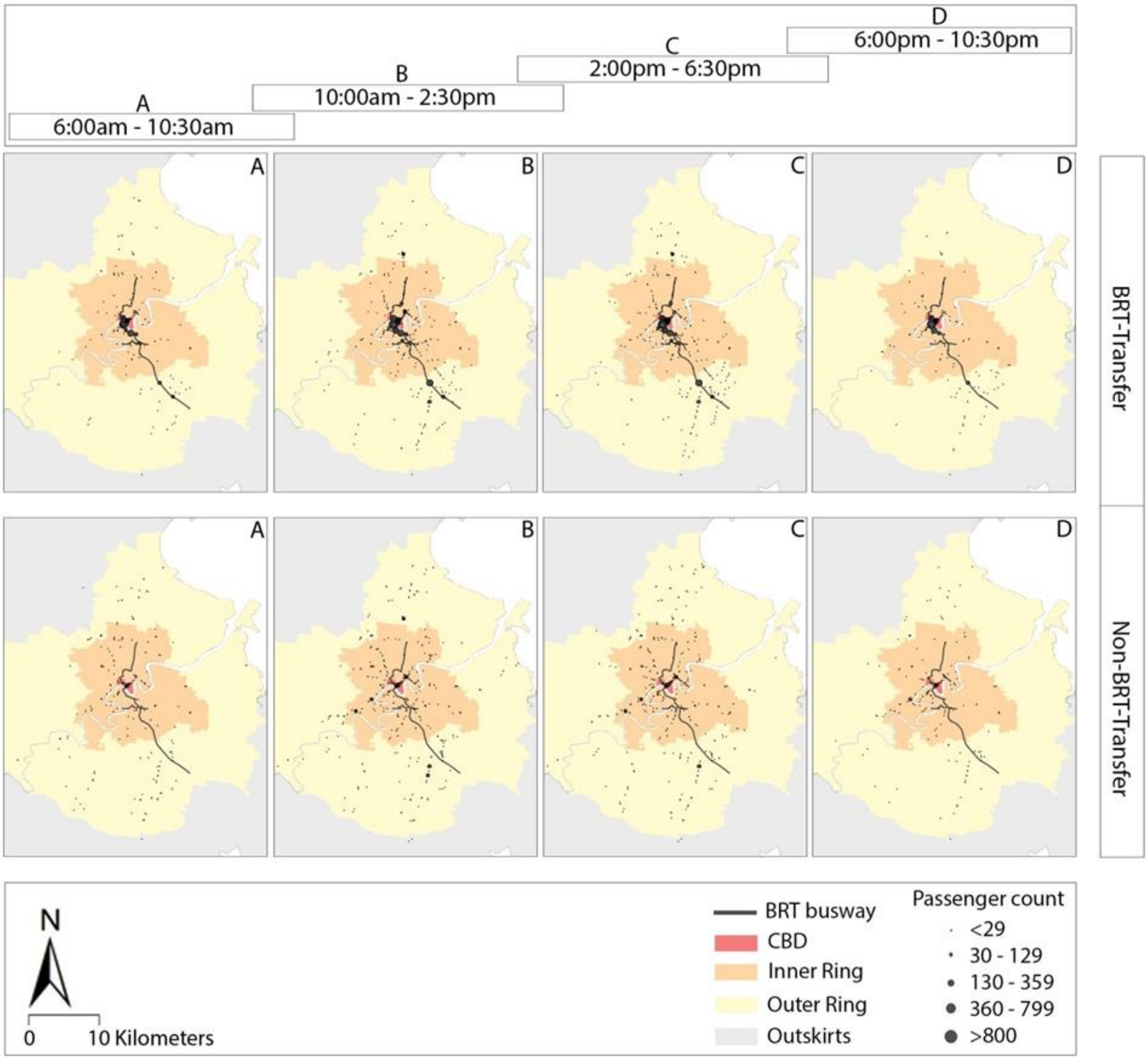
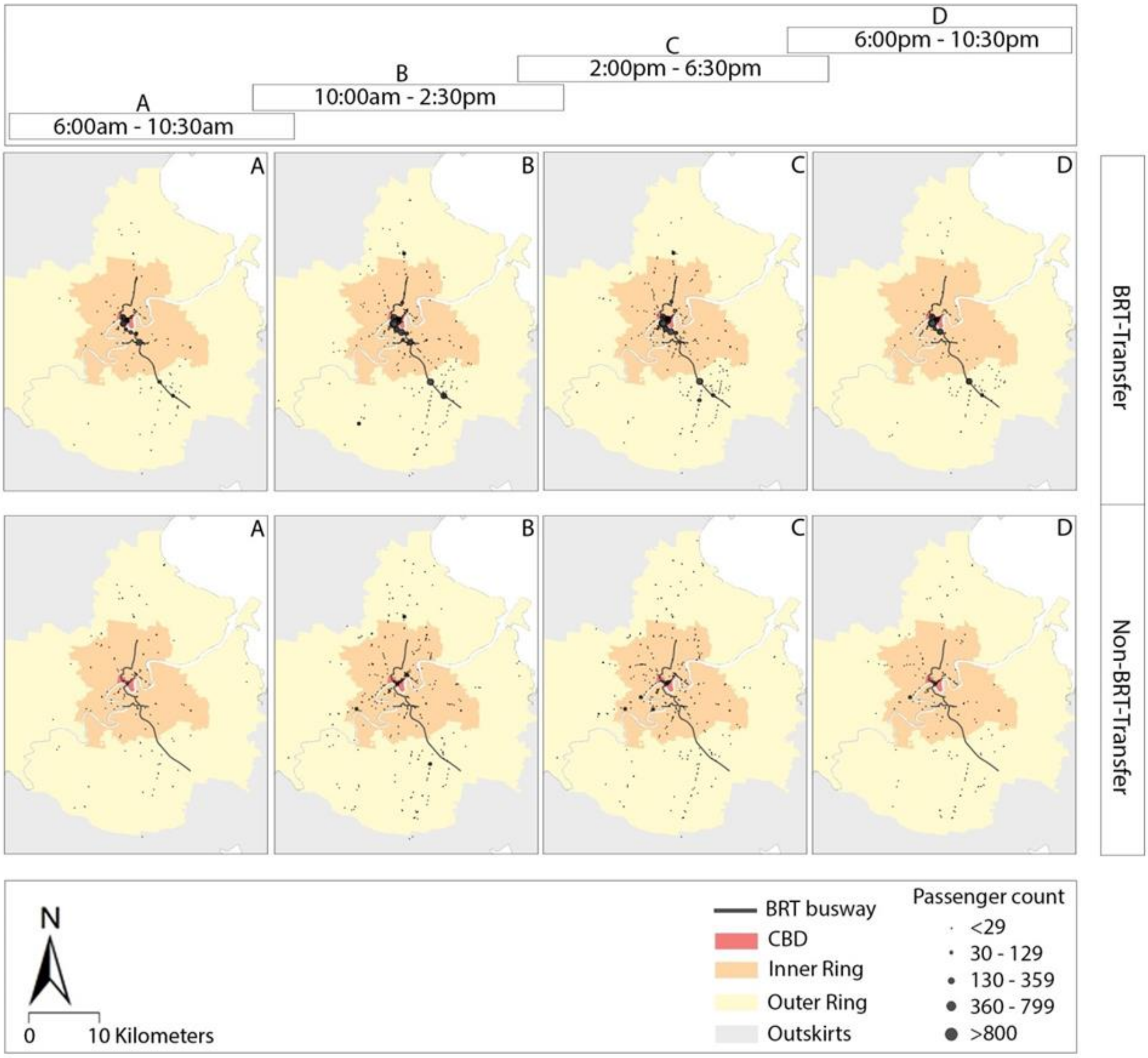


Figure 6.24 Comap of transfer patterns on public holiday (by time of day)



6.6 Passenger flow patterns

Based on the investigation of the stop-level behaviours, this section next explores and compares the spatial-temporal dynamics of passenger flow patterns between BRT and non-BRT trips using the flow-comaps.

Allied with the previous co-maps, the flow-comaps are aligned along vertical and horizontal directions. The vertical direction indicates the continuous temporal segments over a day, i.e., morning (6:00am to 10:30am), noon (10:00am to 2:30pm), afternoon (2:00pm to 6:30pm) and night (6:00pm to 10:30pm). On the horizontal direction, each row belongs to one non-spatial category (e.g., BRT inbound trips, non-BRT outbound trips).

The Jenks natural breaks of the average flow volumes on the workday were calculated as the benchmark for other dates. The flow-comaps did not quantify the spatial distribution (i.e., spatially dispersed or concentrated) of the flows. To add to this information, coefficient of variation (CV) was calculated and added to the right corner of the maps following the algorithm noted in Bell et al (2002). High values of CVs indicate more spatially dispersed patterns, and vice versa.

6.6.1 Flow-comaps of five calendar events

Based on the above description, Figures 6.25 to 6.29 individually depict the flow-comaps of BRT and non-BRT trips for the five calendar events. Across the five dates, both BRT and non-BRT trips have shown a radial pattern that connects the CBD with the immediate and farther suburbs, which is reasonable considering the mono-centric urban structure of Brisbane (BITRE, 2013; Mees and Dodson, 2011). Nonetheless, some systematic distinctions concerning the spatial-temporal variations of the major flow pathways can be identified between the BRT and non-BRT trips.

The flow-comaps on the workday (Figure 6.25) and school holiday (Figure 6.26) are first analysed in juxtaposition, given their similar spatial-temporal patterns. For BRT inbound trips, numerous pathways with high flow volumes formed during the morning period, originating from a number of locales around Brisbane and moving towards the CBD or surrounding areas. As time moved on, while the number of the major pathways decreased, several pathways with relatively high flow volumes remained and persisted throughout the day before evening, channelling into the CBD from the locales including Chermside Shopping Centre, Stafford Heights and the Gap in the north, Inala, Sunnybank Hills and Eight Mile Plains in the South, Indooroopilly Shopping Centre in the west and Carindale Shopping Centre in the east (refer to Figure 6.13). Along these identified pathways, a reversed pattern can be observed for the BRT outbound trips, wherein the amount and passenger volumes of the major flows reached their peak in the afternoon, while diminishing during the rest of the day.

Over these two dates, an examination of non-BRT trips, while indicating similar peak-hour patterns to those found for BRT trips, highlights relatively distinct spatial flow patterns of passengers. For the inbound and outbound trips, well-defined pathways with lower flow volumes can be identified respectively for the morning and afternoon. These pathways connected the CBD with the locales including the Gap, Toombul Shopping Centre, the University of Queensland on the edge of or within the inner ring of Brisbane, as well as Moggill, Riverhills and Tingalpa in the outer ring area (Refer to Figure 6.13). During the rest of the days, many of these pathways vanished drastically. Only a few short pathways among the CBD, the University of Queensland and New Farm Park remained observable.

Examining each of the CVs indicates that both BRT and non-BRT trips were more spatially dispersed during the morning and afternoon periods. Additionally, non-BRT trips were less spatially concentrated than the BRT trips.

A further examination of Figures 6.25 and 6.26 reveals more discernible spatial patterns concerning BRT trips in the south compared to those in the north separated by the Brisbane River. In the south area, several high volume pathways originated from the locales including Inala and Sunnybank Hills (refer to Figure 6.13) and fed into the South East Busway (SEB). In northern Brisbane, a number of strong pathways can be identified as well, i.e., the pathways connecting Stafford Heights, Everton Hills, the Gap and Indooroopilly Shopping Centre with the CBD. However, by comparing the spatial patterns of the northern pathways to the spatial layout of the Northern Busway (NB), it appears that a considerable number of trips following these pathways appear to use only a small section of the NB due to the limited overlap between the two. This suggests that the SEB serves as a stronger collector corridor than the NB. This difference conforms with the findings from a previous study by Currie and Delbosc (2010), where it was suggested that the majority of Brisbane's BRT ridership occurred on the SEB.

In addition to the distinction of BRT usage patterns in the south and north, a further examination shows that two high-volume pathways originated from the inner eastern (Carindale Shopping Centre) and inner western (Indooroopilly Shopping Centre) suburbs and respectively fed into the busway network at Buranda and the CBD. This indicates the existence of consistent and high demand for bus service along these two corridors.

Figure 6.25 Flow-comap for BRT and non-BRT trips on workday (by time of day)

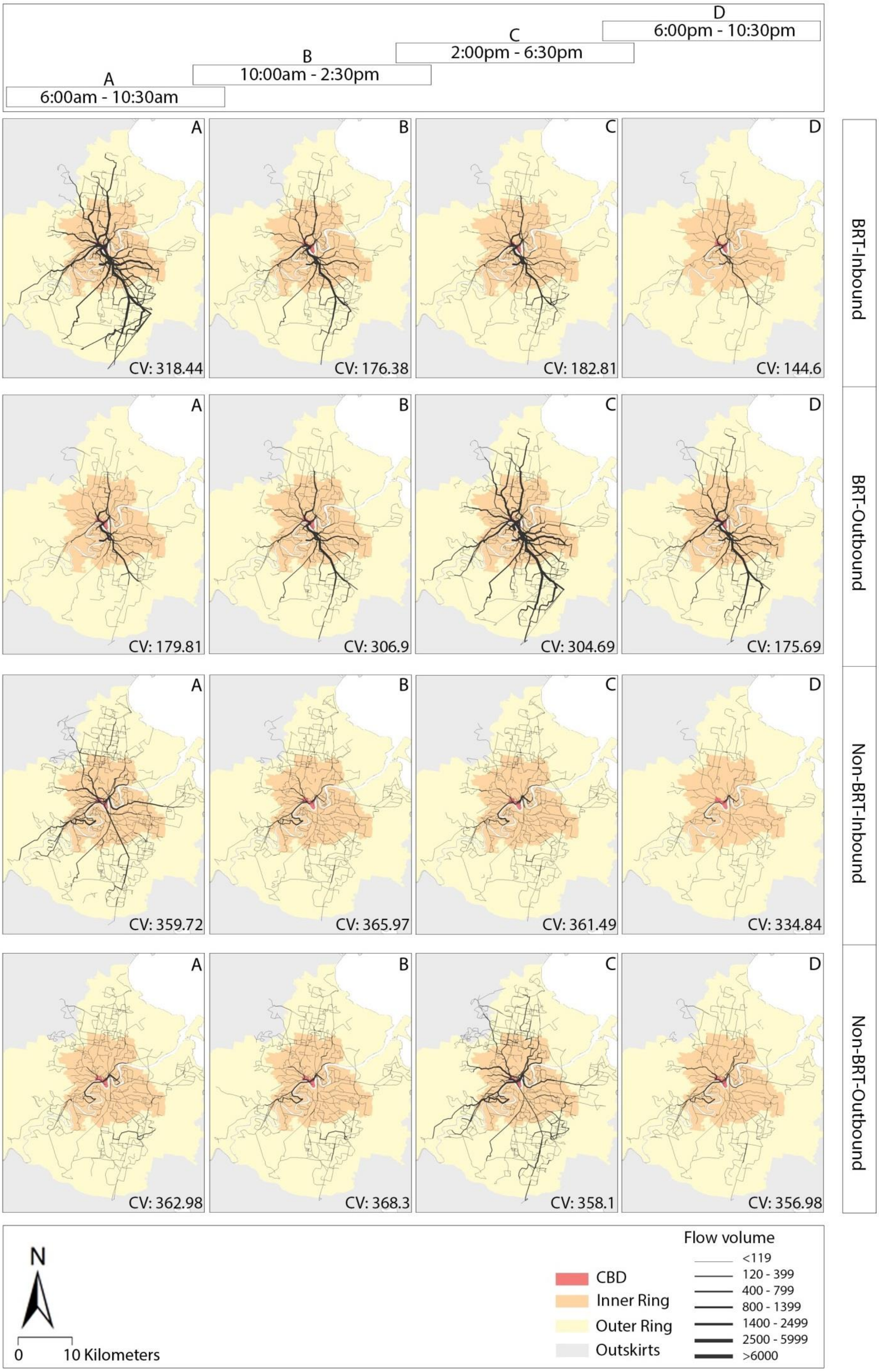
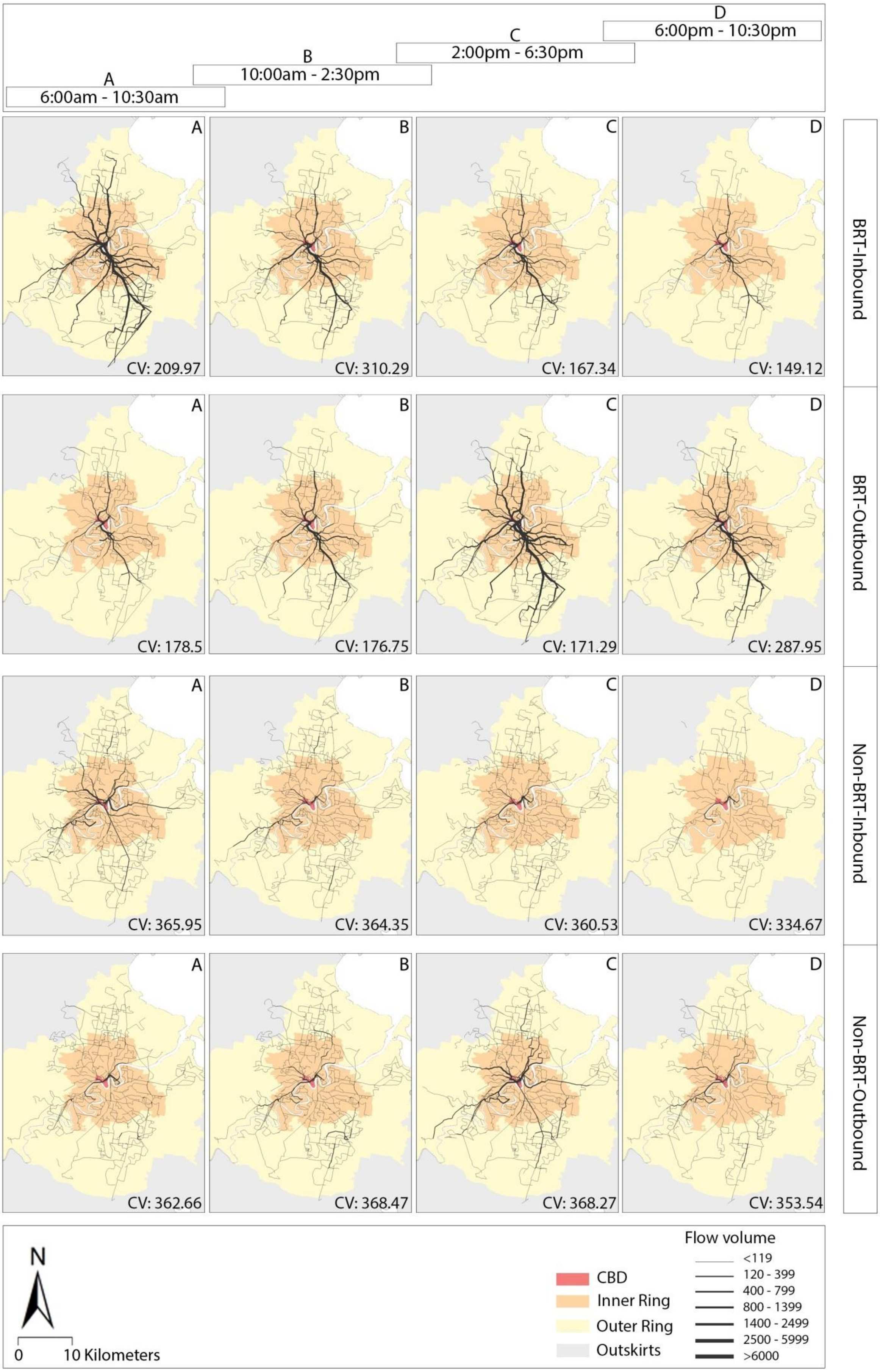


Figure 6.26 Flow-comap for BRT and non-BRT trips on school holiday (by time of day)



Figures 6.27 and 6.28 depict the passenger flow patterns of BRT and non-BRT trips on the Saturday and Sunday. Compared to the workday and school holiday, the spatial patterns and flow volumes of the major pathways on these weekend days are more consistent over the 24 hour period, which agrees with the above findings concerning the temporal boarding patterns.

For BRT trips, it can be found that the major pathways largely overlapped with their counterparts of the workday and school holiday (except for the morning and afternoon peak hours), including those linking suburbs (i.e., Stafford Heights, Inala, Eight Mile Plains and Runcorn) and shopping centres (i.e., Chermside, Carindale and Indooroopilly Shopping Centres, refer to Figure 6.13) with the CBD and surrounding areas.

For non-BRT trips, only a short linkage between the University of Queensland and the CBD remained observable over the two dates, while the majority of the pathways found on the workday and school-holiday disappeared. This indicates a considerable reduction of travel needs for the remainder of the bus services on the weekends.

A scrutiny of the CVs again showed that non-BRT trips were less spatially concentrated compared to the BRT trips, suggesting the existence of lower level and dispersed distribution of passenger demand for the on-road bus services. This might be attributed to the dispersed nature of both urban structure and bus network in Brisbane.

Last, Figure 6.29 depicts the flow-comaps on the public holiday. The flow-patterns on this date are rather similar to that of Sunday, with overlapping of major pathways and further reduction of passenger volumes along the pathways.

Figure 6.27 Flow-comap for BRT and non-BRT trips on Saturday (by time of day)

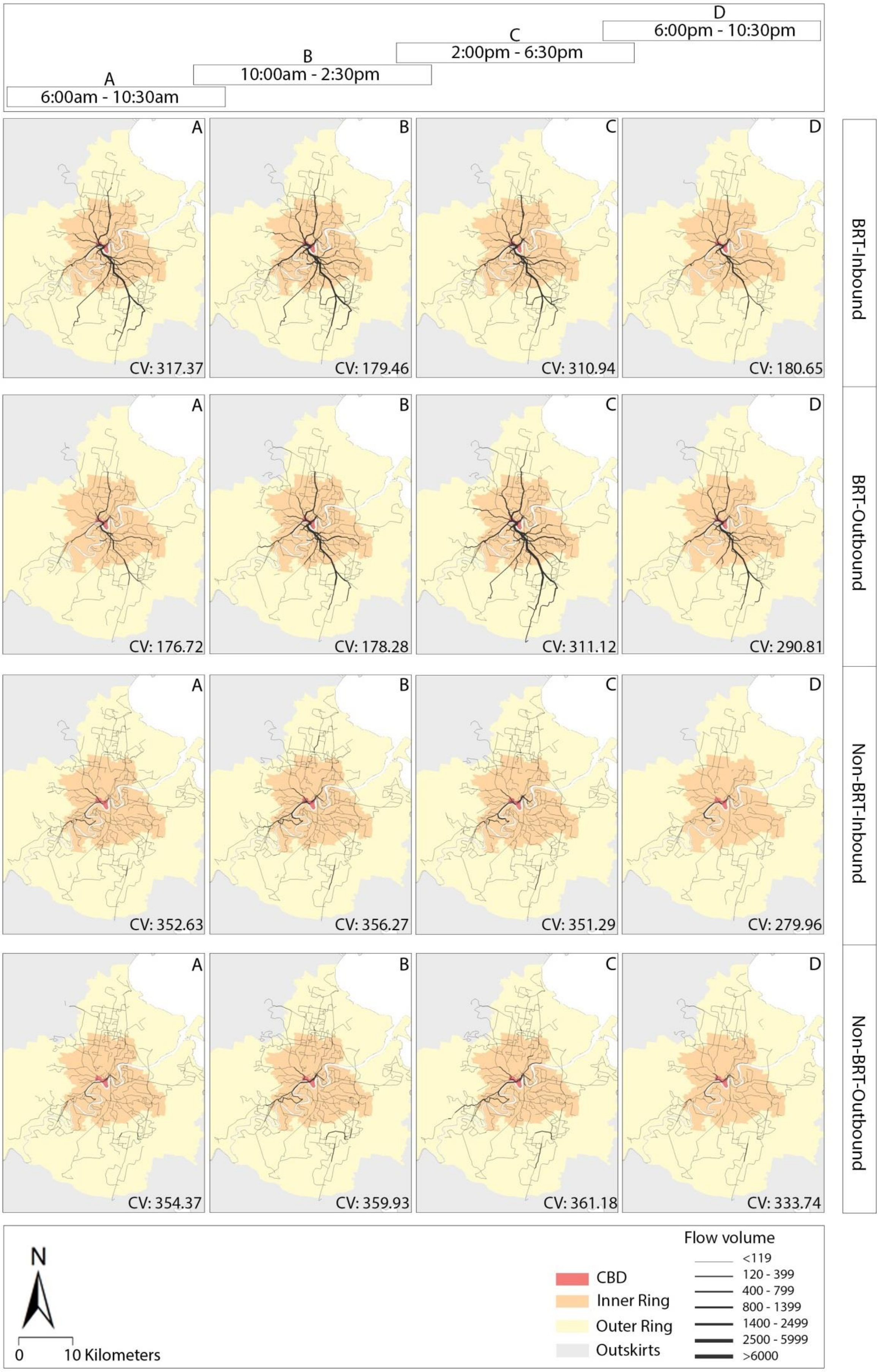


Figure 6.28 Flow-comap for BRT and non-BRT trips on Sunday (by time of day)

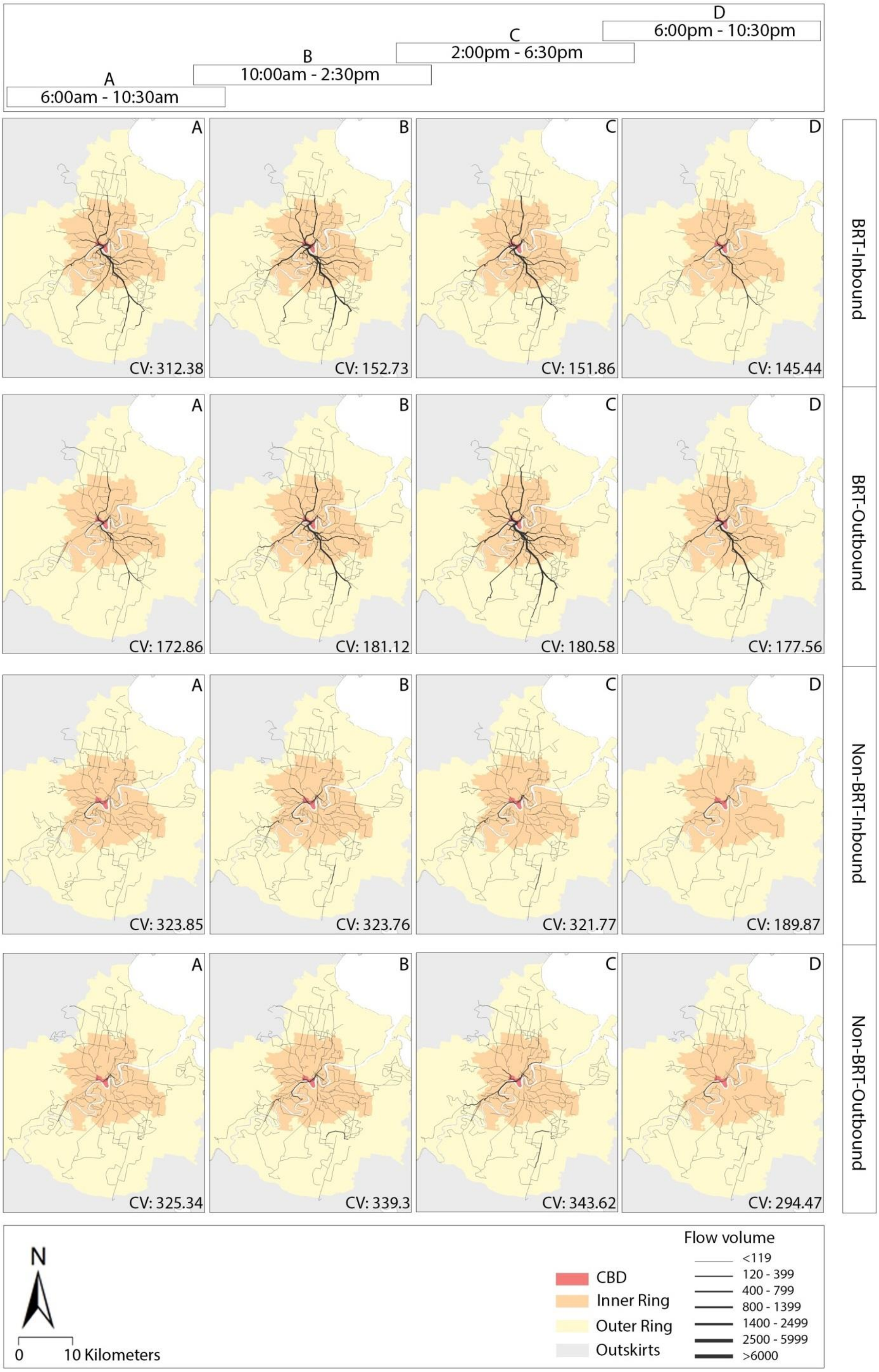
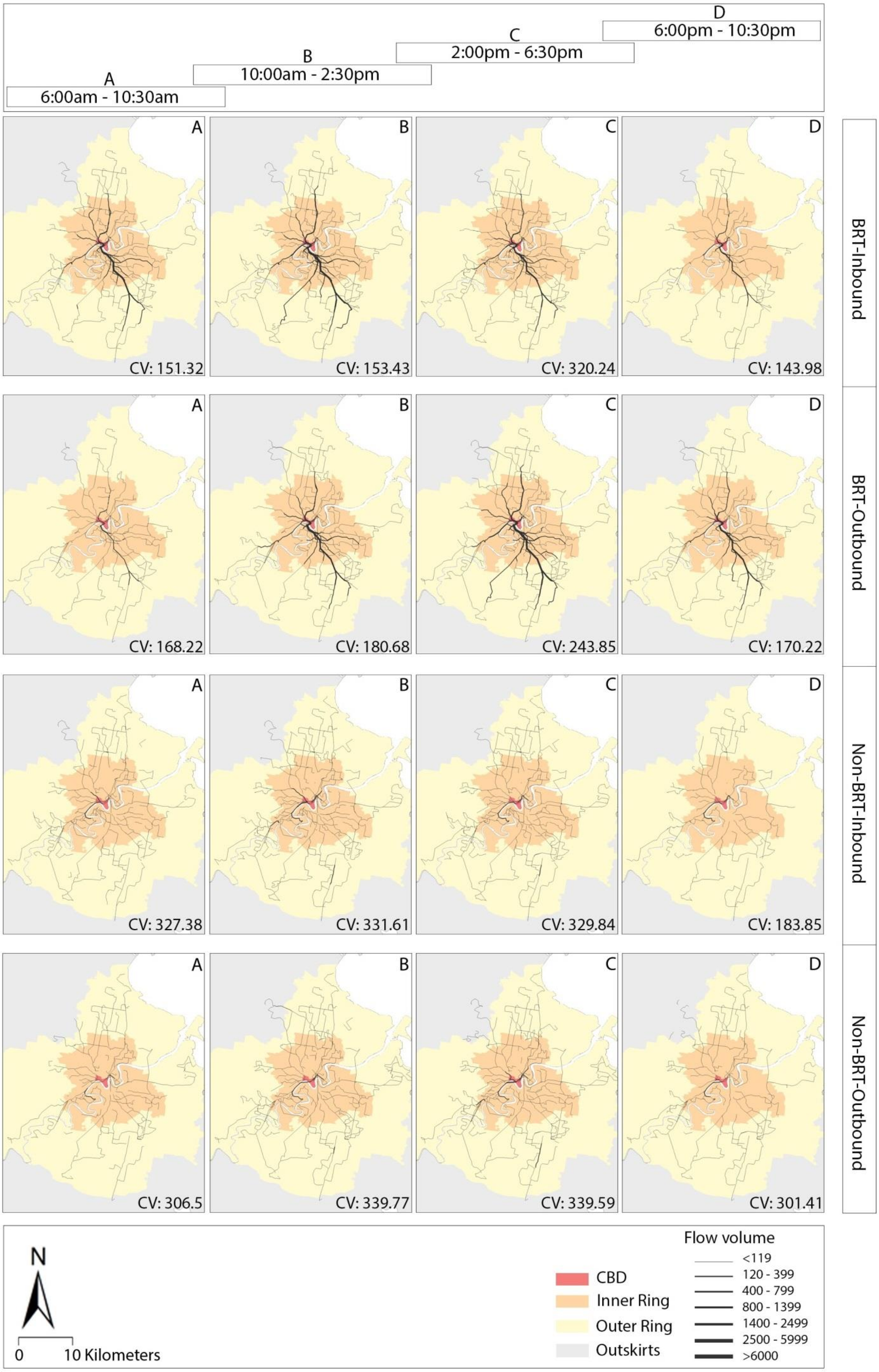


Figure 6.29 Flow-comap for BRT and non-BRT trips on public holiday (by time of day)



The median values of flow volumes (passenger count) and load factors (passenger count per vehicle) at the stop-to-stop segment were also calculated to quantify the network-level demand for the BRT and the remainder of the bus services. In the calculation of load factors, the 'run' entry of the smart card records was used to count the number of vehicles running between two stops, since each run number equates to the 'block number' of a bus route. And according to the GTFS data, a block *'consists of two or more sequential trips made using the same vehicle'* (Google Developers, 2012). An issue with this approach is that a small proportion of trips have 'run' values equating to 'route' number. However, considering that this issue existed for approximately less than 0.13 per cent of all mini-trips (Table 6.5), its impact on results was considered marginal.

Table 6.5 Summary of records with incorrect run values

	Direction	Number of min-trips with incorrect run values	Total number of mini-trips	Percentage (%)
Workday	Inbound	6,593	2,816,459	0.23
	outbound	6,387	3,069,685	0.2
School holiday	Inbound	3,438	2,247,796	0.15
	outbound	1,694	2,405,022	0.07
Saturday	Inbound	1,490	1,230,794	0.12
	outbound	917	1,220,283	0.075
Sunday	Inbound	28	763,584	0.003
	outbound	0	834,911	0
Public holiday	Inbound	12	721,591	0.001
	Outbound	0	723,531	0
Total		20,559	16,033,656	0.128

An examination of flow volumes (the FV column in Table 6.6) shows that BRT inbound trips surpass their counterparts of non-BRT trips at most time periods of the five days in this regard, suggesting the existence of higher demand for the BRT-inbound routes. For the outbound trips, on four dates (the workday, school holiday, Saturday and Sunday), non-BRT trips had higher median flow volumes during the first half of the day (morning and noon) than BRT trips, while the reverse was observed during the second half of the day (afternoon and evening), suggesting the more critical role of BRT-outbound routes in catering for afternoon-peak-hour travel needs. On the public holiday, the flow volumes of

BRT trips were higher than that of non-BRT trips over the one day course.

In terms of load factors (the LF column in Table 6.6), on the workday and school holiday, some differences can be observed between the BRT and non-BRT trips. Yet no obvious pattern exists. On the remaining three dates (i.e., the Saturday, Sunday and public holiday), the patterns were similar to that of flow volumes observed on the workday and school holiday. In other words, BRT routes again experienced higher demand than non-BRT routes across the different calendar events in terms of passenger load factor.

Table 6.6 An examination of flow volumes

	Morning (median)		Noon (median)		Afternoon (median)		Evening (median)	
	FV	LF	FV	LV	FV	LF	FV	LF
Workday								
BRT-Inbound	42	4.8	22	3.2	15	2.3	11	2.2
BRT-Outbound	9	2	13	2.3	36	4.3	22	4
Non-BRT-Inbound	26	4.8	14	2.8	16	3	4	1.6
Non-BRT-Outbound	13	3	15	2.9	27	5	10	2
School Holiday								
BRT-Inbound	40	4.1	18	3	15	2.6	12	2.8
BRT-Outbound	7	1.8	13	2.6	30	3.3	18	3.5
Non-BRT-Inbound	18	2.7	17	3.2	13	2.7	7	2
Non-BRT-Outbound	10	2.3	17	3	22	3	11	2.2
Saturday								
BRT-Inbound	16	3.7	21	3.4	18	3	14	3
BRT-Outbound	9	2.2	12	2.5	19	3.4	18	3.3
Non-BRT-Inbound	8	2.5	14	3	12	2.5	6	2
Non-BRT-Outbound	7	2.5	16	3	13	2.7	7	2
Sunday								
BRT-Inbound	13	4	19	3.8	16	3.1	8	2.4
BRT-Outbound	9	2.2	12	2.8	22	4	16	3.4
Non-BRT-Inbound	7	2.3	13	2.6	12	2.4	5	1.6
Non-BRT-Outbound	6	2.6	14	2.7	13	2.6	7	2
Public holiday								
BRT-Inbound	13	4	16	3.4	16	2.9	8	2.6
BRT-Outbound	6	2	12	3	22	2.8	16	3.5
Non-BRT-Inbound	5	1.8	10	2.1	8	2	4	1.8
Non-BRT-Outbound	3	1.5	9	2	12	2.2	7	2

An examination of the IRSAD pattern (Figure 6.14) in conjunction with the previous flow patterns (particularly Figures 6.25 and 6.26) suggests that while Brisbane’s BRT and non-BRT serve for both advantaged and disadvantaged suburbs, certain distinctions may exist between the catchments and possibly passengers of the two sectors. Specifically, compared to the flow-patterns of BRT trips, the major pathways of non-BRT trips concentrated more in the suburbs of the inner north and outer west of Brisbane, where higher spatial concentration of advantaged suburbs can be observed. Hence, BRT possibly serves for catchments with more mixed socio-economic status along its major pathways compared to the non-BRT counterparts. Such difference suggests that compared to the non-BRT component, the BRT system might have played a more crucial role in improving urban mobility for disadvantaged travellers. Additionally, the major reduction of non-BRT patronage on the weekend and public holiday suggests that, many (and possibly more socio-economically advantaged) travellers only used non-BRT routes at particular time periods (e.g., workdays) while switching to alternative transport (e.g., cars) during other time periods (e.g., weekends).

6.6.2 Comparative analyses of flow-comaps

The results of interrogating the flow-comaps and the existing travel demands (in terms of passenger volume and load factor) are of use in unveiling the major spatial pathways and their variations over the course of a day. Nonetheless, these results are less effective for detecting the more subtle yet important temporal changes of passenger flow patterns. For example, over a one-day period, some linkages might have experienced marked shifts in their roles of carrying passengers compared to the other linkages within the network. To further capture such temporal changes in BRT trips and examine its distinctions from non-BRT trips, it is of value to quantify the differences between flow-patterns of different time windows as the next logically analytic step (Tao et al., 2014a).

To achieve this goal, another type of flow-comaps, *weighted flow-comaps,* a variant of flow-comap (Tao et al., 2014a) were computed. This was achieved by calculating the differences between two map windows (e.g., the difference between two periods of time such as noon versus morning map windows) based on the percentage of the flow-volume for each stop-to-stop segment. This percentage of flow-volume, termed as *‘flow-weight’*, which reflects the relative significance of one stop-to-stop segment compared to the remainder of the bus network in carrying passengers. The differential values of flow-weights were standardised by dividing by the sample standard deviation (the result was binned into categories ranging from <-2.5 to >2.5 for display). Positive values indicate an increase of flow-weights, and vice versa.

Figures 6.30 to 6.34 depict the changes in passenger flow patterns across the five calendar events. The morning flow-patterns were used as the baseline for quantifying differences for other time periods (noon, afternoon and evening). Over the five dates, the major changes of flow patterns occurred along the major pathways observed on the previous flow-comaps. Yet, some marked differences between the BRT and non-BRT trips can be highlighted.

For BRT trips on the workday (Figure 6.30) and school holiday (Figure 6.31), a comparison of inbound and outbound passenger flows highlights markedly distinct patterns between the trips related to the NB and the ones on the SEB. More specifically, regarding inbound passenger flows from morning to the rest of the day, increases of flow-weights can be observed on the pathways along the NB (between the CBD and Kedron Brook). By comparison, the flow-weights on the SEB (between the CBD, the University of Queensland and Eight Mile Plains) experienced considerable reductions during the same time periods (i.e., from morning to the rest of the day). Yet an examination of outbound flows shows that the greatest increase of flow-weights occurred on the SEB. By contrast, the NB experienced less marked and spatially discontinuous increases of flow-weights. Given these differences, the passenger flows related to the SEB showed a stronger peak-hour pattern compared to the ones of the NB. A plausible explanation for this distinction is that BRT passengers using the SEB and the ones using the NB have different activity (e.g., working) schedules.

For non-BRT trips on these two dates, allied with the previous flow-comaps, the changes in flow-weights show strong commuting-based patterns. For inbound flows, the major increases of flow weights occurred along the pathways between the CBD and surrounding locales (including the University of Queensland), while for outbound flows, marked declines of flow-weights can be observed along these pathways. A reverse pattern can be identified for the flows along the relatively longer pathways that connect the CBD with locales including the Gap, Fortitude Valley, Moggill and Tingalpa. Additionally, comparing the changes of BRT-based flow-patterns to non-BRT trips again confirms the spatially complementary roles of the two (i.e., the BRT and non-BRT) in catering for people’s travel needs.

On the Saturday (Figure 6.32), Sunday (Figure 6.33) and public holiday (Figure 6.34), for inbound passenger flows of BRT trips from morning to the rest of the day, the major increases of flow-weights persisted along the NB, as well as the pathways between the CBD and the locales including Carindale (particularly on Sunday) and Indooroopilly Shopping Centre, whereas a major decrease appeared along the SEB. The reverse patterns were found for outbound passenger flows of the NB and the SEB. Moreover, compared to the morning period, the outbound passenger flows along the NB experienced a pronounced decrease of flow-weights during the rest of the days, which differs from the patterns observed on the workday and school holiday wherein increases of flow-weights were observed. By contrast, the temporal changes in passenger flow patterns associated with the SEB appear to be more consistent between different dates. These observations again suggest the possibility that distinguishable activity schedules persist between the BRT users of the SEB and the ones using the NB.

In regards to non-BRT trips, the changes of passenger flow patterns on these three days to a considerable degree resemble their counterparts on the workday and school holiday, with major changes of flow-weights observed along the pathways identified previously. It also appears that marked increases can be identified for outbound flows along the pathways in the more distant areas (e.g., the pathways between Indooroopilly Shopping Centre and Moggill, between Chermside Shopping Centre and Bracken Ridge, and between Sunnybank Shopping Centre and Sunnybank Hills). The changes along these pathways across the three dates are also explainable, given that more shopping trips occurred along these linkages between residential suburbs and their nearby shopping centres.

Figure 6.30 Weighted flow-comap for BRT and non-BRT trips on workday (Morning as baseline)

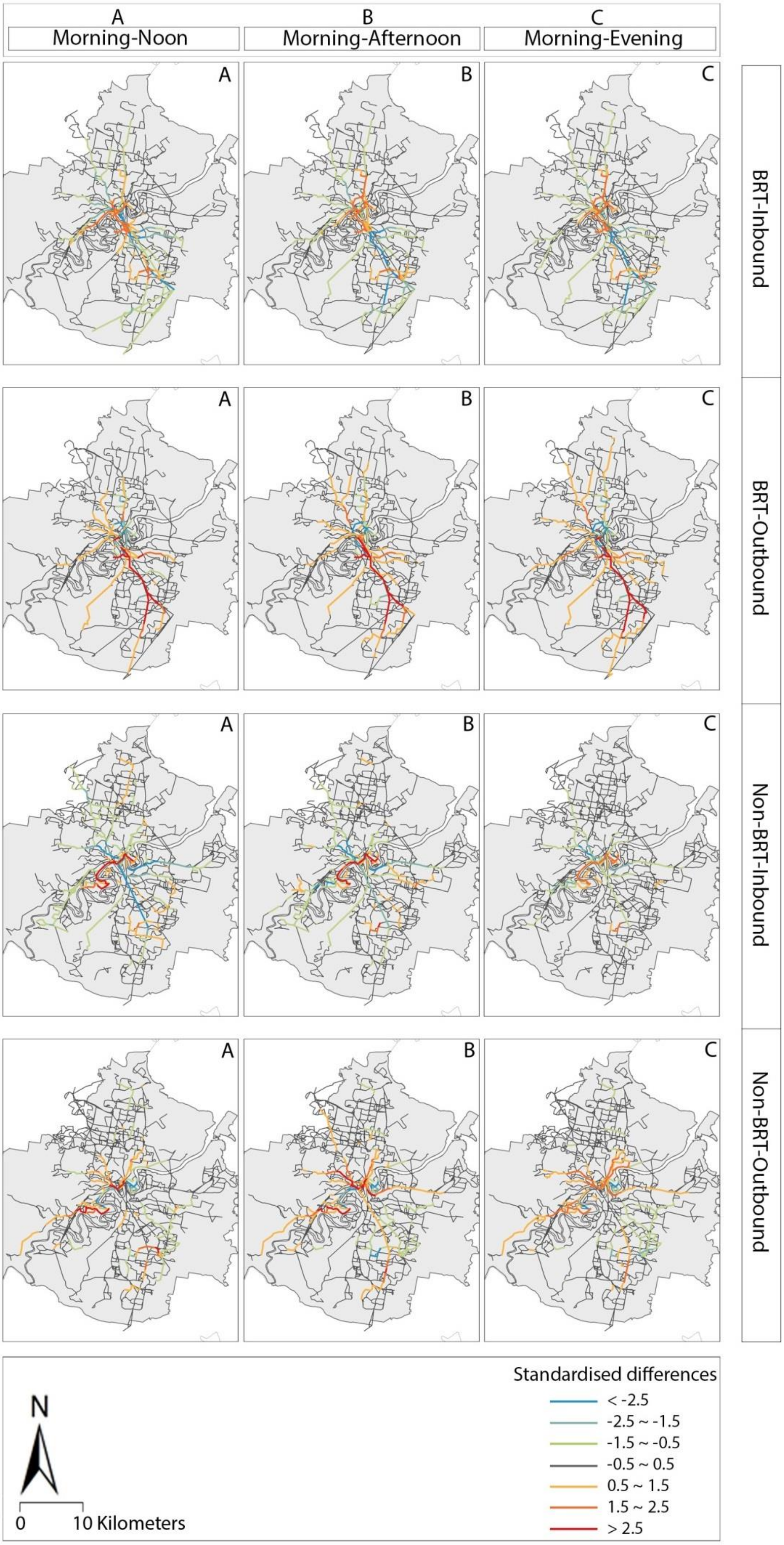


Figure 6.31 Weighted flow-comap for BRT and non-BRT trips on school holiday (Morning as baseline)

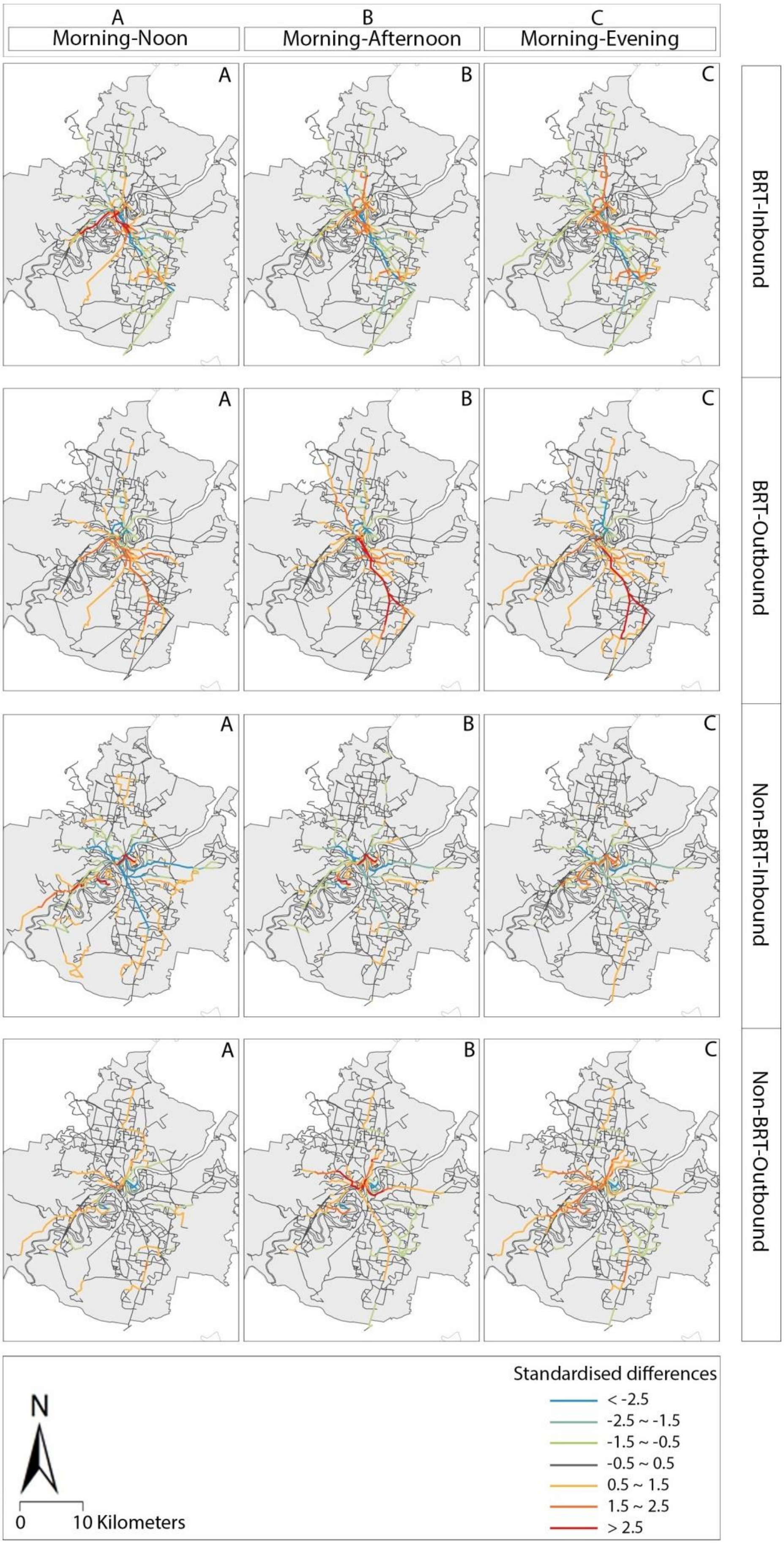


Figure 6.32 Weighted flow-comap for BRT and non-BRT trips on Saturday (Morning as baseline)

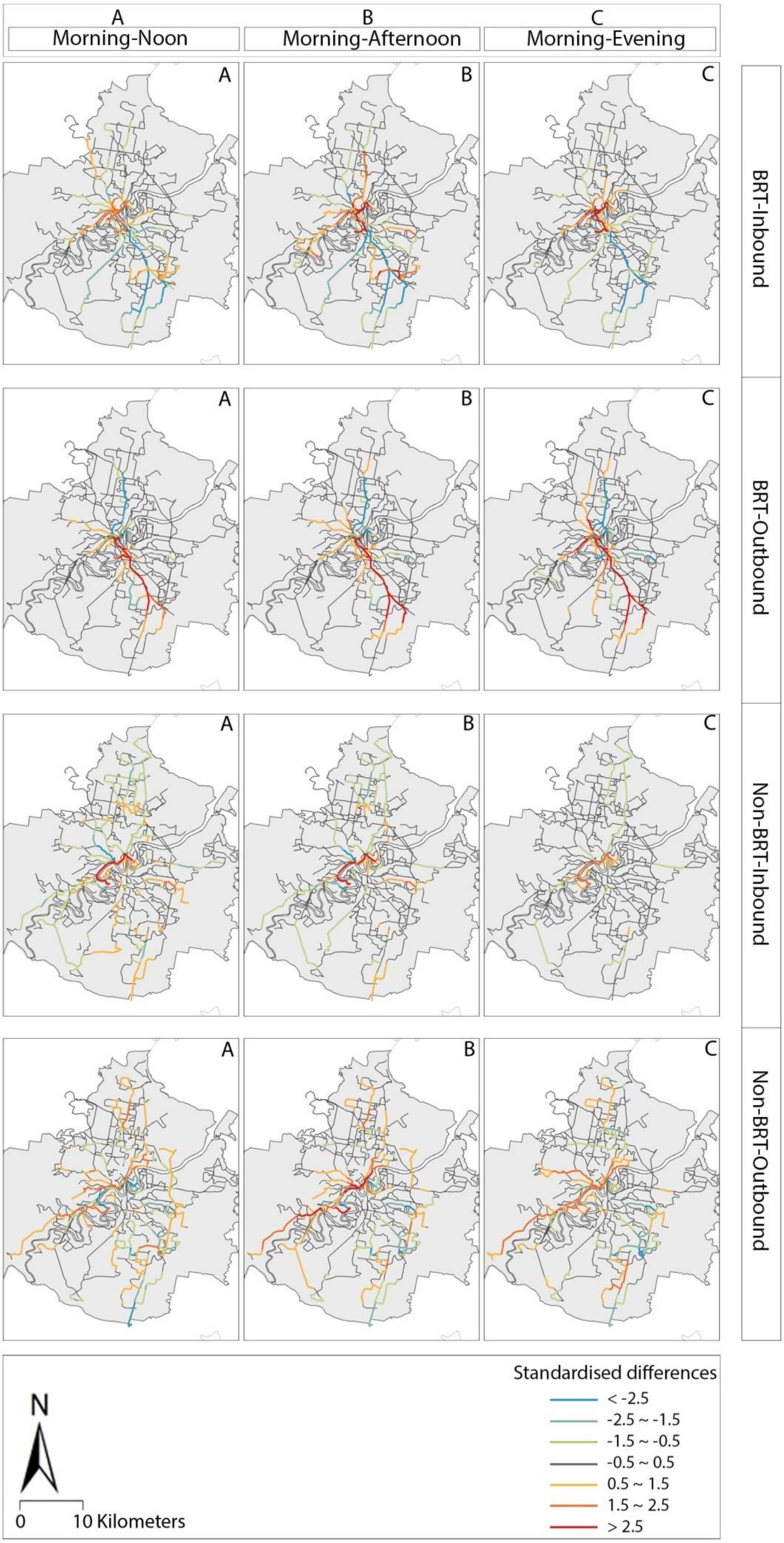


Figure 6.33 Weighted flow-comap for BRT and non-BRT trips on Sunday (Morning as baseline)

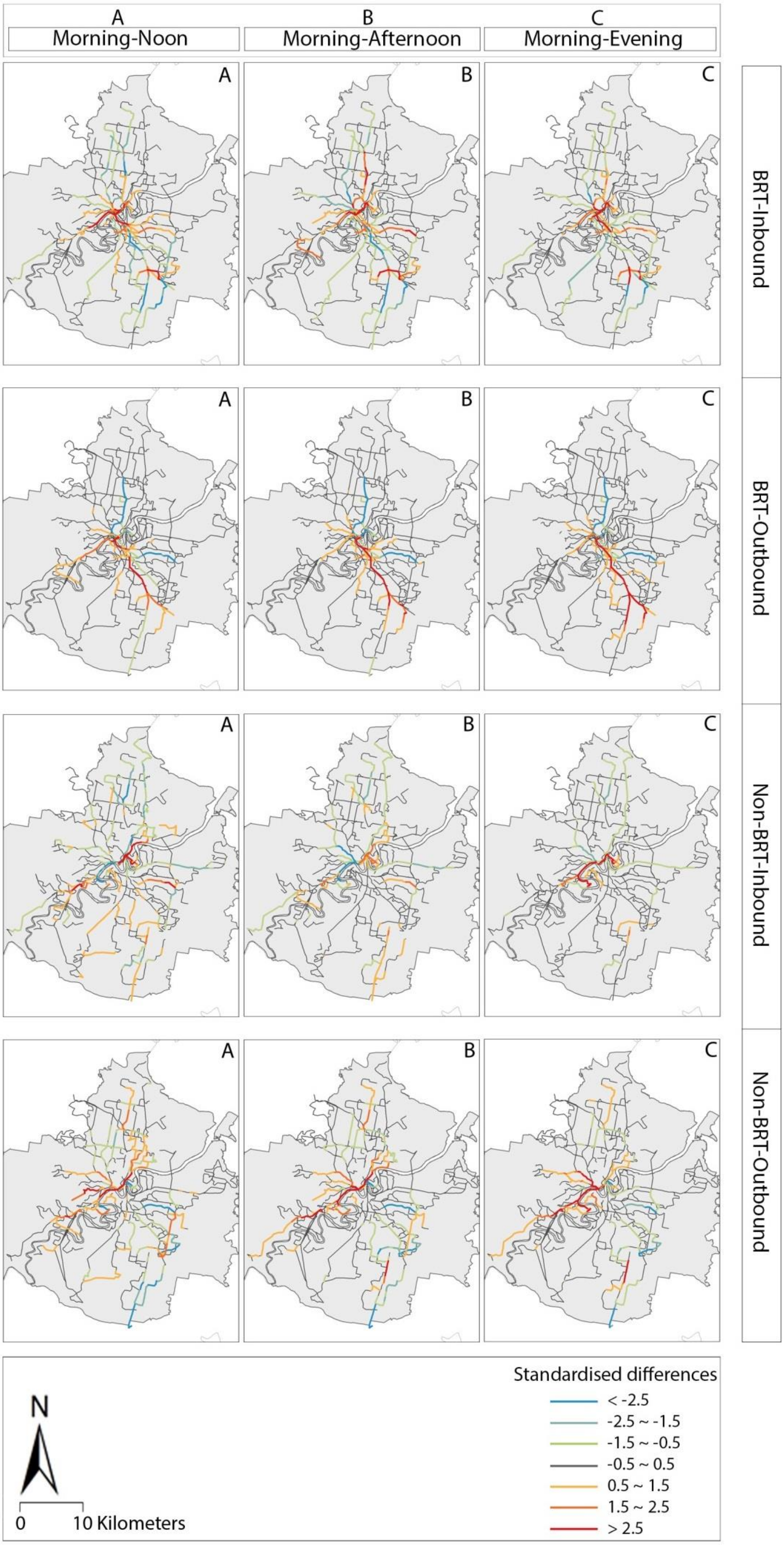
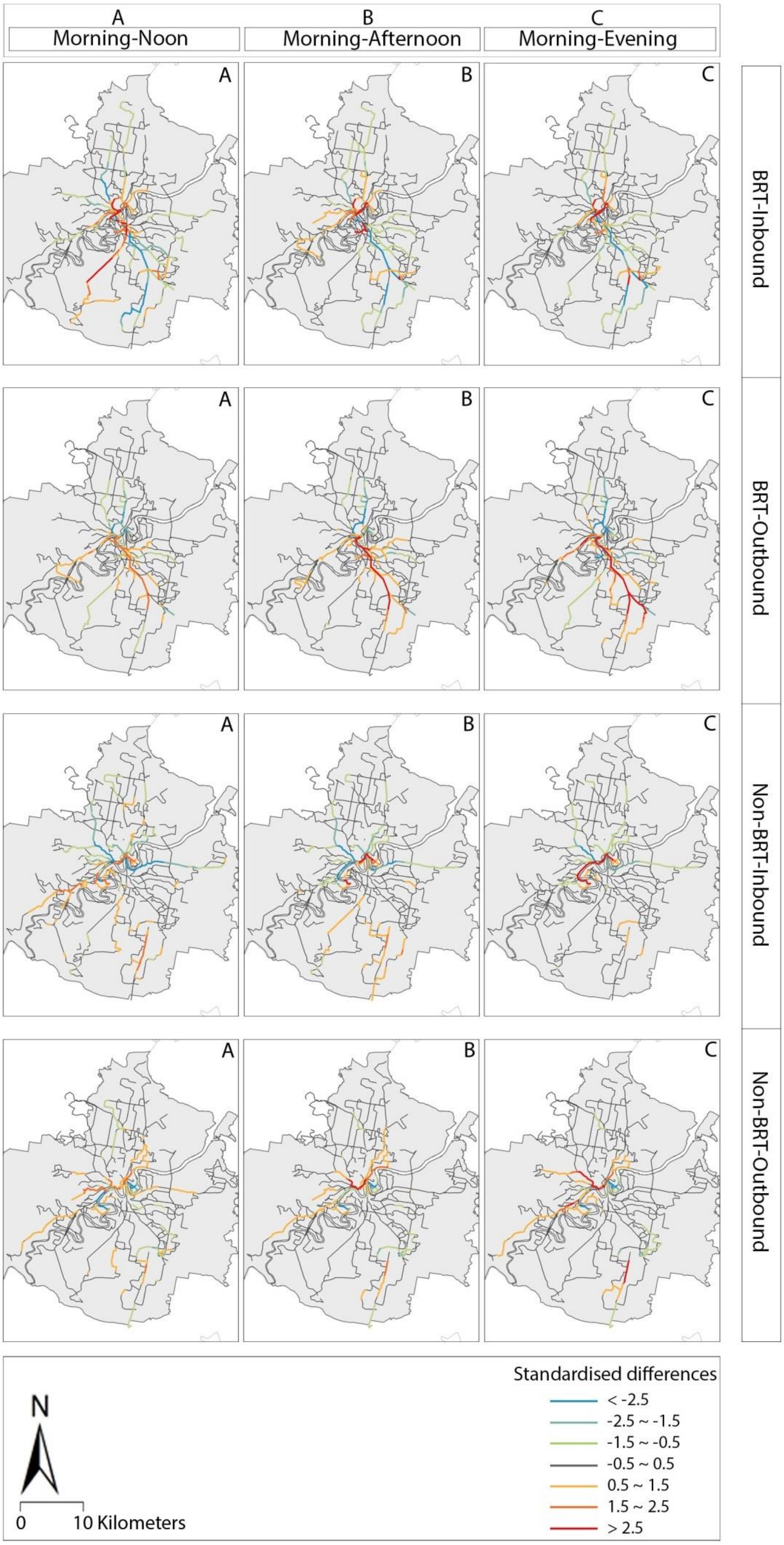


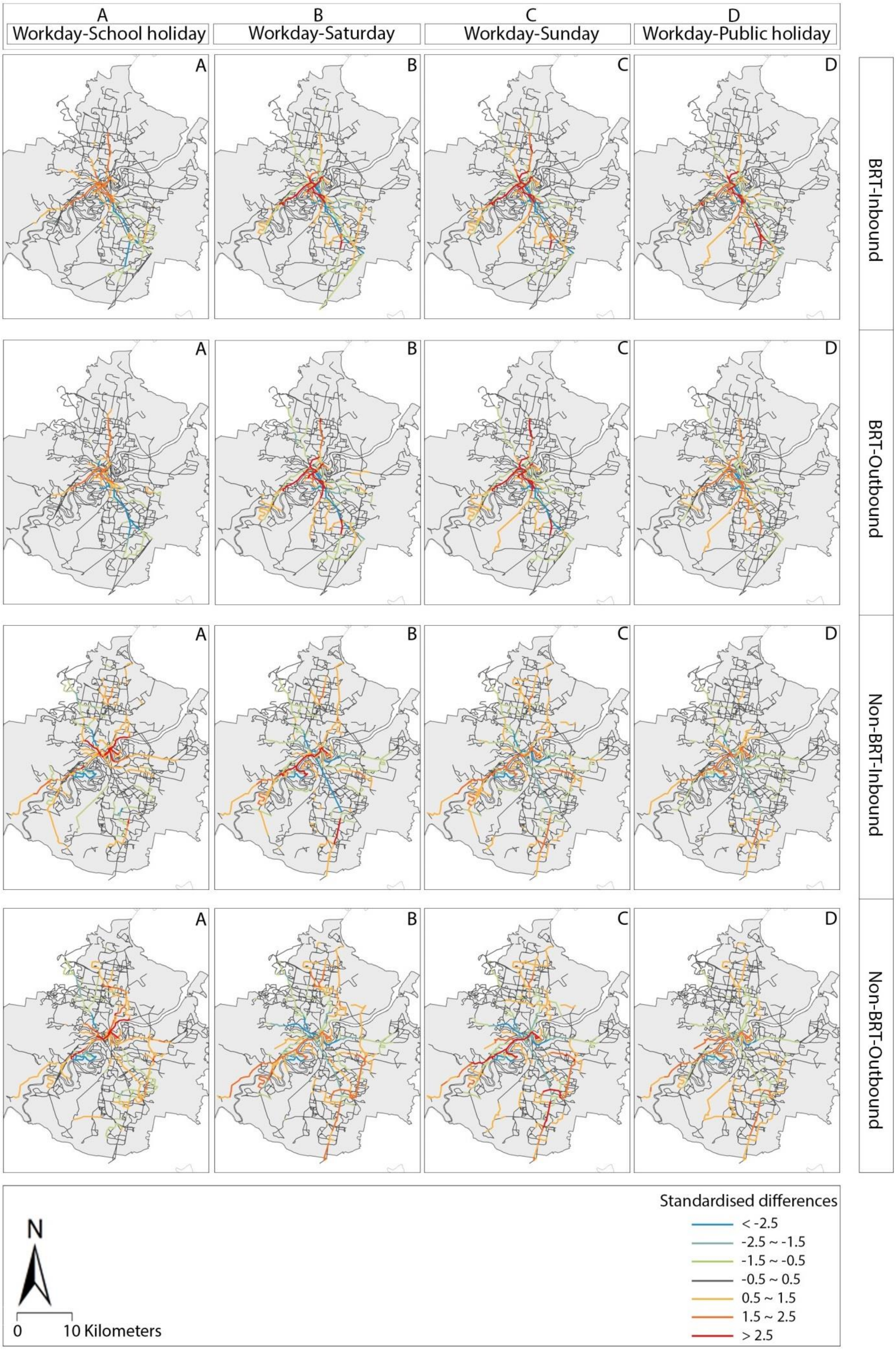
Figure 6.34 Weighted flow-comap for BRT and non-BRT trips on public holiday (Morning as baseline)



Finally, Figure 6.35 quantifies the changes of flow-patterns between different days, with the workday as the baseline. In a comparison between BRT trips taken on the workday and those on the other dates, the major pathways located along the NB (between the CBD and Chermside Shopping Centre) and in western Brisbane (between the CBD and Indooroopilly Shopping Centre) saw increased significance of flow-weights, while the SEB (between the CBD and Eight Mile Plains) experienced decreased flow-weights, except for the public holiday when it is likely that certain holiday activities might have been held in the CBD area. This indicates a shift of spatial patterns of travel behaviour of Brisbane bus travellers from workday to non-workdays and again, highlights the SEB as a trunk commuting corridor.

For non-BRT trips, a number of pathways around Brisbane saw increased flow-weights. It is worth noting that, for both BRT and non-BRT trips, the western pathway between the CBD and Indooroopilly Shopping Centre (and to the farther Moggill for non-BRT trips) persisted as an important corridor associated with more active trip-making of passengers in comparison with other major pathways from workday to non-workdays. Given this, while previous flow-comaps suggest two pathways for future BRT expansion, i.e., this western pathway and an eastern pathway between Coorparoo and Carindale Shopping Centre, it appears that the former might be a more suitable and preferable location for converting ordinary bus service to BRT service. Considering the higher IRSADs along the west Brisbane pathway, introducing a BRT service along this pathway has the potential to enhance the attraction of bus transit for more socio-economically advantaged travellers. Given that a direct link cannot be made between the IRSAD data and smart card data, future research is needed to further clarify this issue.

Figure 6.35 Weighted flow-comap for BRT and non-BRT trips across five days (workday as baseline)



6.7 Summary

This section has presented a series of detailed investigations concerning the spatial-temporal dynamics of BRT trips in comparison to non-BRT trips. More importantly, the developed methodology has been proved to be a powerful tool in investigating the usage of BRT and renders a number of insightful findings. The key findings of this chapter include:

- Descriptive results revealed that the BRT system was associated with a larger proportion of longer trips in Brisbane in comparison to the rest of the bus services.
- The boarding and alighting comaps rendered similar temporal patterns for BRT and non-BRT trips, with peak-hour patterns observed on the workday and school holiday, and non-peak-hour patterns on the weekend and public holiday.
- The transfer comaps indicated that the hotspots for bus-to-BRT transfer concentrated on the BRT stations.
- By comparing the spatial flow patterns between BRT and non-BRT trips, it was revealed that Brisbane's BRT busway served as a backbone component in channelling trips from northern and southern locales to the CBD and the locations on the busway, while the rest of the bus network provided a complementary service in catering for the travel demand from the rest of Brisbane.
- By investigating the detailed patterns within the BRT sector, Brisbane's south busway was found to be a stronger collector corridor in connecting the CBD with suburbs compared to the north busway.
- By computing weighted flow-comaps to quantify differences between map windows of flow-comaps, distinguishable temporal patterns were identified between trips involving the north busway and the ones on the south busway, suggesting potentially different activity patterns (e.g., different working schedules) between the north and south bus travellers.
- Through an examination of the socio-economic pattern of Brisbane, it was found that the BRT system might have benefited disadvantaged travellers by providing an enhanced mobility option.

Chapter 7 Modelling behavioural intentions using survey data

7.1 Introduction

As elaborated in Chapter 2, modelling the behavioural intentions and related attitudinal dimensions is an important component in understanding the attitude mechanisms of public transport users, which has the capability to inform the development of market strategy and soft policy options for shaping more sustainable travel behaviour (e.g., promoting UPT use while reducing private car use).

While Chapters 5 and 6 have drawn upon ABS census and smart card data respectively in order to investigate the cross-lagged and spatial-temporal travel behaviour dynamics within the BRT context, the measurement and investigation of the passengers' attitudes and the behavioural intentions behind their BRT use remained elusive. In contrast, the use of survey method, which is expounded in Chapter 4, can provide a direct measurement of BRT passengers' attitudes and allow the investigation of the attitudinal dimensions of their behaviour. Drawing on the primary data collected by a questionnaire survey, this chapter constitutes the final component of understanding BRT passenger travel behaviour by modelling the behavioural intentions of BRT passengers and related attitudinal dimensions. Two questions are the foci of this chapter:

How do BRT passengers' loyalty and behavioural change intentions vary across socio-demographic and behavioural characteristics?

How do service experience, pro-environmental responsibility and considerations of private car use influence BRT passengers' loyalty and behavioural change intentions?

The first question aims to investigate whether systematic variations of BRT passengers persist across the socio-demographic and behaviour variables. The second question seeks to detect the influences of the related attitudinal dimensions on their behavioural intentions. The analysis of the survey data reveals that a variety of attitudinal variables has significant influence on BRT passengers' behavioural intentions. Another interesting finding is that many passengers may perceive both BRT and private cars as favourable transport options that are not mutually exclusive. It is expected that important implications concerning attaining and reinforcing BRT passenger loyalty and BRT usage can be gained from the results of this chapter.

The rest of the chapter is structured as follows. Section 7.2 provides descriptive statistics concerning the socio-demographic and behavioural characteristics to detect whether serious bias exists in the sample. In accordance with the flow-chart of statistical analysis in Chapter 4, Sections 7.3 to 7.5 present the results of factor analysis, multivariate analysis of variance (MANOVA) and regression modelling in answering the two questions of Objective 3 (i.e., the interactions between the behavioural intentions and socio-demographic and behavioural characteristics, and the relationships between the behavioural intentions and related attitudinal dimensions). Finally, Section 7.6 summarises the findings from this chapter.

7.2 Descriptive results

7.2.1 Socio-demographic characteristics

Table 7.1 summarises the socio-demographic composition of the sample this chapter draws upon. This sample is also compared to the sample of the 2010 South East Queensland (SEQ) Public Transport Survey (TransLink, 2010) to examine whether serious bias is induced. Over half of the sample is female (57%), under 35 years old (57%) and with access to private cars (58%). Full-time workers (45%) and students (26%) together constitute the dominant group of the sample. Over 70% of the sample has marital status of lone person or couple without children. And the income groups are concentrated within the 400-999 (29%) and 1,000-1,999 dollars (30%) per week.

Comparing this sample to the sample of the 2010 South East Queensland (SEQ) Public Transport Survey (TransLink, 2010) does not render much difference in terms of socio-demographic characteristics (particularly gender, age and employment). It however should be noted that the proportion of persons without access to a private car is considerably lower than the finding in the survey (53%). This indicates that BRT passengers with access to a private car might be over-represented in the sample (73.3%).

However, this proportion is still considerably lower than the proportion of dwellings with motor vehicles in the Greater Brisbane area (89.5%) (ABS, 2013). As such, the sample here is considered acceptable for the analysis of this chapter.

Table 7.1 Socio-demographic characteristics of the sample

		Number	Proportion (%)	
			This survey	SEQ survey
1.Gender	Male	192	42	40
	Female	265	58	59
2.Age	18-24	123	27	34
	25-34	133	29	23
	35-49	104	23	19
	>50	77	21	18
3.Education level	Graduate diploma/certificate and above	130	28	-
	Bachelor degree	171	37	-
	No bachelor degree	156	34	-
4.Employment status	Full-time worker	207	45	45
	Part-time worker	79	17	11
	Student	119	26	31
	Unemployed	52	11	5
5.Marital status	Single persons	203	44	-
	Couple family without dependent child/children	147	32	-
	Couple family with dependent child/children	107	23	-
6.Valid driver licence	Yes	386	84	72
	No	71	16	27
7.Access to a private car	Always	267	58	45
	Sometimes	68	15	-
	Seldom/never	122	27	53
8.Weekly household income (dollars/week)	<399	72	16	-
	400-999	135	30	-
	1,000-1,999	139	30	-
	>2,000	111	23	-

7.2.2 Behavioural characteristics

Table 7.2 shows the (past) behavioural characteristics of the sample. Passengers with 1-3 (24%) or over 6.5 years (27%) of BRT use, and using BRT for 3-4 weekdays or every weekday (77%), one weekend or less (62%) account for over half of the sample. Nearly 80 per cent of the sample uses the BRT for commuting purpose on the day of survey. And a similar proportion accesses BRT by walking or public transport.

Table 7.2 Behavioural characteristics of the sample

		Number	Proportion (%)	
			This survey	SEQ survey
1.Length of using the BRT (years)	0-1	64	14	-
	1-3	108	24	-
	3-4.5	71	16	-
	4.5-6.5	90	20	-
	>6.5	124	27	-
2.Weekday use of BRT (on an average week)	Every weekday	226	49	56
	3-4 weekday	131	29	25
	1-2 weekday	51	11	9
	At least one weekday a month and less	49	11	7
3.Weekend use of BRT (on an average month)	Every weekend	82	18	22
	2-3 weekends	86	19	20
	1 weekend	79	17	14
	Less than one weekend	210	46	39
4.Usual means for access to BRT	Walk	255	56	85
	Private car	92	20	15
	Public transport	110	24	-
5.Trip purpose (on the day of survey)	Work/study	364	80	-
	Other	93	20	-
6.Distance to BRT (kilometres)	<0.8	132	29	-
	0.8-3	146	32	-
	3-6	82	18	-
	>6	97	21	-

Comparing this sample to the results of the 2010 SEQ public transport survey shows similar patterns in terms of weekday and weekend use frequency. Comparing these results to the smart-card-data findings in Chapter 6, however, reveals some discernible differences. In particular, both the survey samples of this study and those of the 2010 SEQ public transport survey involve considerably larger proportions of passengers using the BRT (and UPT) with relatively high frequency (3-4 weekdays and every weekend) compared to the results of smart card data. These differences might be attributed to two reasons as discussed in Chapter 6: (1) individual passengers may have multiple smart cards, and (2) frequent passengers are more likely to be surveyed compared to infrequent passengers.

7.3 Results of factor analysis

7.3.1 Behavioural intentions

Nine items measuring loyalty and behavioural change intentions enter the factor analysis to examine factor structures (Table 7.3). The results largely confirm the three-factor structure as initially conceptualised and explain 73% of the measurement variance. All the factor loadings are higher than the cut-off value of 0.5. Thus the measurement of the behavioural intentions is considered acceptable.

Table 7.3 Factor loadings for behavioural intentions

Conceptualised Attitudinal factor	Item No.	Factor loading		
		1	2	3
Loyalty	33	0.932		
	34	0.91		
Intention to shift to private car use	57		0.789	
	58		0.851	
	59		0.779	
	60		0.778	
Intention to increase BRT use	54			0.87
	55			0.88
	56			0.717

7.3.2 Attitudinal variables

Table 7.4 Factor loadings for attitudinal variables

Conceptualised Attitudinal factor	Item No.	Factor loading					
		1	2	3	4	5	6
Perceived service experience	17	0.541					
	18	0.638					
	19	0.659					
	20	0.729					
	21	0.74					
	22	0.669					
	23	0.543					
	24						0.822
	26	0.638					
	27	0.768					
	28	0.784					
	29	0.739					
	30						0.8
	31	0.576					
	32	0.581					
Personal norm	35			0.807			
	36			0.784			
	37			0.841			
	38			0.86			
Social norm over private car use	39				0.633		
	40				0.665		
	41				0.814		
	42				0.815		
Car attitudes	43		0.695				
	44		0.714				
	46		0.611				
	47		0.7				
	48		0.824				
	49		0.71				
PBC over private car use	51					0.851	
	52					0.773	
	53					0.773	

Next, the remaining 35 indicators for measuring the influential attitudinal variables entered the factor analysis. Notably, items 25 (‘Information about bus routes at the busway stations is easy to understand’), 45 (‘Private cars are a low-cost transport mode’) and 50 (‘Using a private car gives on a prestigious image’) did not significantly load on any factors, hence were removed from the analysis. Re-conducting factor analysis on the remaining items (Table 7.4) explained 65% of their variance. Out of the remaining 15 items measuring BRT passengers’ perceived service experience, items 24 and 30 (‘bus fares are cheap’ and ‘the busway service is worth the money it costs me’) loaded on the same factor. Given the contents of these two items, they are considered as capturing the perceived value of BRT, which in this case mainly relates to the monetary costs of using the BRT service. The rest of the items largely conformed to the conceptualised factors.

After examining the factor structure and removing problematic items, six factors were finalised, and explained 65% of the variance of the measures. Factors were named based on their measures: factor one as ‘perceived service experience’ of BRT, factor two as ‘car attitude’, factor three as ‘personal norm’, factor four as ‘social norm over private car use, factor five as ‘perceived behavioural control (PBC) over private car use’ and factor six as ‘perceived value’ of BRT.

7.3.3 Finalised factors

After examining the factor structure and removing problematic items, 9 factors were finalised (Table 7.5). Factor scores for the finalised variables are calculated using the regression method in the SPSS statistics package (Field, 2009), wherein factor scores are sums of measured variables weighted on their factor score coefficients, which capture the unique contributions of measured variables to each factor. The Cronbach’s α for each variable is larger than the cut-off value of 0.7, hence supporting the construct validity of the variables.

Table 7.5 Finalised factors

Factor	Associated items	Mean	Standard Deviation	Cronbach's α
Behavioural intentions				
Loyalty	I am willing to continue to use the busway service.	6.489	1.216	0.881
	I am willing to recommend the busway service to others.			
Intention to shift to private car use	I am likely to use a private car instead of the busway service for more of my regular trips in Brisbane.	6.067	1.757	0.819
	I am willing to use a private car instead of the busway service for more of my regular trips in Brisbane.			
	In general, I prefer a private car instead of the busway service to travel in Brisbane.			
	If using a private car becomes cheaper (for example, cheaper car parking and lower fuel prices), I am willing to use a private car instead of the busway service for more of my regular trips in Brisbane.			
Intention to increase BRT use	I am likely to increase my use of the busway service for my regular trips in Brisbane.	4.646	1.645	0.785
	I am willing to increase my use of the busway service for my regular trips in Brisbane.			
	If the busway network is expanded to connect more localities around Brisbane, I am willing to make more trips by the busway service in Brisbane.			
Attitudinal factors				
Perceived service experience of BRT	Riding the busway service is safe.	5.548	1.291	0.915
	The busway service is frequent.			
	The busway service is on time.			

	Riding the busway service is comfortable.			
	The busway stations are well-equipped.			
	The busway stations are easy to get to.			
	Riding the busway service saves time.			
	Information about bus routes at the busway stations is easy to understand.			
	Bus drivers are always friendly.			
	Overall I am satisfied with the busway service.			
	I always have a good experience when riding the busway service.			
	Overall the busway service exceeds my expectations.			
	The busway service is worth the time I use it.			
	I highly value the busway service.			
Perceived value of BRT	Bus fares are cheap.	1.739	1.577	0.786
	The busway service is worth the money it costs me.			
Personal norm	I strongly feel using the busway service is a way to reduce environmental pollution.	5.109	1.336	0.862
	I strongly feel using the busway service is a way to reduce traffic problems.			
	I strongly feel using a car too much will increase environmental problems.			
	I strongly feel using a car too much will increase traffic problems.			
Car attitudes	Private cars are a reliable transport mode.	2.919	0.808	0.816
	Private cars are a flexible transport mode.			
	Private cars are a time-saving transport mode.			
	Private cars are a safe transport mode.			
	Using a private car is comfortable.			

	Using a private car is enjoyable.			
Social norm over private car use	My family is supportive of me in using a private car for my regular trips in Brisbane.	3.903	1.678	0.795
	My friends are supportive of me in using a private car for my regular trips in Brisbane.			
	My family members use private cars in Brisbane very frequently.			
	My friends use private cars in Brisbane very frequently.			
PBC over private car use	I strongly feel using the busway service is a way to reduce environmental pollution.	6.567	2.157	0.794
	I strongly feel using the busway service is a way to reduce traffic problems.			
	I strongly feel using a car too much will increase environmental problems.			
	I strongly feel using a car too much will increase traffic problems.			

7.4 Results of MANOVA

Based on the factor scores from last section, a series of MANOVA tests were conducted to examine how BRT passengers' behavioural intentions vary across the categorical variables of passengers. In this section, socio-demographic and behavioural characteristics are drawn upon as independent variables (refer to Table 7.1).

MANOVA comprises two parts: multivariate tests and post hoc tests. The first part tests the overall statistical significance across groups in terms of independent variables. Two indicators, Pilai's Criterion and Wilks' Lambda are reported, due to the fact that they are more robust compared to other indicators under the circumstance of the violation of the assumptions of MANOVA (e.g., non-equal variance-covariance matrices across comparison groups) (Hair et al., 2006). Given the statistically significant results of multivariate tests, post hoc comparisons are made to reveal the mean differences of the attitudinal factors between different socio-demographic and behavioural groups of BRT passengers.

7.4.1 Socio-demographic characteristics as independent variables

Table 7.6 MANOVA tests for socio-demographic characteristics

Independent Variable	Statistical tests	F	Sig.	Observed power
		Behavioural intentions		
Gender	Pillai's Criterion	0.084	0.969	0.065
	Wilks' Lambda	0.084	0.969	0.065
Age	Pillai's Criterion	5.194	0.000	1
	Wilks' Lambda	5.292	0.000	0.998
Education level	Pillai's Criterion	0.798	0.572	0.32
	Wilks' Lambda	0.798	0.571	0.32
Employment status	Pillai's Criterion	3.604	0.000	0.992
	Wilks' Lambda	3.671	0.000	0.972
Marital status	Pillai's Criterion	3.644	0.001	0.958

	Wilks' Lambda	3.672	0.001	0.96
Driver licence	Pillai's Criterion	1.768	0.153	0.461
	Wilks' Lambda	1.768	0.153	0.461
Access to private car	Pillai's Criterion	2.318	0.03	0.806
	Wilks' Lambda	2.327	0.03	0.808
Weekly household income	Pillai's Criterion	4.186	0.000	0.997
	Wilks' Lambda	4.231	0.000	0.988

Out of eight groups of socio-demographic variables, age, employment status, marital status, access to private car and weekly household income were found to have significant effects on loyalty and/or behavioural change intentions (at the $p<0.05$ level), while insignificant results were gained for the remaining three groups of variables (i.e., gender, level of education and driver licence) (Table 7.6). The results of the post hoc comparisons are detailed below.

Age

Significant effect is found for age on both behavioural intentions. Post hoc tests indicate that the age group between 35-49 tends to have significantly lower means of intention to shift to private car use, as well as intention to increase BRT use than the other age groups, while the younger age groups (age between 18-24 and between 25-34) have high means on the two behavioural change intentions (Table 7.7).

Table 7.7 Post hoc results: age groups

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to shift to private car use	Age 18-24	Age 35-49	0.932	0.227	0.000
	Age 18-24	Age > 50	1.029	0.232	0.000
	Age 25-34	Age 35-49	0.633	0.223	0.005
	Age 25-34	Age >50	0.73	0.228	0.001
Intention to increase BRT use	Age 18-24	Age 25-34	0.447	0.203	0.028
	Age 18-24	Age 35-49	0.833	0.216	0.000
	Age 35-49	Age >50	-0.229	0.129	0.044

Table 7.8 Post hoc results: employment status

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to shift to private car use	Full-time	Student	-0.44	0.201	0.029
	Unemployed	Student	-0.577	0.291	0.048
Intention to increase BRT use	Full-time	Student	-0.908	0.185	0.000
	Part-time	Student	-0.556	0.233	0.017

Employment status

Employment status is found to have a significant effect on behavioural intentions. Through post hoc tests, the student group is revealed to be mostly different from other groups concerning a number of dependent variables. First of all, this group has high means of intention to shift to private car use as well as intention to increase BRT use (Table 7.8).

Marital status

Marital status is found to have a significant effect on behavioural intentions. Post hoc tests reveal that the single group significantly differ from the group of couple with dependent child/children. Specifically, higher means of loyalty and intention to increase BRT use are found in this group (Table 7.9).

Table 7.9 Post hoc results: marital status

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Loyalty	Single	Couple with dependent child/children	0.292	0.145	0.044
Intention to increase BRT use	Single	Couple with dependent child/children	0.69	0.194	0.000

Access to private car

Access to a private car is found to have a significant effect on behavioural intentions. Two groups that do not always have access (i.e., 'sometimes' and 'never/seldom' groups) to a private car have higher means of intention to increase BRT use (Table 7.10).

Table 7.10 Post hoc results: access to a private car

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to increase BRT use	Always	Sometimes	-0.467	0.221	0.035
	Always	Seldom/never	-0.474	0.178	0.008

Weekly household income

Weekly household income is found to have a significant effect on both behavioural intentions. Post hoc tests reveal a number of variations of dependent variables. Concerning behavioural intentions, the group with lower weekly household incomes (399 or less) has a higher mean of intention to shift to private car use than the other two groups with higher incomes (400-999 and 1000-1999), and a higher mean of intention to increase BRT use than the group with the highest income level (>2000) (Table 7.11).

Table 7.11 Post hoc results: weekly household income

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to shift to private car use	<399	400-999	0.558	0.255	0.029
	<399	1000-1999	0.596	0.254	0.019
Intention to increase BRT use	>2000	<399	-1.177	0.242	0.000
	>2000	400-999	-0.757	0.205	0.000
	>2000	1000-1999	-0.755	0.204	0.000

Through the MANOVA analysis, few significant effects were found for socio-demographic characteristics on loyalty. One exception is that the 'lone person' passenger group showed slightly higher levels of loyalty than those from couple families with dependent child/children.

On the other hand, a series of small yet significant differences were found for the two behavioural change intentions: passenger groups characterised by single persons, limited access (‘sometimes’ and ‘seldom’) to private cars and lower household incomes have higher levels of intentions to increase BRT, while passengers from couple families with and without dependent child/children, and higher household incomes have lower intentions to do so.

One seemingly peculiar result is that younger age groups (between 18-24 years and 25-34 years) appear to rate behavioural change intentions higher than some of the older groups, regardless of increasing private car use or increasing BRT use. The possible explanation is that the younger groups are at a stage with more open (or uncertain) attitudes towards potential transport options compared to other groups. The student group also showed a higher level of behavioural change intentions. This might be attributed to the fact the younger people are largely concentrated within the student group.

7.4.2 Behavioural characteristics as independent variables

Table 7.12 MANOVA tests for behavioural characteristics

Independent Variable	Statistical tests	F	Sig.	Observed power
		Behavioural intentions		
Yeras of using the BRT	Pillai’s Criterion	1.786	0.046	0.89
	Wilks’ Lambda	1.786	0.046	0.837
Weekday use of BRT	Pillai’s Criterion	2.019	0.034	0.864
	Wilks’ Lambda	2.032	0.033	0.769
Weekend use of BRT	Pillai’s Criterion	3.816	0.000	0.995
	Wilks’ Lambda	3.907	0.000	0.98
Usual mean for access to BRT	Pillai’s Criterion	2.724	0.013	0.875
	Wilks’ Lambda	2.742	0.012	0.877
Trip purpose	Pillai’s Criterion	2.594	0.052	0.637
	Wilks’ Lambda	2.594	0.052	0.637
Distance to BRT	Pillai’s Criterion	0.659	0.746	0.333
	Wilks’ Lambda	0.657	0.748	0.268

Out of six groups of past travel behaviour variables, trip purpose and distance to BRT did not have significant effects on the behavioural intentions (Table 7.12). The following discusses the post hoc results for the remaining variables for which significant effects were detected.

Years of using BRT

Years of using BRT is found to have a significant effect on behavioural intentions. Post hoc tests show that major differences are found between groups of shorter length (mainly 1-3 years) of using BRT and the group with longer use (Table 7.13). Notably, the group with 1-3 years of using BRT has higher level of loyalty as well as intention to shift to private car use than longer-use groups (3-4.5 years and >6.5 years). Compared to the 1-3 and >6.5 years groups, the group with 0-1 year of using BRT has a slightly higher mean of intention to increase BRT use.

Table 7.13 Post hoc results: years of using BRT

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Loyalty	1-3	3-4.5	0.439	0.185	0.018
Intention to shift to private car use	1-3	>6.5	0.456	0.23	0.048
	3-4.5	>6.5	0.559	0.26	0.032
Intention to increase BRT use	0-1	1-3	0.527	0.258	0.042
	0-1	>6.5	0.574	0.252	0.023

Weekday use of BRT

Weekday use of BRT is found to have a significant effect on behavioural intentions. Post hoc tests show that the group with the highest weekday BRT use frequency (every weekday) on an average week have lower means of intention to shift to private car use as well as intention to increase BRT use (Table 7.14).

Table 7.14 Post hoc results: weekday use of BRT

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to shift to private car use	Every weekday	3-4 weekdays	-0.388	0.192	0.044
Intention to increase BRT use	Every weekday	3-4 weekdays	-0.39	0.179	0.03
	Every weekday	1-2 weekdays	-0.779	0.252	0.002

Weekend use of BRT

The group with the lowest frequency of BRT use on weekends (less than one weekend) on an average month has lower means of intention to increase BRT use compared to the other three groups (Table 7.15).

Table 7.15 Post hoc results: weekend use of BRT

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to shift to private car use	Every weekend	Less than 1 weekend	-0.482	0.228	0.035
Intention to increase BRT use	Every weekend	Less than 1 weekend	1.053	0.208	0.000
	2-3 weekends	Less than 1 weekend	0.629	0.204	0.002
	1 weekend	Less than 1 weekend	0.619	0.211	0.003

Access mode to BRT station

The group using private cars to access to their BRT stations shows a higher mean of intention to increase BRT use (Table 7.16).

Table 7.16 Post hoc results: access mode to BRT stations

Dependent variable	Groups compared		Mean differences	Standard error	Sig.
Intention to increase BRT use	Walk or	Private car	0.552	0.198	0.006
	Public transport	Private car	0.762	0.23	0.001

Again, few significant effects were found for travel behaviour variables on loyalty. The only significant finding is that the group with 1-3 years of history of using BRT had a higher level of loyalty than the group with 3-4.5 years of using BRT. No significant effects were found for use frequency of BRT (during weekday or weekend) on loyalty. This is in line with previous findings that revealed higher use frequency does not necessarily suggest higher loyalty of UPT passengers (Foote et al., 2001; Jacques et al., 2013).

More discernible patterns can be found concerning the two behavioural change intentions. First, passengers with longer BRT-use years (6.5 years or over) had lower levels of behavioural change intentions compared to those with shorter BRT-use years (particularly 0-1 and 1-3 years). Similarly, the group using BRT every weekday appears to be less willing to change their travel behaviour than the other groups. These results are understandable, since these two groups might have developed rather stable travel patterns that are less subject to change. Second, higher intentions to use private cars and lower intentions to increase BRT services were found for passengers who used BRT less than one weekend on an average month or used private cars for access to the BRT stations. This suggests that these passengers might be more car-preferring than other passengers.

7.5 Results of multiple regression modelling

This section reports the results of multiple regression models that investigate the relationships between loyalty and attitudinal dimensions. A series of hypotheses regarding BRT passengers' behavioural intentions was proposed in Chapter 4 (refer to Table 4.17). It is noted that based on the results of factor analysis, the original three service-experience factors conceptualised (satisfaction, perceived service quality, perceived value) have been reduced to two factors (perceived service experience and perceived value).

7.5.1 Model of loyalty

Three hypotheses are tested regarding BRT passengers' loyalty:

Hypothesis 1: BRT passengers' evaluations of service experience (i.e., perceived service experience and perceived value) will have positive effects on their loyalty.

Hypothesis 2: BRT passengers' personal norm will have positive effects on their loyalty.

Hypothesis 3: BRT passengers' considerations of private car use (i.e., car attitude, social norm and PBC over private car use) will have negative effects on their loyalty.

Table 7.17 shows that a statistically significant model was achieved in terms of BRT passenger loyalty, with adjusted $R^2 = 0.466$, $F(6,456) = 67.323$, $p < 0.001$. Examining the P-P plot of standardised residuals rendered a relatively straight line. Durbin-Watson is reasonably close to two (= 1.913).

Table 7.17 Results of loyalty model

Model Fit		
Adjusted R^2	0.466	
F	67.323	
Durbin-Watson value	1.913	
Independent variables	**β**	**t**
Service experience of BRT	0.427	12.156
Perceived value of BRT	0.283	8.19
Personal norm	0.195	5.632
Car attitude	0.26	7.351
Social norm over private car use	0.189	5.467
PBC over private car use	0.245	6.867

The six attitudinal factors all have statistically significant effects on loyalty, explaining 46.6% of its variance. No factor has a value of Variance Inflation Factor (VIF) larger than the cut-off value of 10, indicating no issue of collinearity. Two factors concerning passengers' experience of using BRT (i.e., service experience of BRT and perceived value of BRT) have the strongest effects on loyalty (β = 0.427 and 0.283 respectively), hence supporting Hypothesis 1. A significantly positive effect was found for personal norm on loyalty (β = 0.195), suggesting that passengers' responsibility for being pro-environmental might also strengthen their intention to use BRT, supporting Hypothesis 2. Significantly positive relationships were also found between loyalty and BRT passengers' considerations of private car use, i.e., passengers' car attitude (β = 0.26), social norm over private car use (β = 0.189) and PBC over private car use (β = 0.245). These results seem to be contradictory to Hypothesis 3. Nonetheless, some plausible explanations can be brought up here.

First, the positive effect found for car attitude suggests that BRT passengers' loyalty may not be an exclusive state of mind. Exclusive loyalty refers to the status of fervently patronising a service while excluding potential alternatives (Gremler and Brown, 1996; Oliver, 1999). Apparently it is not the case here. A more possible explanation of the findings here is that many BRT passengers might view both BRT and private cars as valuable travel options. Second, the positive effects associated with social norm (β = 0.189) and PBC over private car use (β = 0.245) suggest that both feeling approved by significant others concerning private car use and having control over private car use strengthens passengers' loyalty towards BRT. These findings appear to be somewhat contradictory with the previous studies revealing that lack of access to alternative options strengthen one's loyalty to a given transit service, e.g., Jen and Lu (2003), Wen et al (2005). However, these studies only refer alternative options to existing transit services while omitting private cars. Given the findings here, a more plausible mechanism underpinning these findings is that not feeling constrained in terms of private car use from both social (approval from significant others) and situational (perceived controls on private car use) perspectives make passengers more willing (or comfortable) to use BRT for their trip-making.

7.5.2 Models of behavioural change intention

Three hypotheses are tested regarding BRT passengers' intention to shift to private car use:

Hypothesis 4: BRT passengers' evaluations of service experience (i.e., perceived service experience and perceived value) will have negative effects on their intention to shift to private car use.

Hypothesis 5: BRT passengers' personal norm will have negative effects on their intention *to shift to private car use.*

Hypothesis 6: BRT passengers' considerations of private car use (i.e., car attitude, social norm and PBC over private car use) will have positive effects on their intention to shift to private car use.

And another three hypotheses are tested concerning BRT passengers' intention to increase BRT use:

Hypothesis 7: BRT passengers' evaluations of service experience (i.e., perceived service experience and perceived value) will have positive effects on their intention to increase BRT use.

Hypothesis 8: BRT passengers' personal norm will have positive effects on their intention to increase BRT use.

Hypothesis 9: BRT passengers' considerations of private car use (i.e., car attitude, social norm and PBC over private car use) will have negative effects on their intention to increase BRT use.

Significant results were achieved for the model of BRT passengers' intention to shift to private car use, with adjusted $R^2 = 0.205$, $F(6,456) = 20.619$, $p < 0.001$ (Table 7.18). Examining P-P plot and Durbin-Watson value (1.874) also did not raise serious concerns.

In accordance with Hypotheses 4-6, all six factors were found to have the expected effects on BRT passengers' intention to shift to private car use, explaining 20.5% of the variance of this behavioural change intention. Car attitudes appeared to have the strongest positive influence ($\beta = 0.35$). Positive effects were also found for PBC over private car use ($\beta = 0.179$) and social norm over private car use ($\beta = 0.202$). Negative effects were detected for service experience and perceived value of BRT ($\beta = -0.167$ and -0.107 respectively) and personal norm ($\beta = -0.139$). These results echo the findings by Gardner and Abraham (2008; 2010), that passengers' behavioural intentions of car use indeed are influenced by their considerations of alternative transport (BRT in this case). The significant effect found for personal norm again concurs with previous studies, e.g., Matthies et al (2006), Bamberg et al (2007).

Table 7.18 Model results of intention to shift to private car use

Model Fit		
Adjusted R^2	0.205	
F	20.619	
Durbin-Watson value	1.885	
Independent variables	**β**	**t**
Service experience of BRT	-0.167	3.899
Perceived value of BRT	-0.107	2.536
Personal norm	-0.139	3.307
Car attitude	0.35	8.107
Social norm over private car use	0.202	4.779
PBC over private car use	0.179	4.11

Last, significant results were attained for the model of BRT passengers' intention to increase BRT use, with adjusted $R^2 = 0.121$, F (6,456) = 11.5, $p < 0.001$ (Table 7.19). P-P plot and Durbin-Watson value (1.855) were also acceptable.

Table 7.19 Model results of intention to increase BRT use

Model Fit		
Adjusted R^2	0.121	
F	11.5	
Durbin-Watson value	1.857	
Independent variables	**β**	**t**
Service experience of BRT	0.217	4.818
Perceived value of BRT	0.182	4.099
Personal norm	0.191	4.3
Car attitude	-0.085	1.871
Social norm over private car use	-0.002	0.052
PBC over private car use	-0.199	4.343

Four out of six factors had significant effects on passengers' intention to increase BRT use, accounting for only 10.4% of its variance. Positive effects were found for service experience of BRT (β = 0.217), perceived value of BRT (β = 0.182) and personal norm (β = 0.191), supporting Hypotheses 7 and 8. PBC over private car use was the only car-related factor entering the model, with a negative effect (β = -0.199). Hence Hypothesis 9 is not fully supported.

An examination of the model results also indicates that passengers' willingness to increase BRT use is mainly subject to their pro-environmental responsibility as well as the service experience with the BRT, while attitudes towards private car and social norm over car use have little to do with this behavioural change intention. The negative effect of PBC over private car use suggests that the passengers with lower levels of perceived control over private car use are more willing to increase their BRT use. This finding suggests that passengers' intention to increase BRT use is probably prompted by the situational constraints over private car use, which differs from the passenger loyalty that is cultivated by a lack of such situational constraints. Hence the intention to increase BRT use has a more 'forced' component compared to loyalty. This raises some caveats concerning the implications for the management of BRT passengers' behavioural intentions and is discussed in the next chapter.

7.5.3 Full model of loyalty

Three stepwise regression models were computed to examine the collective effects of attitudinal factors as well as socio-demographic and behavioural characteristics on the behavioural intentions of BRT passengers. Thirty three dummy variables were constructed to enter the model, as summarised in Table 7.20.

Table 7.20 Summary of dummy variables

Characteristics	Dummy variables
Gender (Female = 0)	Male
Age (Age 18-24 = 0)	Age 25-34
	Age 35-49
	Age 50 and over
Education level (No bachelor degree = 0)	Graduate diploma and above
	Bachelor
Employment status (Student = 0)	Full-time worker
	Part-time worker
	Unemployed
Marital status (Single person = 0)	Couple without dependent child/children
	Couple with dependent child/children
Driver licence (With a valid driver licence = 0)	Without a valid driver licence
Access to a private car (Always = 0)	Sometimes

	Seldom/never
Weekly household income (399 dollars and less = 0)	400-999 dollars
	1,000-1,999 dollars
	2,000 dollars and above
Years of using BRT (6.5 years and above = 0)	0-1 year
	1-3 years
	3-4.5 years
	4.5-6.5 years
Weekday use of BRT (Every weekday = 0)	3-4 weekdays
	1-2 weekdays
	At leaser one weekday a month and less
Weekend use of BRT (Less than one weekend a month = 0)	2-3 weekends
	1 weekend and less
Access mean to BRT (Private car = 0)	Walk or cycle
	Public transport
Trip purpose (Other = 0)	Work or study
Distance to BRT (0-0.8 kilometre = 0)	0.8-3 kilometres
	3-6 kilometres
	6 kilometres and above

In terms of BRT passenger loyalty, a marginally different result was attained with adjusted $R^2 = 0.486$, F (9,456) = 44.059, Durbin-Watson value = 1.971. VIF values were all around one (lower than the cut-off value of 10) (Table 7.21). All six attitudinal factors entered the model with similar regression weights to those found previously (refer to Table 7.17). Two socio-demographic (seldom or never with access to private car and male) and two travel behaviours (years of using BRT 1-3 years and weekday use of BRT 1-2 weekdays) also entered the model. However, considering that their regression weights were under 0.1, their effects on passenger loyalty appeared to be marginal compared to the attitudinal factors. It seems peculiar that both PBC over private car use and seldom or never with access to private car positively associated with loyalty. However, as identified in a previous study (Foote et al., 2001), choice passengers may include those who deliberately choose not to own a private car. This might explain the positive effects of these two seemingly opposite variables.

Table 7.21 Full model of loyalty

Model Fit		
Adjusted R^2	0.486	
F	44.059	
Durbin-Watson value	1.971	
Independent variables	**β**	**T**
Service experience of BRT	0.415	11.86
Perceived value of BRT	0.281	8.233
Personal norm	0.193	5.645
Car attitude	0.259	7.359
Social norm over private car use	0.192	5.654
PBC over private car use	0.326	6.997
Seldom or never with access to private	0.107	2.401
Male	-0.085	2.458
1-2 weekdays	-0.08	2.34
1-3 years	0.068	2.008

7.5.4 Full models of behavioural change intentions

Table 7.22 Full model of intention to shift to private car use

Model Fit		
Adjusted R^2	0.247	
F	19.649	
Durbin-Watson value	1.893	
Independent variables	**β**	**T**
Service experience of BRT	-0.143	3.376
Perceived value of BRT	-0.144	3.456
Personal norm	-0.127	3.08
Car attitude	0.331	7.833
Social norm over private car use	0.197	4.803
PBC over private car use	0.227	5.234
Age 35-49	-0.209	4.739
Age 50 and over	-0.154	3.471

In the full model of intention to shift to private car use, slightly higher variance (24.7% compared to 20.5%) was found compared to the previous model results (refer to Table 7.18), with F (9,456) = 19.649, Durbin-Watson value = 1.893, VIF values around one (Table 7.22). All six factors remained in the model with similar regression weights, again echoing the above findings. The age groups between 35 and 49 years and 50 years and above were found to have lower intentions to shift to private car use compared to the age group between 18 and 24 years. This result largely confirmed the findings of MANOVA that younger passengers are more willing to change their travel behaviour patterns.

A notable improvement of explanation power (17.9% compared to 12.1%, with F (11,456) = 10.959, Durbin-Watson value = 1.935) was attained by adding socio-demographic and travel behaviour variables into the model of intention to increase BRT use (Table 7.23) compared to the previous model results (refer to Table 7.19). Three factors (service experience, perceived value of BRT and personal norm) remained significant, whilst PBC over private car use was excluded and a marginal effect was found for car attitude.

Table 7.23 Full model of intention to increase BRT use

Model Fit		
Adjusted R^2	0.179	
F	10.959	
Durbin-Watson value	1.935	
Independent variables	**β**	**T**
Service experience of BRT	0.168	3.913
Perceived value of BRT	0.124	2.803
Personal norm	0.164	3.832
Car attitude	-0.086	1.991
Weekly household income of 2,000 dollars and above	-0.144	3.216
Fulltime worker	-0.108	2.33
Every weekend	0.17	3.558
1 weekend	0.137	2.961
Public transport (access to BRT station)	0.114	2.636
2-3 weekends	0.099	2.093

Six dummy variables entered the model, including two socio-demographic variables and four behavioural variables. In terms of socio-demographic variables, the passenger groups with higher weekly household income (2,000 dollars and above) and fulltime workers had lower intentions to increase BRT use compared to other groups. Regarding travel behaviour variables, all three variables of weekend use of BRT entered the model. In accordance with the findings of MANVOA, the three groups that use BRT during weekends showed higher intentions to increase BRT use than the remaining group that rarely or never use BRT during weekends (using BRT once or less than one time on an average month). Finally, the group that accesses BRT by public transport (bus or train) showed slightly higher intention to increase their BRT use.

In summary, the results of full models of behavioural change intentions (Tables 7.21 to 7.23) largely confirmed the findings in the original models (Tables 7.17 to 7.19). Based on the modelling results, two groups of passengers (age 18 to 24 years with weekend use of BRT) were further highlighted. First, the age group between 18 and 24 years was more willing to switch to private car use, while the group that uses BRT during weekends showed higher willingness to increase BRT use. This suggests that these two groups should be the major target groups for policies that aim at promoting BRT use.

7.6 Summary

This chapter has modelled the behavioural intentions (i.e., loyalty, intention to shift to private car use and intention to increase BRT use) as a core component of understanding the attitudinal mechanisms of BRT passengers. Both attitudinal factors and the more conventional variables (socio-demographic and behavioural characteristics) were found to have significant effects on BRT passengers' behavioural intentions. Yet, on an overall level, attitudinal factors were found to have considerably larger explaining powers.

Specifically, through a MANOVA analysis, it has been found:

- BRT passengers' loyalty is less associated with their socio-demographic and travel behaviour characteristics compared to their behavioural change intentions.
- Relatively socio-economically disadvantaged groups showed a higher willingness to increase BRT usage compared to the more advantaged groups.
- Younger groups of passengers (18-24 years and 25-34 years) had higher willingness to increase BRT and private car use.
- Experienced and frequent BRT passengers had lower intentions to change their current use of BRT, whilst infrequent and multimodal (private cars in particular) passengers showed higher intention to shift to private-car use and lower intention to

increase BRT use.

The key findings of the regression models include:

- Service experience, perceived value of BRT and personal norm were highlighted to have positive effects on BRT passengers' loyalty. Positive effects were also found for BRT passengers' car attitude and social norm of private car use on their loyalty.
- Positive effects were found for car attitude, social norm and PBC over private car use on BRT passengers' intention to shift to private car use, while negative effects were found for service experience, perceived value of BRT and personal norm.
- Service experience, perceived value of BRT and personal norm were revealed to have positive effects on BRT passengers' intention to increase BRT use, while no significant effects were attained for attitudinal factors related to private car use.
- Age and weekend use were further highlighted as key socio-demographic and past travel behaviour characteristics in identifying passenger group for managing modal shift (younger passengers) and increasing BRT use (weekend BRT users).

Chapter 8 Discussion and conclusions

Through the empirical investigations detailed in Chapters 5, 6 and 7, a number of insights concerning BRT passengers' travel behaviour and behavioural intentions were revealed. In addition, the study has undertaken significant work in addressing some critical methodological challenges and theoretical issues related to the investigation of UPT passenger travel behaviour. This final chapter aims to draw together and critically discuss each of the contributions, by first revisiting the key findings before examining their implications for future BRT policy and planning and finally, examining the limitations of this study and identifying a series of potential avenues for future research.

8.1 Key findings and contributions

Considering the challenges of promoting BRT within a highly motorised context, this thesis proposed the research question: *What are the travel behavioural dynamics of BRT passengers and how can our understanding of these dynamics enhance the understanding about BRT passengers' loyalty and change intentions?* This question was addressed through investigating three complementary behavioural dimensions (i.e., changes in travel patterns, spatial-temporal dynamics, and behavioural intentions of passengers) as they relate to Brisbane's BRT. Collectively the investigation of the three behavioural dimensions presented a detailed and comprehensive picture concerning BRT passengers' travel behaviour dynamics within the study context. The follow sections summarise the key findings related to each of the three behavioural dimensions, and discuss the knowledge contribution to the broader BRT and UPT context as well.

8.1.1 Key findings

To provide a more complete understanding of the behavioural dynamics of BRT passengers, this thesis identified and investigated three behavioural dimensions considered complementary, which encompass travel pattern change over time, spatial-temporal trip patterns and attitudinal dimensions of BRT passengers. The findings from the empirical investigations collectively address the overall research question through providing a suite of evidence that revealed the course of change in travel patterns over time, the current spatial-temporal trip patterns and loyalty and change intentions of existing BRT passengers.

First, through conducting a time-series analysis, Objective 1 showed that after five years of BRT implementation, there were a 1.6-2.7% increase in bus shares and a 3.1-4.8% decrease in private car shares for work-based trips within the walk-in (800 metres) and drive-in/bus-in (3 kilometres) catchments of BRT. In addition, by developing a series of regression models, a positive relationship between bus modal share and vehicle ownership was revealed within the 800-metre distance to BRT stations, suggesting the possibility of choice passengers, i.e., those who used BRT instead of private cars for their commuting trips. These findings advanced previous studies (e.g., Callaghan and Vincent, 2007, Deng and Nelson, 2013, Levinson et al., 2003b) by providing specific evidence concerning the effects of BRT in changing travel behaviour at different catchment areas. However, it also appeared that the impact of BRT in stimulating greener travel behaviour has been moderate, hence suggesting there is a need to further enhance the attractiveness of BRT in order to maintain and increase its ridership.

Objective 2 sought to elucidate the role of BRT in facilitating passengers' trip making across a UPT network expressed by their spatial-temporal trip dynamics. Such knowledge of travel behaviour is an important component for evidence-based UPT service planning and management in response to passengers' travel demands (Munizaga and Palma, 2012; Pelletier et al., 2011), yet is largely absent in the current BRT literature (Tao et al., 2014; Lleras, 2002; Estupiñán and Rodríguez, 2008). A series of flow-comaps ware computed, revealing that BRT-based trips involved a number of high volume pathways originating from the south and north of Brisbane and flowing into the CBD across five typical calendar events (i.e., a workday, a school holiday, a Saturday, a Sunday and a public holiday). More noticeably, spatial heterogeneity of passengers' trip patterns using the BRT busway across the UPT network were detected, highlighting that: (1) the South East Busway (SEB) serves a stronger corridor than the Northern Busway (NB) in channelling trips from around Brisbane to the city centre and (2) weighted flow-comaps highlighted the distinct temporal travel patterns associated with the passengers using the SEB against the ones using the NB across different calendar events (i.e., a weekday, weekends, public and school holidays). These findings hold a number of implications for BRT provision within Brisbane as well as other BRT contexts as detailed in Section 8.2.1.

Last, Objective 3 was concerned with examining BRT passengers' attitudinal mechanisms. Particular attention was placed on modelling BRT passengers' behavioural intentions, given their potential to influence passengers' future BRT use. Largely allied with previous studies (Bamberg et al., 2007; Jen et al., 2011), passengers' perceived service experience, perceived value of BRT and personal norm were positively related with their loyalty and intention to increase BRT use, while negatively associated with their intention to shift to private car use. More interestingly, while attitudes concerning private cars, social norm and PBC over private car use were positively associated with passengers' intention to shift to private car use, regressing loyalty on these factors revealed positive relationships. Given these findings, two insights can be obtained: (1) BRT passengers may not necessarily perceive BRT and private cars as mutually competing travel options, but rather viewing them both as valuable travel options; and (2) the feeling of not being constrained about using private cars both socially and situationally strengthens passengers' willingness to continue using BRT. Through these findings, some cautions and recommendations may be raised concerning strategies for BRT marketing and service management as elaborated in Section 8.2.2.

8.1.2 Contributions to the broader BRT and UPT context

In addition to the key findings summarised above, this thesis also holds contributions to the broader BRT and UPT context both for Australia and internationally in three main ways.

From an overarching perspective, the developed research design encapsulated the three behavioural dimensions namely, changes in travel patterns, spatial-temporal dynamics and attitudinal mechanisms. This adopted framework allowed a more holistic and structured approach to capture complementary travel behavioural dynamics of BRT passengers. In addition, the strengths and weaknesses of various data sources were taken into consideration to identify datasets most suited for investigating different behavioural dimensions of BRT passengers. Built upon both theoretical and methodological considerations, this research design may serve as a template to guide future research to investigate passenger travel behaviour within BRT or UPT context.

The second contribution pertains to the employment of a series of geo-based methods to investigate BRT passenger trip patterns. Due to the interactions among various social and environmental factors, people usually demonstrate spatially dependent (or varied) behavioural patterns in term of their trip-making decisions (e.g., trip origin, destination, and mode choice) (Páez, 2006; Wang and Khattak, 2011). Given such potential spatial variations of travel behaviour, capturing detailed geographic patterns has become increasingly important in the field of travel behaviour studies by offering empirical support to guide the development of more responsive public transportation systems (Páez, 2006; Wang and Khattak, 2011). However, previous investigation of travel behaviour within the BRT context has largely been ‘aspatial’, and overlooked the possibility that BRT usage and demand may vary across an urban space. Through the application of a series of geo-visualisation techniques to a large smart card data, this thesis was able to identify a number of nuanced yet noticeable differences in terms of BRT use across an urban space. This was achieved through two methodological improvements pertaining to the utility of smart card data. First, smart card records were reconstructed as travel trajectories at a stop-to-stop level of granularity. Second, a series of flow-comaps were computed to visually depict flow patterns of transit passengers. These improvements collectively proved to have the capacity to help investigate the critical links across a UPT network in carrying passengers and their variations under different conditions (e.g., workday versus weekend), which may serve as a platform to support evidence-based BRT or UPT planning (Tao et al., 2014a).

Last, modelling BRT passengers’ behavioural intentions constitutes another contribution to the broader BRT and UPT context. Previous research found that transit passengers may hold different levels of loyalty towards a transit service, which in turn may influence their future decision of using that service (Figler et al., 2011; Foote et al., 2001). In addition, considering car dependency as a major barrier to promote public transport (Hensher, 1998; Steg, 2003), passengers’ attitudes towards private car use may also posit influences on their future transit use that are important to capture. Yet these issues concerning behavioural intentions have been limitedly investigated within the BRT and other public transport context. Through a series of statistical analysis, this thesis identified that with similar levels of loyalty, some BRT passenger groups (e.g., weekend versus non-weekend riders) might demonstrate different levels of intentions to shift to private car use. In addition, BRT passengers' attitudes towards private car use were found to have significant effects on their loyalty (albeit in an unexpected direction). These findings suggest that a more comprehensive inclusion of behaviour intentions and attitudinal factors (in particular, the attitudes towards private car use) is needed to better understand BRT passengers' tendency concerning their future mode choice behaviour, which may help BRT agencies within highly motorised city contexts to manage their market and sustain patronage against car dependency.

8.2 Recommendations

Having discussed the key findings and contributions by addressing the three objectives targeted at changes in travel patterns, spatial-temporal dynamics and attitudinal mechanisms, this section moves on to address the final objective of this research:

Objective 4: To draw on the outcomes from Objectives 1, 2 and 3 to develop recommendations for BRT policy and planning.

The recommendations for future BRT-related policy and planning are developed and discussed from two perspectives: (1) operational (e.g., future service provision and infrastructure expansion of BRT); and (2) strategic (e.g., marketing and soft policy options to manage existing BRT passengers). The following sections first discuss these recommendations for the study context (i.e., Brisbane) followed by their broader relevance to both Australia and internationally.

8.2.1 Recommendations on BRT operations

Brisbane

First, the outcomes originating from Objective 1 have the potential to offer empirical support of local government policy to invest in BRT as a sustainable transport option within

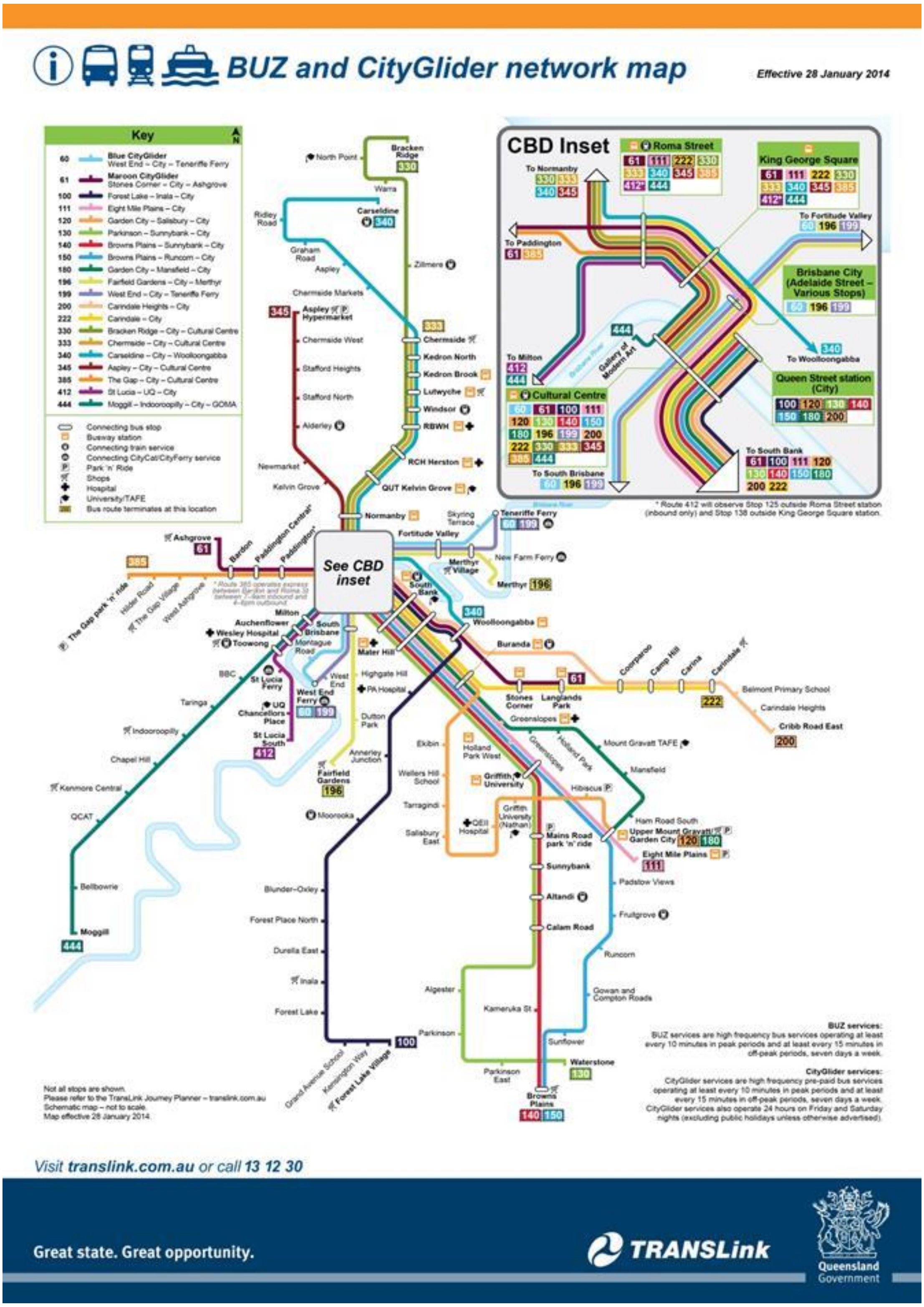
Brisbane. Results highlighted a modal shift from car to bus in addition to higher proportion of pedestrian walking within the vicinity of BRT stations following its implementation. Furthermore, by modelling modal share patterns in relation to socio-demographic characteristics, the BRT stations were also shown to have attracted passengers who have access to private cars in its vicinity, which as suggested in previous studies (Foote et al., 2001; Figler et al., 2011; Miller et al., 1999) to be crucial for the survival of UPT within a highly motorised context, given that attracting such choice passengers to use public transport instead of cars is considered one of the key means to alleviate car dependency .

The results of Objective 2 provide a number of detailed recommendations for evidence-based BRT planning within Brisbane. In particular, the revealed passenger travel patterns (e.g., passenger flow patterns over weekday and weekends) have the potential to inform BRT-related bus services in better meeting the travel needs of bus passengers. Currently 20 high frequency bus routes are the core BRT services, collectively termed the “BUZ” (Bus Upgrade Zone) service (Hoffman, 2008; Translink, 2014a). A comparison between the current service map (Figure 8.1) and the passenger flow patterns in Chapter 7 (in particular on a workday and a school holiday) indicates that while the majority of the high-volume pathways are served by the BUZ network, there is potential to expand the current BUZ services along several pathways, including between the CBD and Riverhills, Queensland University of Technology and Everton Hills, and Mater Hospitals and Tingalpa (refer to Figure 6.25 and 6.26 in Chapter 6). Introducing higher frequency bus routes along these pathways may result in a virtuous cycle, wherein the increase of service frequency has the potential to induce growth in passenger demand (Hoffman, 2008; Levinson and Krizek, 2008). In addition, the identified temporal changes of the major pathways across the five calendar events (i.e., a weekday, weekends, public and school holidays) can be used to help establish more flexible route allocation mechanisms in reaction to the varied travel demand across different calendar events (e.g., setting up special lines on public holidays) (Tao et al., 2014).

Implications for managing BRT-based service can also be drawn from the spatial heterogeneity of passenger trip patterns using the BRT busway across the UPT network.

Here, the SEB was found to be a stronger corridor than the NB in channelling trips from around Brisbane into the CBD. In accordance with this finding, previous studies (Currie, 2006; Currie and Delbosc, 2010) have found that the ridership and headways of Brisbane's SEB were considerably higher than their counterparts on the NB (i.e., on annual basis, 47.1 million passengers and 259 buses per hour on the SEB versus 13 million passengers and 131 buses per hour on the NB). Given these findings and the identical infrastructure designs (particularly the exclusive busways) between the SEB and the NB, there appears to be potential to enhance the utility of the NB by directing some of the travel demand from nearby locales e.g., Stafford Heights, and Toombul Shopping Centre, to the NB through, for example, allocating more bus routes on the NB. Doing so also has the potential of further improving the mobility for relatively socio-economically disadvantaged (e.g., lower income and young) bus travellers, given that a number of high-volume BRT passenger flows originated from low IRSAD suburbs (ranked in the lower five deciles) of northern Brisbane.

Figure 8.1 BUZ network, source: Translink (2014a)



* Route 412 will observe Stop 125 outside Roma Street station (inbound only) and Stop 138 outside King George Square station.

Not all stops are shown.
Please refer to the TransLink Journey Planner – translink.com.au
Schematic map – not to scale.
Map effective 28 January 2014.

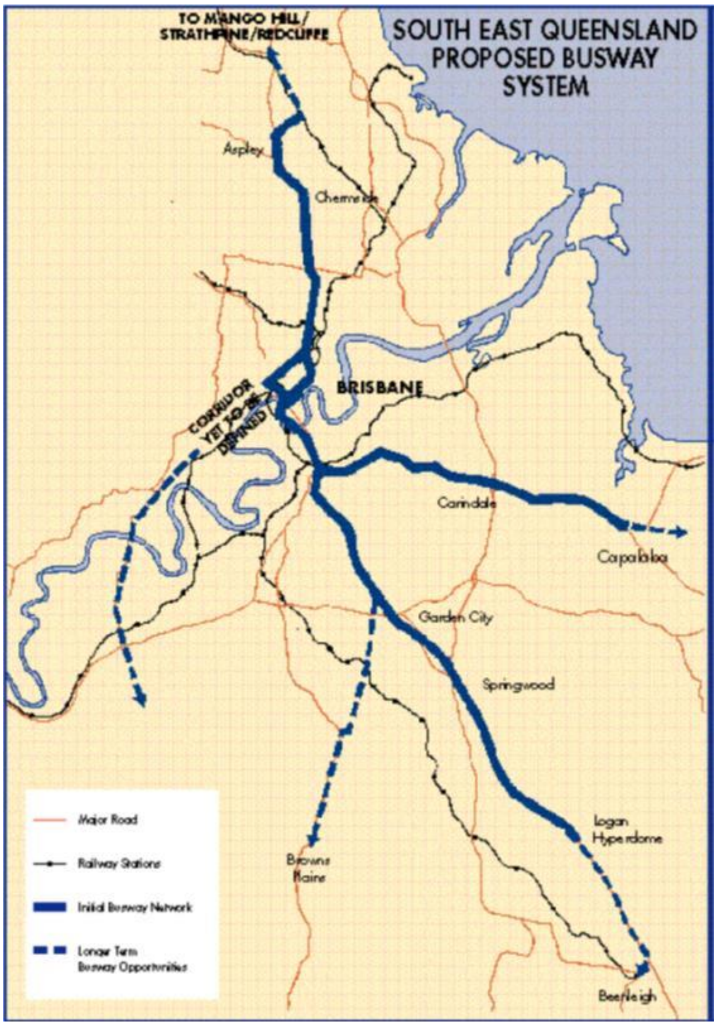
BUZ services:
BUZ services are high frequency bus services operating at least every 10 minutes in peak periods and at least every 15 minutes in off-peak periods, seven days a week.

CityGlider services:
CityGlider services are high frequency pre-paid bus services operating at least every 10 minutes in peak periods and at least every 15 minutes in off-peak periods, seven days a week. CityGlider services also operate 24 hours on Friday and Saturday nights (excluding public holidays unless otherwise advertised).

Should future policies be targeted at enhancing the utility of the NB, two points may deserve particular attention from Brisbane's BRT agency. First, the weighted flow-comaps in this study highlighted differing temporal travel patterns associated with the passengers using the SEB against the ones using the NB across the five dates. For example, the trip patterns of the NB were found to be less commuting-oriented compared to that of the SEB. This suggests that the service schedules for the bus services on the SEB and NB should be adjusted in response to the temporal variety of passengers' travel needs. Second, as suggested by Dodson et al (2011), Mees and Dodson (2011), multiple routes running along the same pathway may cause confusions for people to find and catch their aimed bus service. Given this, the enhancement of the NB's utility should focus more on increasing service frequency (supported by feeder lines from nearby areas) instead of the number of bus routes running on the NB. Furthermore, the issue of parallel bus routes probably already exists on the SEB, given that over 140 bus routes currently operate (Currie and Delbosc, 2010). The identified major pathways here can again be used as the basis to determine the stops between which the re-routing of bus services into fewer routes should be located.

Finally, recommendations for future BRT busway expansion can also be obtained from Objective 2 (Tao et al., 2014). It has been revealed that two high-volume pathways originated from eastern and western locales of Brisbane (Carindale and Indooroopilly Shopping Centres) and fed into the existing busway network across the five dates. Future busway expansion can be considered along these two pathways to form western and eastern busway sections. This potential expansion supports the Brisbane busway plan in 1997 (Figure 8.2) (Queensland Transport, 1997), which however was envisaged largely based on political reasons instead of concrete evidence (Hoffman, 2008; Mees and Dodson, 2011). In addition, based on the results of weighted flow-comaps, it has been highlighted that the introduction of a western busway might be more important than an eastern busway, given the higher and more consistent passenger demand associated with the former across different calendar events. This suggestion is somewhat contradictory to the latest plan that supports the extension of busway in eastern Brisbane (at Carindale Shopping Centre and further east) while suggesting the establishment of 'transit way' in the west that is mainly supported by bus-priority signals (Queensland Government, 2011). Given this, there is a need to investigate other aspects of evidence, including on-road vehicle flows and speed, travel patterns (e.g., trip schedule, O-D distribution) of the surrounding catchments of travellers, in addition to the travel patterns detected here to re-affirm (or refute) the suggestions of extending the current busway network in both western and eastern Brisbane.

Figure 8.2 The 1997 South East Queensland Proposed Busway System, source: Hoffman (2008)



Australia and internationally

While the recommendations previously discussed are highly context-specific, the BRT provision within other Australian cities, in particular Sydney and Melbourne, may also benefit from this study from a methodological perspective.

Different from Brisbane’s CBD-oriented BRT system, both Sydney’s and Melbourne’s BRT mainly serve for their outer suburbs and employ an on-street design whereby the exclusive bus lanes are spatially fragmented (Currie and Delbosc, 2010; 2011). Within these two cities, BRT passengers’ travel experience (e.g., travel time and transfer) are expectedly more vulnerable to the impacts of on-road traffic. In such case, capturing detailed local spatial-temporal patterns related to BRT as well as the remainder of the UPT network appears to be even more crucial, as it relates to having a comprehensive understanding of how BRT and the UPT network functionally interact with each other and hence to identifying areas for improvement. The flow-comap method developed in this thesis provides a new visual analytic tool with the capacity to examine passenger trip patterns within the BRT systems of Melbourne and Sydney and therefore support their evidence-based planning. As demonstrated in this thesis, by doing so, the BRT planning and management of Melbourne and Sydney may be enhanced in two main ways. First, the spatial-temporal trip patterns revealed may be drawn upon to examine and adjust the detailed spatial layout and schedule of BRT-based routes to better meet the existing travel needs during different calendar events (e.g., weekdays versus weekends) within these two cities. Second, the spatial disparity between the existing passenger trip patterns and the exclusive bus way may be identified especially for the segments where high volume of passenger flows persists. This information can be used to guide future expansion of the BRT system in terms of exclusive bus lanes and bus-priority signals at crossroads.

Furthermore, the method to reconstruct travel trajectories from smart card data demonstrated in this thesis could be also utilised to examine the spatial patterns of other trip characteristics such as travel time, distance and speed associated with BRT trips. Such information, along with the detailed passenger flow patterns, has the potential to formulate a detailed empirical evidence base for Sydney and Melbourne, from which transport planners would have the capacity to design the spatial layout of their BRT-related bus routes and identify locales for future expansion of exclusive bus lanes. Such a geographic based method may also be applied to other BRT and UPT systems internationally to examine nuanced spatial-temporal dynamics of BRT and UPT passengers' travel patterns and their spatial heterogeneity, which may help transit agencies to help establish more service-oriented transit systems.

8.2.2 Strategic-level recommendations

Brisbane

In addition to the operational recommendations derived from Objectives 1 and 2, Objective 3 holds a series of strategic recommendations to manage current BRT passengers as an additional way to sustain and enhance BRT usage.

First, there is the potential to establish different marketing strategies targeted at passengers with varying behavioural intentions. Within the study context, passengers who rarely used BRT on weekends (less than once a month) were identified to be less secured than others, given their higher intentions to shift to private car use instead of the BRT for their general trip-making and lower intentions to increase BRT use. Given this, the marketing goal for this group of passengers should be targeted at enhancing their loyalty and modifying their intention of modal shift. By contrast, efforts can be made to increase the BRT usage of passengers characterised by lone person status, limited access to private cars and lower household income as well as those who used BRT on weekends more than once a month., given their willingness to do so. Last, higher intentions for both car use and increasing BRT use were identified for passengers 35 years old or below. A plausible explanation is that compared to more senior groups, these younger passengers face less constraints originating from their social and family roles, such as the responsibility of parenting (Kitamura, 2009; Zimmerman, 1982). Consequently they are associated with a more open state of mind (or uncertainty) concerning their future travel behaviour and related life style. Considering the high level of vehicle ownership within Brisbane, the appropriate strategy should be to maintain their BRT use and avoid car dependency once private cars become accessible.

Some implications can also be obtained concerning managing BRT passengers' behavioural intentions. In accordance with previous studies, enhancement of BRT service in terms of service experience (Joewono et al., 2012; Jen and Lu, 2003; Minser and Webb, 2010), perceived value (Jen and Hu, 2003), and pro-environmental responsibility (Collins and Chambers, 2005; Nordlund and Garvill, 2003) should be the priority to maintain and promote BRT use, as well as averting modal shift to private car use, given their significant relationships revealed with all three behaviour intentions. In addition, passengers' perceptions of service experience may be enhanced through information-based strategy (dell'Olio et al., 2010), for example, dispatching detailed service information of the BUZ service in terms of route and timetable.

Concerning perceived value, monetary incentives, such as discounted fares (Fujii and Kitamura, 2003; Ampt, 2004) during certain time periods can be applied to reinforce (infrequent) passengers' loyalty towards the BRT and the willingness to use it for more of their trips. Currently within Brisbane, a discount program termed 'Make nine journeys then travel free' (Translink, 2014b) is utilised to encourage passengers' bus use (including BRT). However, there might be concern that marked increase of bus use can be achieved through this program. First, it is likely that making nine bus-based journeys a week exceeds many passengers travel needs by BRT and bus in general. Merely 10 per cent of current smart card holders use the BRT and/or on-road bus services on frequent basis, i.e., more than three workdays per week. Thus the offered discount may have limited appeal to the majority of the smart card holders and therefore stimulate a limited increase in the perceived value of BRT among them. In addition, as found previously in the Australian context, different people could react very differently to monetary incentives as a means to promote UPT use (Ampt, 2004). Given this, individualised approaches may be more appropriate to provide monetary incentives, for example by identifying those who are not very opposed to the idea of increasing BRT use and discovering what trips are actually valuable to them in terms of monetary and other types of costs (Ampt, 2004).

Last, some caveats can be raised concerning the information of private car use in designing soft policy options to promote BRT usage. To briefly recall, the findings of Objective 3 showed that: (1) many BRT passengers may not view BRT and private cars as competing travel modes; and (2) feeling unconstrained and not disapproved in terms of using private cars appear to strengthen passengers' willingness to continue using the BRT service. These findings echo those of certain previous studies that examined the effects of soft policy in promoting UPT usage among car users in Australia, e.g., Ampt (2004) and in a European context, e.g., Tertoolen et al (1998), Beale and Bonsall (2007). They found that car users were rather ‘defensive’ concerning their usage of private cars and could be irritated by campaigns explicitly targeted at restricting car use (for example, stressing environmental and financial issues associated with private car use) and as a result, continued or even increased their car use. Instead, it should be highlighted that BRT has the potential to benefit passengers’ trip-making in tandem with private cars as a viable (or potential) alternative.

Australia and internationally

Other BRT agencies both in Australia and internationally can also draw on the concepts of loyalty and behavioural change intentions to better understand and more effectively segment their existing passengers. As demonstrated in the empirical results associated with the survey method of this thesis, this approach can help better identify passenger groups who are more loyal to the BRT compared to those who are less so. Such knowledge may in turn serve as basis for further investigation by BRT agencies concerning the satisfaction or dissatisfaction held by each group associated with different service attributes (e.g., service frequency, punctuality and stop amenities) of BRT-related services, which provides guidance for the service management of BRT. For example, for commuters who are found to be more dissatisfied about the service frequency of a particular BRT-related route, transit agency may examine the actual possibility of enhancing the service frequency of that route in addition to providing information concerning the updated service timetable and alternative routes to this group of passengers.

BRT agencies should also pay attention to passengers’ attitudes concerning private car use and their influences on loyalty. Caution should also be taken when employing campaigns that are deliberately targeted at restricting private car use in the desire to promote BRT use and maintain BRT passengers’ loyalty within Australian cities. This is due to the fact that passengers may perceive such campaigns unfavourably and behave in an opposite manner to the initial intent, given that private cars are commonly perceived favourably within Australian and other highly motorised cities (Ampt, 2004; Beale and Bonsall, 2007).

8.3 Limitations and future research

Some limitations are inherent in the research design, data and methodology applied in this study, which must be considered so that the findings and implications derived here can be interpreted with necessary caution. Therefore this section aims to detail these limitations and propose related avenues for future research.

8.3.1 Single case study

As detailed in Chapter 4, Brisbane was carefully selected as the study case based on the characteristics of its BRT system and urban context. However, given the limitation of single case studies in terms of generalisability (Yin, 2003), it cannot be stated that the findings of this study (e.g., the spatial-temporal patterns of BRT use, and the behavioural intentions and related attitudes of passengers) will speak for the situations of other Australian or developed cities with high levels of motorisation. Therefore, future studies are now needed to investigate the extent to which the findings of this study are replicable within other developed city contexts and in doing so, adding to a more reliable evidence base concerning BRT system dynamics.

8.3.2 Census data

Three limitations can be identified associated with the use of census data drawn upon in this study. First, the census data is provided in geographically aggregated units instead of for individual travellers. Second, only information for work trips is provided in the census data, while other trips are omitted. Third, due to major changes in the geographical base between the 2006 and 2011 censuses, it is infeasible to make comparisons of the modal share patterns between these years. Given these limitations, the findings concerning the changes in travel patterns and socio-demographic characteristics of BRT catchments should be considered as tentative rather than definitive. To address these limitations, it is necessary to draw on other datasets, such as household travel surveys (if available) before and after BRT implementation within the study context to re-affirm (or reject) the findings here.

8.3.3. Smart card data

Limitations of smart card data mainly relate to their information deficiency. As discussed in

Chapter 2, while containing rich spatial and temporal information for UPT trips, the smart card dataset used here lacks certain important information that includes: the service information (e.g., route, direction) for railway and ferry trips; trips outside the UPT network (e.g., a drive before taking the BRT); personal information (e.g., residential address, socio-demographic information of the smart card holder) and trip purpose. These issues influence the results of this study in two ways. First, the missing information concerning transport modes other than bus (e.g., railway, ferry and private car) renders some of the passengers travel patterns captured here incomplete. Second, it is not possible to establish a linkage between smart card records with specific individuals and activity purposes, which largely hinders the investigation of BRT usage between different socio-demographic groups and their associated activity-travel patterns. To address this information deficiency of smart card data, future research in two possible directions is needed. First, location-aware devices, such as GPS (Asakura and Hato, 2004), can be employed to record the trip information omitted in the smart card data for each (or a sample of) the smart card users. Second, travel survey method can be applied to attain socio-demographic information from smart card users (Pelletier et al., 2011; Utsunomiya et al., 2006). Moreover, providing the above two measures are applied together, more detailed itineraries of activity-travel behaviours may be captured and subjected to further analysis (e.g., individual-based activity-travel pattern analysis).

Other analytical tasks can be undertaken to further the findings here. First, while this research revealed the spatial-temporal patterns of BRT usage under typical calendar events, it did not investigate the behaviour dynamics over continuous days largely due to the limitations associated with the available computing resources for big data. Future research should examine this issue by drawing on a number of consecutive days of smart card data (e.g., several weeks to months). Doing so is likely to unveil more detailed insights into subtle variations of BRT dynamics and provide a more robust basis to inform the long-term management of the BRT, e.g., Trépanier et al (2012), Buliung et al (2008). Second, more advanced analytical methods, such as complex-network analysis drawn from the area of physics (Boccaletti et al., 2006; Guo, 2009), may be applied to smart card data to reveal more insightful spatial-temporal patterns. This however should be driven by specific questions, such as detecting the level of network connectivity related to the BRT systems.

8.3.4. Survey method and data

Limitations related to survey method and data of this research are twofold. First, compared to the results of smart card data, infrequent passengers (in particular those using BRT less than one weekday on an average week) were found to be underrepresented in the survey sample. Hence the findings here might be more reliable concerning the more frequent passengers (i.e., using BRT for one weekday or more on an average week). Future research could draw on other samples of BRT passengers to re-affirm the findings concerning the behavioural intentions revealed in this study. Second, some other attitudinal factors that potentially relate to BRT passengers' behavioural intentions are not included in this study, social norm of BRT use, public image of the BRT agency, to name but a few. This is due to the two following reasons. First, these factors are less central to the questions of interest in this study as outlined in Chapters 2 and 3. Second, given the length of the current questionnaire (a total of 60 questions), the inclusion of these questions may run the risk of reducing response rate and threatening the quality of the completed questionnaires (Sarantakos, 2005; Denscombe, 2007). Nonetheless, further studies are needed to address the effects of these additional attitudinal factors on behavioural intentions of BRT passengers to provide complementary insights to this study.

In addition to the limitations of the survey method and data used, two avenues for research tasks can be identified as well. First, based on the findings of this study, it would be of value to design and carry out information-based experiments and detect their effects in influencing BRT passengers' behavioural intentions and travel behaviour. Previous studies (Ampt, 2004; Seethaler and Rose, 2004) have provided a series of psychological techniques that can be drawn upon in designing such experiments. By doing so, more knowledge concerning the marketing strategy and soft policy to maintain and promote BRT usage for different passenger cohorts can be obtained. Furthermore, given the potential bias induced by a self-report survey concerning the disparity between reported attitudes and actual behaviour (Morton and Mees, 2005), it would be of interest to apply a panel survey method to investigate the longitudinal causal relationships between the attitudinal factors in this study and BRT passengers' travel behaviour. Previous studies recommended that a design of three waves of survey at one year intervals may capture medium to long term causal relationships, e.g., Kitamura (1990), Thøgersen (2006).

8.4 Concluding remarks

Despite the rising trend of BRT implementation as a means to progress towards more sustainable urban transport, little is known regarding its associated travel behaviour dynamics, which critically hinder on the on-going management and planning of BRT systems. This research has sought to bridge this knowledge gap by addressing the research question of '*What are the travel behavioural dynamics of BRT passengers and how can our understanding of these dynamics enhance the understanding about BRT passengers' loyalty and change intentions?*', and in doing so to provide an enhanced evidence base to better inform future BRT-related policy and planning. In achieving the overarching research goal, the research was carried out based on a proposed framework that integrated three complementary aspects namely, the modal share patterns of BRT catchments, the spatial-temporal dynamics of BRT usage and the attitudinal mechanisms concerning BRT passengers' behavioural intentions in order to obtain a more holistic and multi-layered understanding of travel behaviour dynamics related to BRT passengers. Based on the considerations of the strength and weaknesses of different travel behaviour data sources, three formerly disparate datasets (i.e., census, smart card and primary survey data) were drawn upon to investigate the three behavioural dimensions.

The empirical investigations of this research generate a number of valuable insights that shed new light on (1) the extent to which BRT stimulated modal shift from private car use to public transport use in its catchments; (2) the role of BRT in catering for UPT passengers' travel needs expressed by their spatial-temporal trip dynamics across a UPT network; and (3) the variations of the behavioural intentions of BRT passengers and their related attitudinal dimensions. Furthermore, it has been discussed and shown that these results have critical potential to inform future BRT policy and planning within the context of the study from the perspectives of (1) the service provision (in particular the provision and reassignment of the BUZ routes) and infrastructure expansion of the BRT (the exclusive busway) to better meet the local travel needs of passengers and (2) the design of marketing strategy and soft policy (e.g., information-based approach) to maintain and promote BRT usage among passengers.

Some important theoretical and methodological contributions were also progressed in this research. From an overarching perspective, this research demonstrates a paradigm of the application of different data sources in investigating complementary dimensions of UPT passenger travel behaviour. This paradigm can serve as a foundation which future researches can draw upon. In addition, the development and application of a geo-visualisation-based method (the flow-comap) (Tao et al., 2014a) has been shown to critically enhance the utility of smart card data for the investigation of UPT passenger travel behaviour in two ways: (1) the reconstruction of smart card records as travel trajectories at a stop-to-stop level of spatial granularity and (2) the creation of flow-comaps (as well as weighted flow-comaps) from the reconstructed smart card data. Through the application in this study the developed method has proved to be a useful tool for transit providers to monitor and understand nuanced spatial-temporal trip patterns of UPT passengers. Last, by modelling BRT passengers' behaviour intentions in relation to a series of attitudinal dimensions, this study was able to present some novel theoretical insights. In particular, it has highlighted that a more comprehensive inclusion of behaviour intentions (loyalty and behavioural change intentions) coupled with the considerations of alternative transport (in particular private cars) was necessary to obtain a better understanding of UPT passengers' intentions of future mode choice behaviour, from which critical caveats can be attained concerning the design of soft policy options to shape greener travel behaviour (e.g., encouraging BRT use).

While this research has highlighted a series of valuable insights, it also discloses a series of avenues that are worth future research effort, including: (1) empirical studies within other city contexts with BRT systems; (2) additional spatial-temporal analysis of BRT-related travel behaviour using smart card data; (3) further augmenting smart card data by linking with other datasets (e.g., GPS data, survey data); (4) modelling behavioural intentions with a more comprehensive set of attitudinal factors; and (5) designing and testing information-based approaches to maintain and promote BRT usage among passengers.

In conclusion, should a BRT system be implemented as a strategy for sustainable public transport, a reliable evidence base concerning travel behaviour is crucial for its ongoing management and planning. Through a series of empirical investigations of travel behaviour, this research provides a more reliable evidence base that has the potential to better inform future BRT-related policy. It is also hoped that more research in this area will be stimulated to inform and guide the establishment of smarter BRT systems worldwide.

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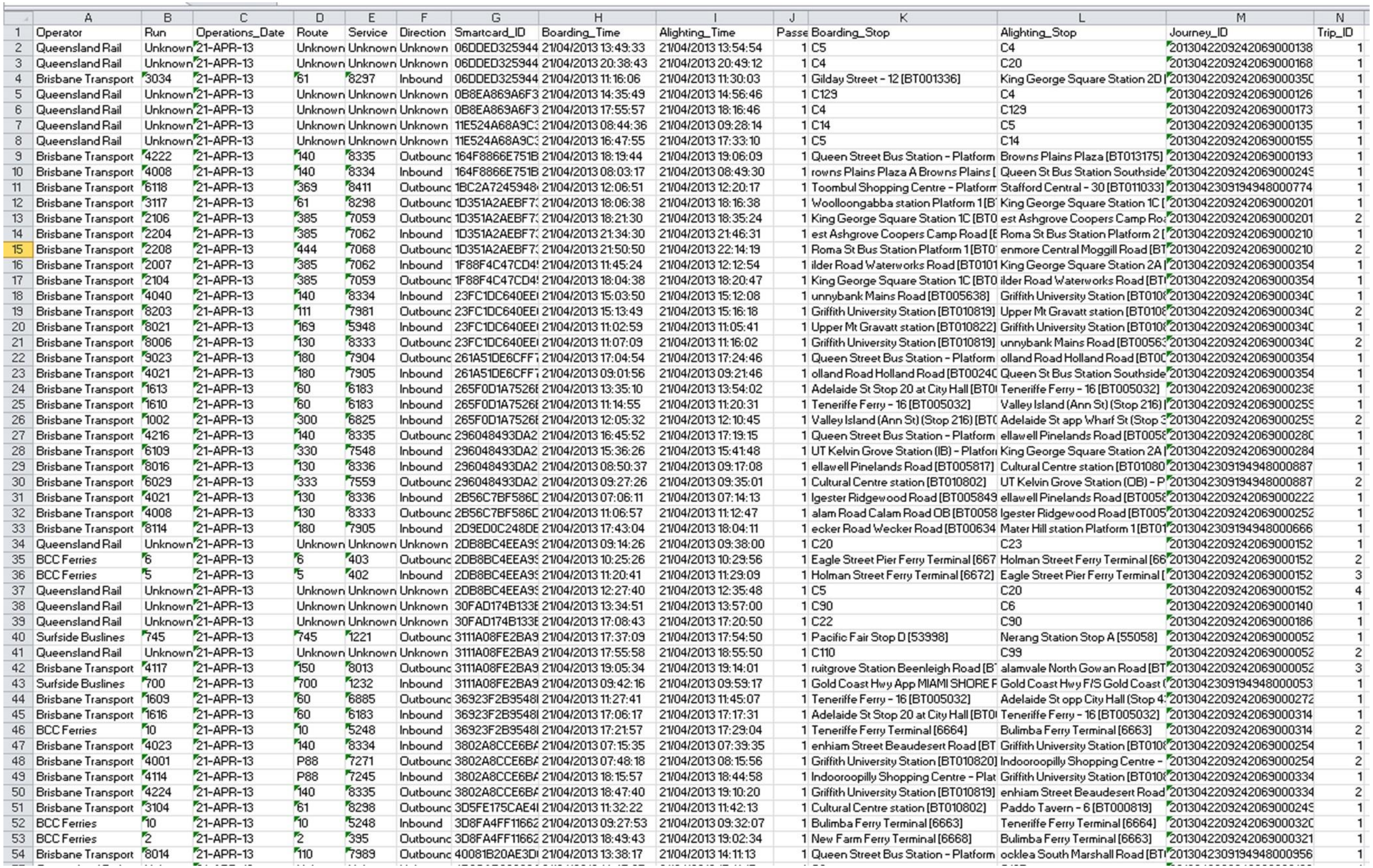
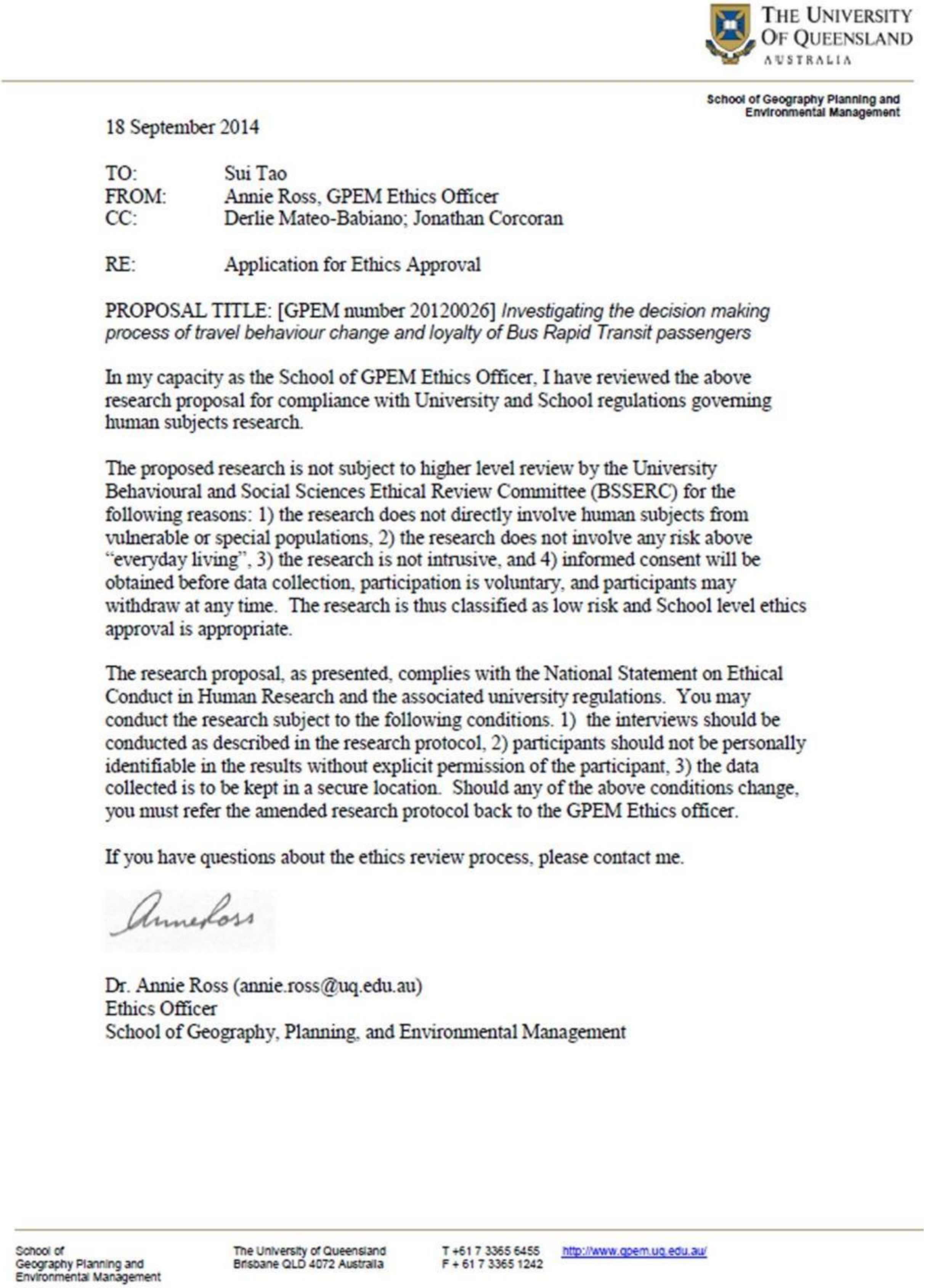
Appendix 1



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Operator	Run	Operations_Date	Route	Service	Direction	Smartcard_ID	Boarding_Time	Alighting_Time	Passe	Boarding_Stop	Alighting_Stop	Journey_ID	Trip_ID
2	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	06DDED325944	21/04/2013 13:49:33	21/04/2013 13:54:54	1	C5	C4	2013042209242069000138	1
3	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	06DDED325944	21/04/2013 20:38:43	21/04/2013 20:49:12	1	C4	C20	2013042209242069000168	1
4	Brisbane Transport	3034	21-APR-13	61	8297	Inbound	06DDED325944	21/04/2013 11:16:06	21/04/2013 11:30:03	1	Gilday Street - 12 [BT001336]	King George Square Station 2D [	2013042209242069000350	1
5	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	0B8EA869A6F3	21/04/2013 14:35:49	21/04/2013 14:56:46	1	C129	C4	2013042209242069000126	1
6	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	0B8EA869A6F3	21/04/2013 17:55:57	21/04/2013 18:16:46	1	C4	C129	2013042209242069000173	1
7	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	11E524A68A9C	21/04/2013 08:44:36	21/04/2013 09:28:14	1	C14	C5	2013042209242069000135	1
8	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	11E524A68A9C	21/04/2013 16:47:55	21/04/2013 17:33:10	1	C5	C14	2013042209242069000155	1
9	Brisbane Transport	4222	21-APR-13	140	8335	Outbounc	164F8866E751B	21/04/2013 18:19:44	21/04/2013 19:06:09	1	Queen Street Bus Station - Platform	Browns Plains Plaza [BT013175]	2013042209242069000193	1
10	Brisbane Transport	4008	21-APR-13	140	8334	Inbound	164F8866E751B	21/04/2013 08:03:17	21/04/2013 08:49:30	1	rowns Plains Plaza A Browns Plains [	Queen St Bus Station Southside	2013042209242069000249	1
11	Brisbane Transport	6118	21-APR-13	369	8411	Outbounc	1BC2A7245948	21/04/2013 12:06:51	21/04/2013 12:20:17	1	Toombul Shopping Centre - Platform	Stafford Central - 30 [BT011033]	2013042309194948000774	1
12	Brisbane Transport	3117	21-APR-13	61	8298	Outbounc	1D351A2AEBF7	21/04/2013 18:06:38	21/04/2013 18:16:38	1	Woolloongabba station Platform 1 [B	King George Square Station 1C [	2013042209242069000201	1
13	Brisbane Transport	2106	21-APR-13	385	7059	Outbounc	1D351A2AEBF7	21/04/2013 18:21:30	21/04/2013 18:35:24	1	King George Square Station 1C [BT0	est Ashgrove Coopers Camp Ro	2013042209242069000201	2
14	Brisbane Transport	2204	21-APR-13	385	7062	Inbound	1D351A2AEBF7	21/04/2013 21:34:30	21/04/2013 21:46:31	1	est Ashgrove Coopers Camp Road [E	Roma St Bus Station Platform 2 [	2013042209242069000210	1
15	Brisbane Transport	2208	21-APR-13	444	7068	Outbounc	1D351A2AEBF7	21/04/2013 21:50:50	21/04/2013 22:14:19	1	Roma St Bus Station Platform 1 [BT0	enmore Central Moggill Road [BT	2013042209242069000210	2
16	Brisbane Transport	2007	21-APR-13	385	7062	Inbound	1F88F4C47CD4	21/04/2013 11:45:24	21/04/2013 12:12:54	1	ilder Road Waterworks Road [BT0101	King George Square Station 2A [	2013042209242069000354	1
17	Brisbane Transport	2104	21-APR-13	385	7059	Outbounc	1F88F4C47CD4	21/04/2013 18:04:38	21/04/2013 18:20:47	1	King George Square Station 1C [BT0	ilder Road Waterworks Road [BT	2013042209242069000354	1
18	Brisbane Transport	4040	21-APR-13	140	8334	Inbound	23FC1DC640EE	21/04/2013 15:03:50	21/04/2013 15:12:08	1	unnybank Mains Road [BT005638]	Griffith University Station [BT010	2013042209242069000340	1
19	Brisbane Transport	8203	21-APR-13	111	7981	Outbounc	23FC1DC640EE	21/04/2013 15:13:49	21/04/2013 15:16:18	1	Griffith University Station [BT010819]	Upper Mt Gravatt station [BT010	2013042209242069000340	2
20	Brisbane Transport	8021	21-APR-13	169	5948	Inbound	23FC1DC640EE	21/04/2013 11:02:59	21/04/2013 11:05:41	1	Upper Mt Gravatt station [BT010822]	Griffith University Station [BT010	2013042209242069000340	1
21	Brisbane Transport	8006	21-APR-13	130	8333	Outbounc	23FC1DC640EE	21/04/2013 11:07:09	21/04/2013 11:16:02	1	Griffith University Station [BT010819]	unnybank Mains Road [BT0056	2013042209242069000340	2
22	Brisbane Transport	9023	21-APR-13	180	7904	Outbounc	261A51DE6CFF	21/04/2013 17:04:54	21/04/2013 17:24:46	1	Queen Street Bus Station - Platform	olland Road Holland Road [BT0C	2013042209242069000354	1
23	Brisbane Transport	4021	21-APR-13	180	7905	Inbound	261A51DE6CFF	21/04/2013 09:01:56	21/04/2013 09:21:46	1	olland Road Holland Road [BT0024C	Queen St Bus Station Southside	2013042209242069000354	1
24	Brisbane Transport	1613	21-APR-13	60	6183	Inbound	265F0D1A7526	21/04/2013 13:35:10	21/04/2013 13:54:02	1	Adelaide St Stop 20 at City Hall [BT0	Teneriffe Ferry - 16 [BT005032]	2013042209242069000238	1
25	Brisbane Transport	1610	21-APR-13	60	6183	Inbound	265F0D1A7526	21/04/2013 11:14:55	21/04/2013 11:20:31	1	Teneriffe Ferry - 16 [BT005032]	Valley Island (Ann St) (Stop 216) [	2013042209242069000259	1
26	Brisbane Transport	1002	21-APR-13	300	6825	Inbound	265F0D1A7526	21/04/2013 12:05:32	21/04/2013 12:10:45	1	Valley Island (Ann St) (Stop 216) [BT	Adelaide St app Wharf St (Stop 3	2013042209242069000259	2
27	Brisbane Transport	4216	21-APR-13	140	8335	Outbounc	296048493DA2	21/04/2013 16:45:52	21/04/2013 17:19:15	1	Queen Street Bus Station - Platform	ellawell Pinelands Road [BT005	2013042209242069000280	1
28	Brisbane Transport	6109	21-APR-13	330	7548	Inbound	296048493DA2	21/04/2013 15:36:26	21/04/2013 15:41:48	1	UT Kelvin Grove Station (IB) - Platfor	King George Square Station 2A [	2013042209242069000284	1
29	Brisbane Transport	8016	21-APR-13	130	8336	Inbound	296048493DA2	21/04/2013 08:50:37	21/04/2013 09:17:08	1	ellawell Pinelands Road [BT005817]	Cultural Centre station [BT01080	2013042309194948000887	1
30	Brisbane Transport	6029	21-APR-13	333	7559	Outbounc	296048493DA2	21/04/2013 09:27:26	21/04/2013 09:35:01	1	Cultural Centre station [BT010802]	UT Kelvin Grove Station (OB) - P	2013042309194948000887	2
31	Brisbane Transport	4021	21-APR-13	130	8336	Inbound	2B56C7BF586	21/04/2013 07:06:11	21/04/2013 07:14:13	1	lgester Ridgewood Road [BT005849	ellawell Pinelands Road [BT005	2013042209242069000222	1
32	Brisbane Transport	4008	21-APR-13	130	8333	Outbounc	2B56C7BF586	21/04/2013 11:06:57	21/04/2013 11:12:47	1	alam Road Calam Road OB [BT0058	lgester Ridgewood Road [BT005	2013042209242069000252	1
33	Brisbane Transport	8114	21-APR-13	180	7905	Inbound	2D9ED0C248DE	21/04/2013 17:43:04	21/04/2013 18:04:11	1	ecker Road Wecker Road [BT00634	Mater Hill station Platform 1 [BT01	2013042309194948000666	1
34	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	2DB8BC4EEA9	21/04/2013 09:14:26	21/04/2013 09:38:00	1	C20	C23	2013042209242069000152	1
35	BCC Ferries	6	21-APR-13	6	403	Outbounc	2DB8BC4EEA9	21/04/2013 10:25:26	21/04/2013 10:29:56	1	Eagle Street Pier Ferry Terminal [667	Holman Street Ferry Terminal [66	2013042209242069000152	2
36	BCC Ferries	5	21-APR-13	5	402	Inbound	2DB8BC4EEA9	21/04/2013 11:20:41	21/04/2013 11:29:09	1	Holman Street Ferry Terminal [6672]	Eagle Street Pier Ferry Terminal [	2013042209242069000152	3
37	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	2DB8BC4EEA9	21/04/2013 12:27:40	21/04/2013 12:35:48	1	C5	C20	2013042209242069000152	4
38	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	30FAD174B133	21/04/2013 13:34:51	21/04/2013 13:57:00	1	C90	C6	2013042209242069000140	1
39	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	30FAD174B133	21/04/2013 17:08:43	21/04/2013 17:20:50	1	C22	C90	2013042209242069000186	1
40	Surfside Buslines	745	21-APR-13	745	1221	Outbounc	3111A08FE2BA9	21/04/2013 17:37:09	21/04/2013 17:54:50	1	Pacific Fair Stop D [53998]	Nerang Station Stop A [55058]	2013042209242069000052	1
41	Queensland Rail	Unknown	21-APR-13	Unknown	Unknown	Unknown	3111A08FE2BA9	21/04/2013 17:55:58	21/04/2013 18:55:50	1	C110	C99	2013042209242069000052	2
42	Brisbane Transport	4117	21-APR-13	150	8013	Outbounc	3111A08FE2BA9	21/04/2013 19:05:34	21/04/2013 19:14:01	1	ruitgrove Station Beenleigh Road [B	alamvale North Gowan Road [BT	2013042209242069000052	3
43	Surfside Buslines	700	21-APR-13	700	1232	Inbound	3111A08FE2BA9	21/04/2013 09:42:16	21/04/2013 09:59:17	1	Gold Coast Hwy App MIAMI SHORE F	Gold Coast Hwy F/S Gold Coast (	2013042309194948000053	1
44	Brisbane Transport	1609	21-APR-13	60	6885	Outbounc	36923F2B9548	21/04/2013 11:27:41	21/04/2013 11:45:07	1	Teneriffe Ferry - 16 [BT005032]	Adelaide St opp City Hall (Stop 4	2013042209242069000272	1
45	Brisbane Transport	1616	21-APR-13	60	6183	Inbound	36923F2B9548	21/04/2013 17:06:17	21/04/2013 17:17:31	1	Adelaide St Stop 20 at City Hall [BT0	Teneriffe Ferry - 16 [BT005032]	2013042209242069000314	1
46	BCC Ferries	10	21-APR-13	10	5248	Inbound	36923F2B9548	21/04/2013 17:21:57	21/04/2013 17:29:04	1	Teneriffe Ferry Terminal [6664]	Bulimba Ferry Terminal [6663]	2013042209242069000314	2
47	Brisbane Transport	4023	21-APR-13	140	8334	Inbound	3802A8CCE6B	21/04/2013 07:15:35	21/04/2013 07:39:35	1	enhiam Street Beaudesert Road [BT	Griffith University Station [BT010	2013042209242069000254	1
48	Brisbane Transport	4001	21-APR-13	P88	7271	Outbounc	3802A8CCE6B	21/04/2013 07:48:18	21/04/2013 08:15:56	1	Griffith University Station [BT010820]	Indooroopilly Shopping Centre -	2013042209242069000254	2
49	Brisbane Transport	4114	21-APR-13	P88	7245	Inbound	3802A8CCE6B	21/04/2013 18:15:57	21/04/2013 18:44:58	1	Indooroopilly Shopping Centre - Plat	Griffith University Station [BT010	2013042209242069000334	1
50	Brisbane Transport	4224	21-APR-13	140	8335	Outbounc	3802A8CCE6B	21/04/2013 18:47:40	21/04/2013 19:10:20	1	Griffith University Station [BT010819]	enhiam Street Beaudesert Road	2013042209242069000334	2
51	Brisbane Transport	3104	21-APR-13	61	8298	Outbounc	3D5FE175CAE4	21/04/2013 11:32:22	21/04/2013 11:42:13	1	Cultural Centre station [BT010802]	Paddo Tavern - 6 [BT000819]	2013042209242069000249	1
52	BCC Ferries	10	21-APR-13	10	5248	Inbound	3D8FA4FF11662	21/04/2013 09:27:53	21/04/2013 09:32:07	1	Bulimba Ferry Terminal [6663]	Teneriffe Ferry Terminal [6664]	2013042209242069000320	1
53	BCC Ferries	2	21-APR-13	2	395	Outbounc	3D8FA4FF11662	21/04/2013 18:49:43	21/04/2013 19:02:34	1	New Farm Ferry Terminal [6668]	Bulimba Ferry Terminal [6663]	2013042209242069000321	1
54	Brisbane Transport	8014	21-APR-13	110	7989	Outbounc	40081B20AE3D	21/04/2013 13:38:17	21/04/2013 14:11:13	1	Queen Street Bus Station - Platform	ocklea South Marshall Road [BT	2013042309194948000956	1

Appendix 2



THE UNIVERSITY
OF QUEENSLAND
AUSTRALIA

School of Geography Planning and
Environmental Management

18 September 2014

TO: Sui Tao
FROM: Annie Ross, GPEM Ethics Officer
CC: Derlie Mateo-Babiano; Jonathan Corcoran

RE: Application for Ethics Approval

PROPOSAL TITLE: [GPEM number 20120026] *Investigating the decision making process of travel behaviour change and loyalty of Bus Rapid Transit passengers*

In my capacity as the School of GPEM Ethics Officer, I have reviewed the above research proposal for compliance with University and School regulations governing human subjects research.

The proposed research is not subject to higher level review by the University Behavioural and Social Sciences Ethical Review Committee (BSSERC) for the following reasons: 1) the research does not directly involve human subjects from vulnerable or special populations, 2) the research does not involve any risk above "everyday living", 3) the research is not intrusive, and 4) informed consent will be obtained before data collection, participation is voluntary, and participants may withdraw at any time. The research is thus classified as low risk and School level ethics approval is appropriate.

The research proposal, as presented, complies with the National Statement on Ethical Conduct in Human Research and the associated university regulations. You may conduct the research subject to the following conditions. 1) the interviews should be conducted as described in the research protocol, 2) participants should not be personally identifiable in the results without explicit permission of the participant, 3) the data collected is to be kept in a secure location. Should any of the above conditions change, you must refer the amended research protocol back to the GPEM Ethics officer.

If you have questions about the ethics review process, please contact me.

Dr. Annie Ross (annie.ross@uq.edu.au)
Ethics Officer
School of Geography, Planning, and Environmental Management

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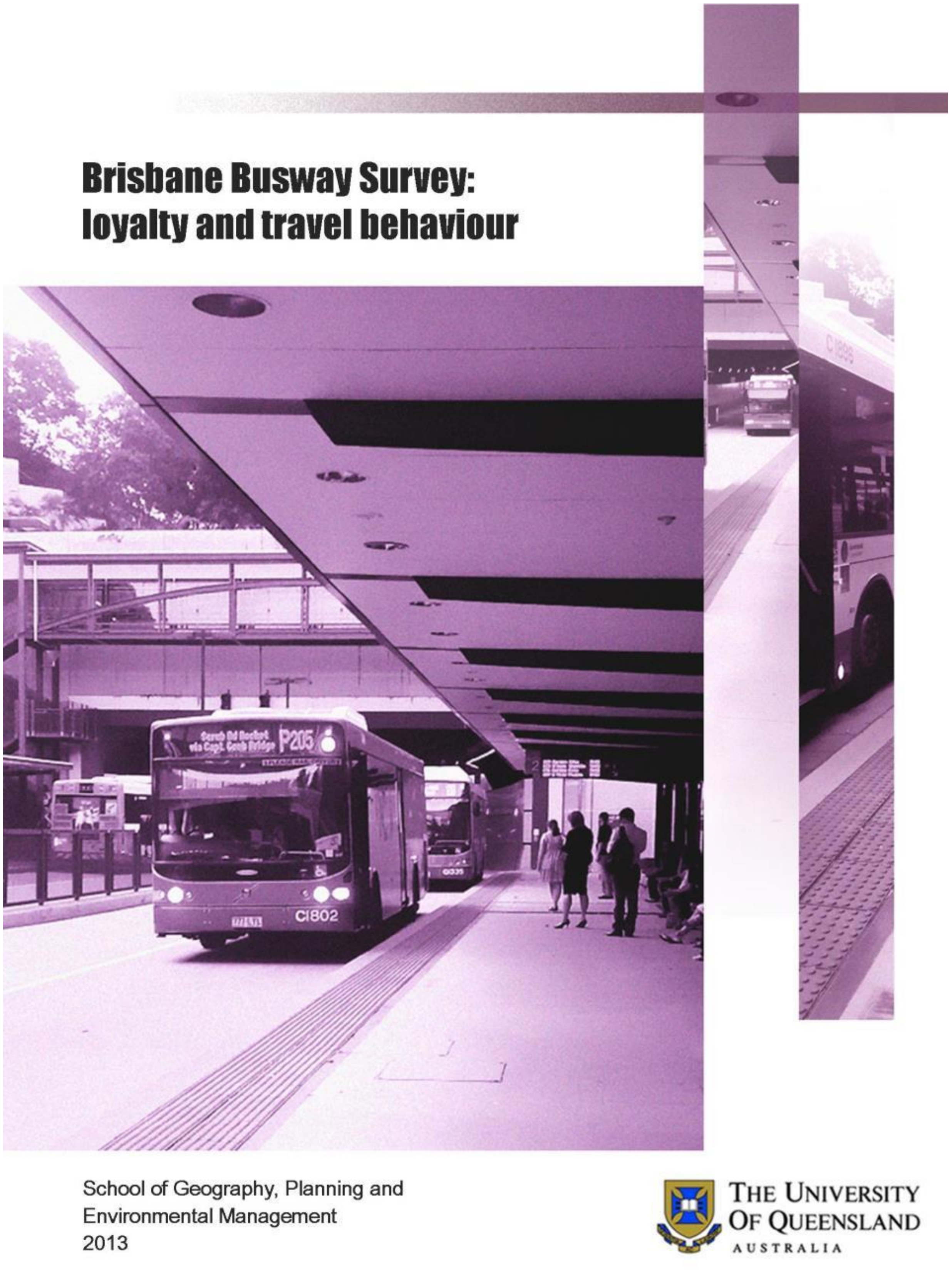
Appendix 3



Brisbane Busway Survey: loyalty and travel behaviour

School of Geography, Planning and
Environmental Management
2013

THE UNIVERSITY
OF QUEENSLAND
AUSTRALIA

Thank you for taking part in this busway survey. The survey will take approximately 12-15 minutes to complete. Please return the completed questionnaire using the **postage-paid envelope**.

THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

School of Geography, Planning and Environmental Management

CRICOS PROVIDER NUMBER 00025B

INFORMED CONSENT FORM

Name of Project: Investigating the decision making process of travel behaviour change and loyalty of Bus Rapid Transit passengers
Investigator: Sui Tao

Consent Agreement

1. I have read the Project Information Sheet and confirm that I am willing to participate in this research, and I understand the nature of the research and my role in it.
2. I understand that I am free to withdraw from the project at any time and to withdraw any data I have contributed that has not already been processed.
3. I understand that while information gained during the study will be published, my personal information will remain confidential.
4. I give permission for my responses in the survey to be used and published by Sui Tao.

☐ Yes ☐ No

Signature of participant:______________________________

Date: / /

Researcher's signature: Sui Tao

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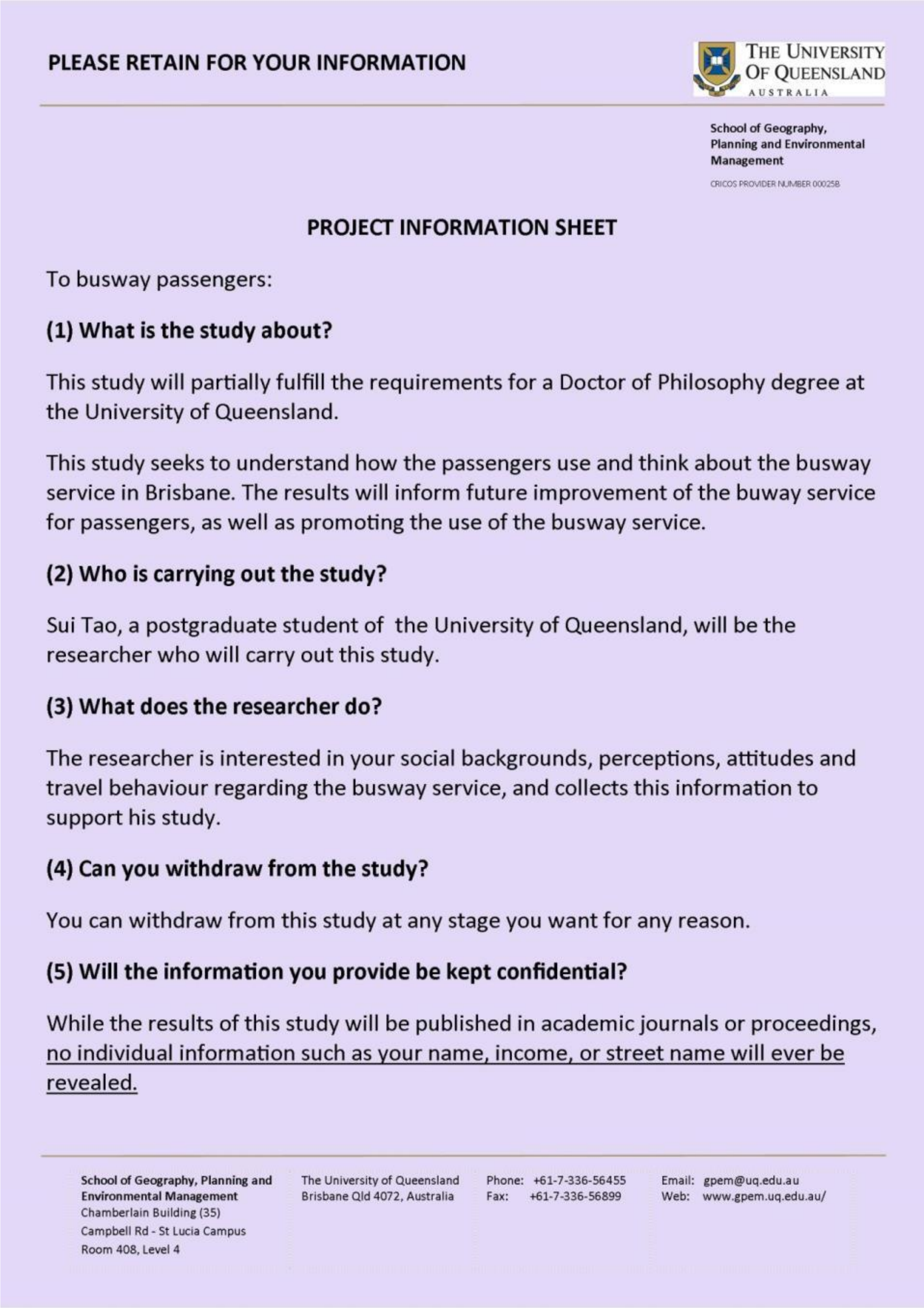

PLEASE RETAIN FOR YOUR INFORMATION

THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

School of Geography, Planning and Environmental Management

CRICOS PROVIDER NUMBER 00025B

PROJECT INFORMATION SHEET

To busway passengers:

(1) What is the study about?

This study will partially fulfill the requirements for a Doctor of Philosophy degree at the University of Queensland.

This study seeks to understand how the passengers use and think about the busway service in Brisbane. The results will inform future improvement of the buway service for passengers, as well as promoting the use of the busway service.

(2) Who is carrying out the study?

Sui Tao, a postgraduate student of the University of Queensland, will be the researcher who will carry out this study.

(3) What does the researcher do?

The researcher is interested in your social backgrounds, perceptions, attitudes and travel behaviour regarding the busway service, and collects this information to support his study.

(4) Can you withdraw from the study?

You can withdraw from this study at any stage you want for any reason.

(5) Will the information you provide be kept confidential?

While the results of this study will be published in academic journals or proceedings, no individual information such as your name, income, or street name will ever be revealed.

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Web: www.gpem.uq.edu.au/

(6) What if you require further information?

You may access to the results from this study, by contacting the researcher of this project. The contact details are provided below.

This study adheres to the Guidelines of the ethical review process of The University of Queensland.

Whilst you are free to discuss your participation in this study with the researcher (contact name: Sui Tao, phone number: +61 (0) 7 336 56534, email address: s.tao@uq.edu.au), if you would like to speak to an officer of the University not involved in the study, you may contact Dr Annie Ross, Ethics Officer on +61 (0) 7 3365 1450; or +61 (0) 7 3365 6084; or annie.ross@uq.edu.au.

Your participation in this survey will be very valuable to my study. I would like to thank you in advance for your participation.

Sui Tao

PhD candidate | School of Geography, Planning and Environmental Management
The University of Queensland, St. Lucia, Qld 4072, Australia

First of all, please tell me a little about yourself *(Please cross one response)*:

① Your gender: ☐ Male ☐ Female

② Your age last birthday: ______________

③ Your highest level of educational attainment:

☐ Postgraduate degree ☐ Graduate diploma/certificate ☐ Bachelor degree
☐ Advanced diploma/diploma ☐ Certificate level ☐ Senior high school
Other______________________

④ Your employment status: ☐ Part-time work ☐ Full-time work ☐ Retired
☐ Student ☐ Unemployed Other__________________________

⑤ Your marital status: ☐ Single ☐ Single with dependent child/children
☐ Couple with dependent child/children ☐ Couple without dependent children
Other_______________________________

⑥ Do you have a valid driver's license? ☐ Yes ☐ No

⑦ Do you have a private car at your disposal?

☐ Yes, always ☐ Yes, sometimes ☐ No, seldom/never

⑧ Your weekly household income (in $):

☐ <399 ☐ 400-599 ☐ 600-799 ☐ 800-999 ☐ 1,000-1,250
☐ 1,250-1,499 ☐ 1,500-1,999 ☐ 2,000-2,500 ☐ 2,500-3,000 ☐ >3,000

⑨ How long have you been using the busway service? ______Years ______Months

⑩ From Monday to Friday, how often do you use the busway service on average?

☐ Every weekday ☐ 3 to 4 weekdays ☐ 1 to 2 weekdays
☐ At least one weekday a month ☐ Less than one weekday a month

⑪ On weekends, how often do you use the busway service in an average month?

☐ Every weekend ☐ 2 to 3 weekends ☐ 1 weekend ☐ Less than 1 weekend

⑫ What is the name of your usual busway station: ______________________________

⑬ How do you usually arrive at your usual busway station?

☐ Walk ☐ Cycle ☐ Private car ☐ Train ☐ Bus Other_____________

⑭ What is the main purpose of your trip today?

☐ Work/Study ☐ Shopping ☐ Recreation Other__________________________

Following the last section:

⑮ What is your postcode of your usual residence: ☐ ☐ ☐ ☐

⑯ What is your street name of your usual residence: ______________________

The next section includes 44 questions. **PLEASE CIRCLE** the number for each question from 1 to 7 that best captures your answer, with **1-strongly disagree, 2-disagree, 3-slightly disagree, 4-neutral (neither agree nor disagree), 5-slightly agree, 6-agree, and 7-strongly agree.**

Here is an example of how to respond to a question:

Q1. The Brisbane busway service is convenient. 1 2 3 4 [✓ 5] 6 7

What do you think about the busway service?

	Strongly Disagree			Neutral			Strongly Agree
⑰ Riding the busway sevice is safe.	1	2	3	4	5	6	7
⑱ The busway service is frequent.	1	2	3	4	5	6	7
⑲ The busway service is on time.	1	2	3	4	5	6	7
⑳ Riding the busway service is comfortable.	1	2	3	4	5	6	7
㉑ The busway stations are well-equipped.	1	2	3	4	5	6	7
㉒ The busway stations are easy to get to.	1	2	3	4	5	6	7
㉓ Riding the busway service saves time.	1	2	3	4	5	6	7
㉔ Bus fares are cheap.	1	2	3	4	5	6	7
㉕ Information about bus routes at the busway stations is easy to understand.	1	2	3	4	5	6	7
㉖ Bus drivers are always friendly.	1	2	3	4	5	6	7

How satisfied are you with the busway service?

㉗ Overall I am satisfied with the busway service.	1	2	3	4	5	6	7
㉘ I always have a good experience when riding the busway service.	1	2	3	4	5	6	7
㉙ Overall the busway service exceeds my expectations.	1	2	3	4	5	6	7

	Strongly Disagree			Neutral			Strongly Agree

How valuable is the busway service to you?

㉚ The busway service is worth the money it costs me.	1	2	3	4	5	6	7
㉛The busway service is worth the time I use it.	1	2	3	4	5	6	7
㉜ I highly value the busway service.	1	2	3	4	5	6	7

How committed are you to the busway service?

㉝ I am willing to continue to use the busway service.	1	2	3	4	5	6	7
㉞ I am willing to recommend the busway service to others.	1	2	3	4	5	6	7

Do environmental concerns encourage you to use the busway service?

㉟ I strongly feel using the busway service is a way to reduce environmental pollution.	1	2	3	4	5	6	7
㊱ I strongly feel using the busway service is a way to reduce traffic problems.	1	2	3	4	5	6	7
㊲ I strongly feel using a car too much will increase environmental problems.	1	2	3	4	5	6	7
㊳ I strongly feel using a car too much will increase traffic problems.	1	2	3	4	5	6	7

Are your family and friends supportive of you in using a private car for regular trips (such as traveling to or from work/study/shopping) in Brisbane ?

㊴ My family are supportive of me in using a private car for my regular trips in Brisbane.	1	2	3	4	5	6	7
㊵ My friends are supportive of me in using a private car for my regular trips in Brisbane.	1	2	3	4	5	6	7
㊶ My family members use private cars in Brisbane very frequently.	1	2	3	4	5	6	7
㊷ My friends use private cars in Brisbane very frequently.	1	2	3	4	5	6	7

What do you think about private cars?	Strongly Disagree			Neutral			Strongly Agree
㊸ Private cars are a reliable transport mode.	1	2	3	4	5	6	7
㊹ Private cars are a flexible transport mode.	1	2	3	4	5	6	7
㊺ Private cars are a low-cost transport	1	2	3	4	5	6	7
㊻ Private cars are a time-saving transport	1	2	3	4	5	6	7
㊼ Private cars are a safe transport mode.	1	2	3	4	5	6	7
㊽ Using a private car is comfortable.	1	2	3	4	5	6	7
㊾ Using a private car is enjoyable.	1	2	3	4	5	6	7
㊿ Using a private car gives one a prestigious image.	1	2	3	4	5	6	7

Is it easy for you to use a private car in Brisbane?

(51) If I want to use a private car in Brisbane, one is always available.	1	2	3	4	5	6	7
(52) I am confident in driving a private car in Brisbane.	1	2	3	4	5	6	7
(53) For me, driving a private car in Brisbane is affordable.	1	2	3	4	5	6	7

In the near future, do you intend to increase your use of the busway service for your regular trips (such as traveling to or from work/study/shopping) in Brisbane?

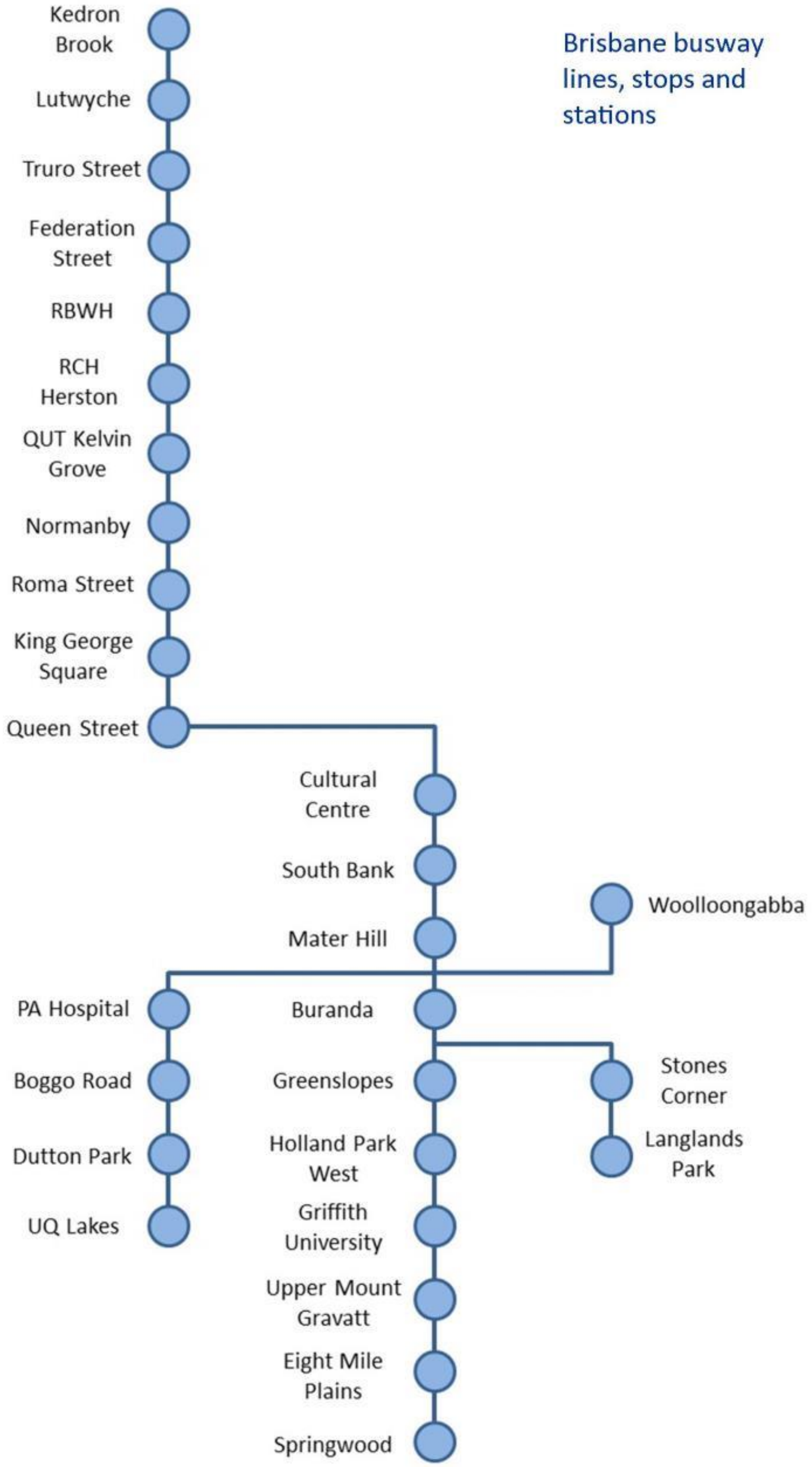
(54) I am likely to increase my use of the busway service for my regular trips in Brisbane.	1	2	3	4	5	6	7
(55) I am willing to increase my use of the busway service for my regular trips in Brisbane.	1	2	3	4	5	6	7
(56) If the busway network is expanded to connect more localities around Brisbane, I am willing to make more trips by the busway service in Brisbane.	1	2	3	4	5	6	7

	Strongly Disagree			Neutral			Strongly Agree

In the near future, do you intend to use a private car instead of the busway service for more of your regular trips (such as travelling to or from work/study/shopping) in Brisbane?

(57) I am likely to use a private car instead of the busway service for more of my regular trips in Brisbane.	1	2	3	4	5	6	7
(58) I am willing to use a private car instead of the busway service for more of my regular trips in Brisbane.	1	2	3	4	5	6	7
(59) In general, I prefer a private car to the busway service to travel in Brisbane.	1	2	3	4	5	6	7
(60) If using a private car becomes cheaper (for example, cheaper car parking and lower fuel prices), I am willing to use a private car instead of the busway service for more of my regular trips.	1	2	3	4	5	6	7

Thank you for your time in completing this survey. Your input is very valuable.


Brisbane busway lines, stops and stations
Kedron Brook
Lutwyche
Truro Street
Federation Street
RBWH
RCH Herston
QUT Kelvin Grove
Normanby
Roma Street
King George Square
Queen Street
Cultural Centre
South Bank
Woolloongabba
Mater Hill
PA Hospital
Buranda
Stones Corner
Boggo Road
Greenslopes
Langlands Park
Dutton Park
Holland Park West
UQ Lakes
Griffith University
Upper Mount Gravatt
Eight Mile Plains
Springwood