Travel Based Multitasking on the Mumbai Local and Metro: Measurement, Classification and Variation

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Abstract

Review of travel based multitasking (TBM) behavior has shown that activities performed during travel is of growing interest in the field of transportation planning and mobility behavior. There is a lack of literature looking at this subject in cities in developing countries. This thesis examines TBM activities occurring on mass transit modes in the Mumbai Metropolitan Region. It takes the Western Line of the Mumbai Suburban Railway and the upcoming Line II and III of the Mumbai Metro as case studies to understand TBM activities in the Indian context. Firstly, this thesis calculates the influence of socio-economic and trip-related variables on the occurrence of ICT-related and social TBM activities through a framework of Positive Utility of Travel (PUT). Secondly, it identifies the possible causes of variation of TBM among different socio-economic groups. Thirdly, it charts how policy and infrastructure decisions on the Mumbai Suburban Railway and the Mumbai Metro can be informed by ICT-related and social TBM activities performed by riders during on-board travel time. An on-board intercept survey of 196 riders conducted in August 2018 on the Western line of the Mumbai Suburban Railway was used to analyze revealed and stated preferences of TBM activities. Results of choice models were further deconstructed with insights from unstructured interviews. Age and willingness to pay per minute were the strongest predictors of TBM activities. Riders younger than 34 years of age on the Mumbai Suburban Railway and younger than 29 years of age on the Mumbai Metro were more inclined to engage in ICT-related TBM activities. Female riders displayed a higher tendency to socialize on mass transit when compared to male riders and frequently perceived general compartments on the Mumbai Suburban Railway as unsafe to perform ICT-related activities.

Thesis Supervisor: Jinhua Zhao

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I dedicate this thesis to my mother and father.

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Terms and Abbreviations Used

BNL – Binomial Logistic

CMP – Comprehensive Mobility Plan

MM – Mumbai Metro

MNL –Multinomial Logistic Regression

MMR – Mumbai Metropolitan Region

MMRDA – Mumbai Metropolitan Regional Development Authority

MSR – Mumbai Suburban Railway

PUT– Positive Utility of Time

RF – Random Forest

RP – Revealed preference

SP – Stated Preference

TBM – Travel Based Multitasking

TNC – Transportation Network Companies

VOT – Value of Time

VTTS – Value of Travel Time Savings

WTP – Willingness to Pay

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1. Introduction

Multitasking activities that riders perform on public transit have been changing rapidly in the last decade. Compared to the pre-information era, riders now have greater opportunity to use phones, tablets or laptops (collectively known as Information and Communications Technology or ICT) and productively spend their waiting and on-board travel time. In India, this has been evident in the Mumbai Metropolitan Region, where commutes on the Suburban Railway average 1.5 hours a day or 432 hours a year. Trips to and from work on the suburban train absorb a sizeable portion of the average commuter's workday. The quality of multitasking activities on which a Mumbai commuter spends her time gains importance.

To support travel-based multitasking (TBM), transit agencies design policies that help a commuter – or any rider – effectively perform activities such as reading, listening to music or watching videos. However, in Mumbai, there exists a gap between policy goals and emerging types of multitasking activities on the Suburban Railway and Metro. Policies in Mumbai fail to address social and ICT-related activities and the rare policies that address them are designed with limited understanding of multitasking behavior and the factors that support them.

This thesis aims to fill the gap by designing a set of recommendations for policies and infrastructure that can promote appropriate TBM such as the use of ICT- related or social activities among commuters. It charts a comparison of TBM activities that take place during on-board travel on the Mumbai Suburban Railway (MSR) and the Mumbai Metro (MM) by taking the Western Line and the upcoming metro lines as case studies.

Firstly, this thesis identifies the influence of socio-economic and trip-related variables on the occurrence of TBM activities through a framework of Positive Utility of Travel (PUT). Secondly, it compares the influence of these variables in predicting multitasking behavior on the two modes of transportation mentioned above. Thirdly, it analyzes the root causes behind certain TBM behavior on the Mumbai Suburban Railway and the Mumbai Metro. Evidence to support the thesis is drawn from on-board intercept surveys and unstructured interviews conducted in August 2018 on the Western line of the Mumbai Suburban Railway.

By developing quantitative models, the thesis aims to design a set of best practices for policy and infrastructure decisions that support multitasking and improve the overall rider experience on the Mumbai Metro and the Mumbai Suburban Railway.

1.1 Motivations

The value of time spent in travelling has been researched in the field of transportation behavior for the past three decades. It was introduced through articles that pioneered the concepts of place-time allocation and utility maximization in the 1970s. Becker (1965) and DeSerpa (1971) proposed an economic framework of utility maximization that was subject to income constraints and minimization of time needed to perform activities (USDOT 2011). The nascent concepts helped Jara-Díaz & Guevara (1999) and Mackie et al. (2001) develop microeconomic theories on travel time valuation.

These theories, based on an assumption that riders are rational consumers, suggested that travel time carried negative utility (Ben-Akiva & Lerman, 1985). The idea of negative utility of travel time was used to explain the motivation of modal choice in trips of all purposes – travel was viewed as a means to an end with no pleasure or benefit embedded in the experience of traveling itself. The theory of negative utility of travel time has since guided cost-benefit analysis to justify new infrastructure project spending. Benefits were measured by the time that a rider saves by performing a trip on a new mode of transportation when compared to an existing mode of transportation. Then, total funds that a transportation project required were weighed against aggregate benefits to riders. In this process, the disutility of time could be measured in monetary terms for each rider through a parameter called Value of Travel Time Savings (VTTS). The negative utility of time framework was considered the best way to approach infrastructure cost-benefit analysis. However, the assumption of negative utility for all types of travel was challenged in 2005 by transportation behavioral scientists Salomon and Mokhtarian (1998) through the theory of positive utility of travel (PUT).

PUT suggested that positive utility may be associated with different aspects of travel – activities at the destination, multitasking activities during travel, or the experience of the travel itself. Also, not all travel was to be considered a derived demand – rather the activity of travel in itself can provide benefit when the trip is undirected. The importance of simultaneous activities that are conducted through multitasking was highlighted and VTTS evolved to capture the true savings in travel time. With the introduction of positive utility of travel time, riders' travel experience began to be evaluated in terms of the ability to multitask during in-vehicle travel and waiting in addition to the actual time saved.

Transportation planning agencies in developed countries have been implementing policies to assist the appropriate use of travel time through multitasking. For example, the 'Books on the Underground' lending project in the London tube encourages riders to read books while traveling. Also, Amtrak has introduced the 'Quiet Car' program on their Northeast corridor trains where passengers are provided with a quiet and peaceful environment to work productively. However, in the context of developing countries, cities have been slow to adapt policies that directly address the need to support TBM activities. Riders face a multitude of problems – loud compartments, unsafe environments, poor ICT infrastructure or cultural norms – that hinder multitasking during travel. This is the case in Mumbai, where riders face to multitask effectively on the MSR.

Taking these issues into consideration, this thesis is motivated by three ideas:

First, the central motivation behind this thesis is to measure and understand TBM activities in the context of a rapidly growing city. Most research on TBM has been done in cities in countries that have vastly different cultures when compared to Mumbai. In this sense, this thesis can provide a starting point for future research on TBM in the Mumbai Metropolitan Region (MMR).

Secondly the thesis aims to provide decision makers at the MSR and MM an understanding of TBM in the context of the MMR. The lack of policies aimed at improving travel experience has caused inconvenience to riders on the MSR and MM. This need has to be addressed by designing policies for types of riders that are have a disadvantage for multitasking.

Finally, beyond just the identification of the influence of the factors on multitasking, this thesis wishes to explore the possibilities of understanding multitasking behavior in a transportation mode which will be operational in the future. Previous TBM research has been focused on understanding multitasking behavior in existing transportation modes rather than make predictions in upcoming ones. A future outlook can be used to improve the rider experience from the first day of opening the transit infrastructure. Policies that have been based on assumptions rather than user preferences can be informed and modified to provide benefits to the riders that need it.

It can be argued that studying transportation mode choice behavior due to TBM activities holds greater importance than understanding how it informs facility and infrastructure policy. While this is a valid point, mode choice behavior can be modeled only when there is established research on multitasking behavior in the setting – which is not the case in the Mumbai Metropolitan Region. Rather than address mode choice due to multitasking, this thesis chooses to provide a foundation for future studies on TBM in the Mumbai context. Policies that improve the quality or occurrence of multitasking can potentially lead to better quality of time spent in activities of a rider's choice for nearly 1.5 hours every day on average.

1.2 Objectives

This thesis aims to answer the following research questions:

- How do riders of the Mumbai Suburban Railway and the Mumbai Metro spend their on-board travel time?
- How do socio-economic and trip-related variables affect social interaction and ICT-related activities on the Mumbai Suburban Railway and the Mumbai Metro in the MMR?
- How can infrastructure and policy decisions be informed to improve service quality and travel experience on mass transit modes in the MMR?

Three primary objectives guide these questions:

Firstly, this thesis aims to find out the type of activities and the time that riders of mass transit in Mumbai spend. This aim includes the exploration of TBM activities that are unique to the MMR.

Secondly, this thesis aims to chart the influence of socio-economic and trip-related factors on multitasking during travel on the Suburban Railway and the Metro in the MMR. Directly addressing this objective, this thesis envisions an audience of decision makers in mass transit agencies in the MMR and is intended to directly inform the policy decisions taken by them.

Thirdly, this thesis provides a framework to understand the savings of travel time on modes of mass transit under construction and tests a hypothesis that the Mumbai Metro infrastructure provides a better rider experience in multitasking during travel. This hypothesis is tested through a stated preference survey on perceptions of multitasking during travel on the Mumbai Metro.

Finally, the thesis aims to chart out policy recommendations for the MSR and the MM that promote appropriate TBM activities during on-board travel.

1.3 Research Approach and Methods

This thesis uses a combination of quantitative and qualitative methods. First, quantitative analyses of stated and revealed preferences of multitasking options are conducted on primary data collected through an on-board intercept survey. Next, qualitative analysis of follow-up interview data is used to support policy recommendations on the Suburban Railway and the Metro.

Primary data for the quantitative models was collected through an on-board intercept survey that includes socio-economic data, trip characteristics, revealed preferences of multitasking behavior on the Suburban trains and stated preferences on the Mumbai metro taken from riders of the Western Line of the Suburban Railway in the MMR. A separate follow-up qualitative questionnaire that targeted a sample of the intercepted riders provides a basis to understand perceptions of comfort and productivity.

1.4 Organization of the Thesis

This thesis is organized into 7 chapters. Chapter 2 discusses the development of theories on travel time and previous TBM research. Chapter 3 introduces the Mumbai context, which charts the motivation behind the development of the Mumbai Suburban Railway and the Mumbai Metro. Then, Chapter 4 details the design and implementation of the on-board intercept surveys, which are used in subsequent quantitative and qualitative analyses. Chapter 5 interprets the determinants of TBM on the Western Line of the Suburban Railway and upcoming lines of the Mumbai Metro through quantitative models. Chapter 6 then details how the findings of the thesis can inform policy and infrastructure decisions for the Mumbai Metro. Chapter 7 mentions venues of future research that can be explored in this field for cities in developing countries and states the final conclusions of the research. Finally, an appendix with data and visualizations used in this thesis follows Chapter 7.

2. Literature Review

In cities around the world, commuters spend a considerable part of their workday traveling to and from their workplace. In India, commute times can stretch up to 45 minutes a day, which is the case in the Mumbai Metropolitan region. Multitasking during commutes provides opportunities for riders to make good use of their travel time. The productivity of the time spent on multitasking may depend on several factors – the type of activity, trip-related factors, socio-economic factors, psychological factors and comfort. Engagement in multitasking may also be influenced by cognitive resources used for the activity of travel itself – such as when taking public transit where the rider needs only to be aware of where to disembark. Before looking into the factors analyzed in this thesis, this chapter establishes some background on the development of TBM through the review of existing literature.

First, to understand the theoretical framework for TBM, a background on the concept of positive utility of travel (PUT) is introduced. Next, this chapter establishes the definition of travel based multitasking (TBM) used in this research, explores the types and classification of multitasking activities and research conducted on the incorporation of travel time savings into transportation planning cost-benefit analysis. Finally, this chapter reviews significant factors that have been found to influence TBM in developed countries and the strategies that transit agencies in developing countries have adopted to improve rider travel experience.

2.1 Positive Utility of Travel (PUT)

In traditional transportation trip-based modelling and forecasting techniques, travel time is considered wasted, carrying negative utility and hence has to be minimized. Travel had been theorized only as a means to reach to a destination and an activity whose demand is derived from the purpose of reaching a destination. The paradigm of derived demand was used in calculations of the cost to the provider and benefit to riders during a trip (Mokhtarian, Papon, Goulard, & Diana, 2014). The reduction or minimization of travel time, substitution of travel by information technology and reduction of travel distance were used to support decisions related to infrastructure (Lyons & Urry, 2005; Mokhtarian & Saloman, 2001). While making transportation infrastructure decisions, travel time savings – which represent 70 to 90 percent of the total economic benefits from trips – are guided by travel time savings, despite being in the order of only a few minutes (Welch & Williams, 1997). Despite efficiently modelling certain types of trips, trip-based modeling falls short in its explanation of the variation of a rider's utility due to activities that she performs during a day.

To accommodate the drawbacks of the trip-based modeling approach, there was a shift from trip-based to activity-based approach to modeling in the 1990s. The activity-based approach evolved the concept of a trip to something beyond just the cost associated with the trip – the complex relationship between individual activity and travel behavior. Bhat and Koppelmann (1999) explain the difference between trip-based and activity-based modeling:

> A fundamental difference between the trip-based approach and the activity-based approach is the way time is conceptualized and represented in the two approaches (Pas 1996; Pas & Harvey 1997). In the trip-based approach, time is reduced to being simply a "cost" of making a trip. The activity-based approach, on the other hand, treats time as an all-encompassing continuous entity within which individuals make activity/travel participation decisions (Kurani & Lee-Gosselin 1996). Thus, the central basis of the activity-based approach is that individuals' activity-travel patterns are a result of their timeuse decisions. Individuals have 24 hours in a day (or multiples of 24 hours for longer periods of time) and decide how to use that time among activities and travel (and with whom) subject to their schedule, socio-demographic, locational, and other contextual constraints.

The main tenet of trip-based modeling – that negative utility is derived from the necessity of travel due to the spatial separation of places with activity potential (Bhat & Koppelman, 1999), evolved to accommodate activity based modelling which considered that the trip fulfils a requirement for single activity or multiple activities. However, the activity-based framework still fell short in explaining trips that could result in positive utility. In some trips, due to travel-based multitasking (TBM) activities, the utility or benefit that a rider gained from the productive usage of time, decreases the disutility associated with travel time.

Mokhtarian and Salomon (2001) challenged the framework of the disutility of time and proposed a positive utility of travel (PUT) framework associated with travel. They suggested that future transportation planning principles could be enriched by regarding travel as 'good' and 'bad' in utility due a tripartite nature for the affinity to travel.

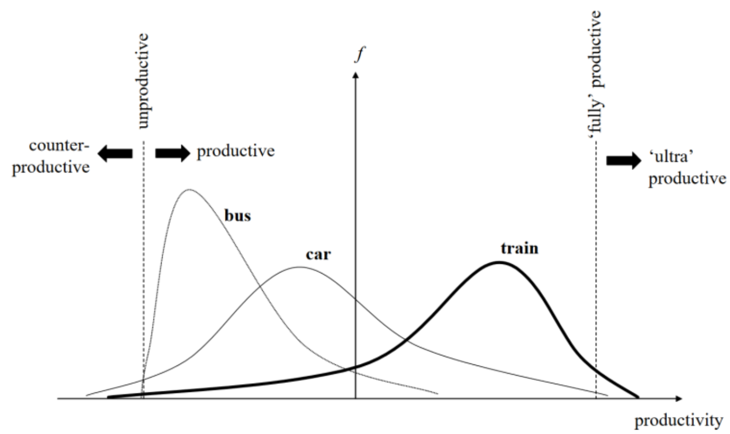
The tripartite nature for the affinity to travel has been classified based on associated activities:

i. activities conducted at the destination,
ii. activities conducted while travelling and
iii. the activity of travelling itself (Mokhtarian & Salomon, 2001).

Activities conducted at the destination are driven by the purpose of reaching the destination. This has been the core of both trip-based and activity-based modeling techniques. The journey may in itself be the activity of positive utility. For example, the scenery during a train ride or the health benefits of biking or jogging is the purpose of the trip and provides positive utility. The destination loses relevance and may be chosen arbitrarily. Active or passive multitasking activities conducted by the rider during travel may provide benefits through the perceived productive use of time. It might add to the positive utility of travel time, even if the multitasking activity is not the purpose of the trip (although there have been instances of that).

Productivity of travel time through multitasking is hypothesized to be the highest on train journeys among journeys on bus, car and train (Lyons & Urry, 2005). This might be due to factors related to the conditions of the travel such as level of crowding, temperature, noise and availability of seating. Or, it might be due to individual characteristics such as socio-economic status, health, life stage, other modes of transportation in the trip or the level of advance planning done for the journey. This hypothesis, proposed by Lyons & Urry (2005) still remains one due to the multitude and complexity of factors that influence the productivity on-board. This thesis focuses only on selected socio-economic and trip-related factors.

Figure 2-1: Illustrative Frequency Distributions of 'Productivity' of Travel Time by Mode



(Source: Lyons & Urry 2001)

2.2 Definition of Multitasking/ Simultaneous Activities

Before delving into factors affecting TBM activities, the definition of multitasking needs to be made clear because it guides the design of surveys to find primary data and delineate the scope of research. Through a review of academic papers on multitasking, Kenyon (2010) concluded that the term 'multitasking' has been used academic papers, however, only explained through examples to illustrate its concept.

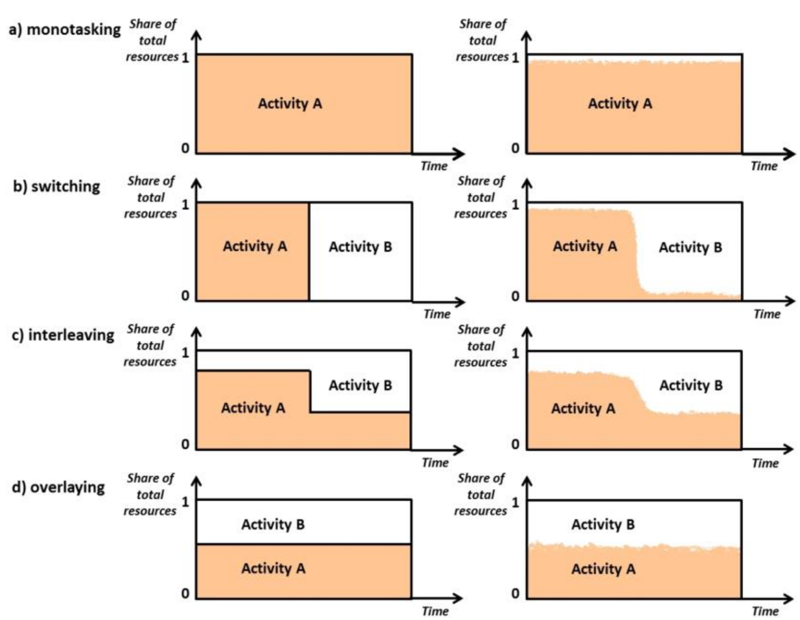
According to Ironmonger (2014), multitasking refers to the state of performing more than one activity simultaneously. Multitasking activities have been referred to as "Simultaneous Activities", "Overlapping Activities", "Concurrent Activities", "Parallel Activities", "Primary and Secondary Activities", "Multi-tasking" and "Polychronic Time Use". Among these terms, multitasking and its more scholarly version 'polychronicity' has been used frequently in a literature. Multitasking has been referred to as simultaneous-conducted activities or switching between activities as illustrated by Figure 2-2 (Cirella, Mokhtarian, & Poff, 2012). In this thesis, the term 'multitasking' was more relevant since the scope only extends to the behavior itself rather than the preference of engaging in multitasking activities. This ddifference is explained by Cirella, Mokhtarian, & Poff (2012):

> Although polychronicity and multitasking are sometimes used interchangeably (even within a single study), in this study we adopt the logical distinction suggested by Persing (1999) and Waller

(2007), and further refined by König and Waller (2010) as well as Poposki and Oswald (2010). Specifically, we use "multitasking" to refer to the behavior of conducting more than one activity at the same time, and "polychronicity" to mean the degree of preference for such behavior (with natural counterparts "monotasking" and "monochronicity").

In TBM, secondary activities that are conducted when traveling is the primary activity – that is, the overarching purpose of traveling – and the multitasking activity such as reading, listening to music, having a face-to-face conversation, watching videos, people watching – is 'incidental' to travel as mentioned in the tripartite of affinity to travel by Mokhtarian and Saloman (2001). The act of travel in a Suburban Train or Metro is the passive activity due to the absence or negligible level of cognitive function used directly for the purpose of travel. For example, driving a car, as opposed to riding in a train requires greater cognitive resources for the activity of travel itself. This relates back to the aspect of productivity as outlined by Lyons and Urry (2005) to be highest during travel on trains as shown by Figure 2-1. Higher cognitive resource is spent conducting the secondary or 'incidental' multitasking activity, giving it an 'active' nature when compared to the simultaneously occurring primary and passive activity – travelling. However, during train rides, a small part of cognitive resource is spent in finding seats, embarking or disembarking the train.

Figure 2-2: Types of Multitasking Behavior by Use of Cognitive Resources

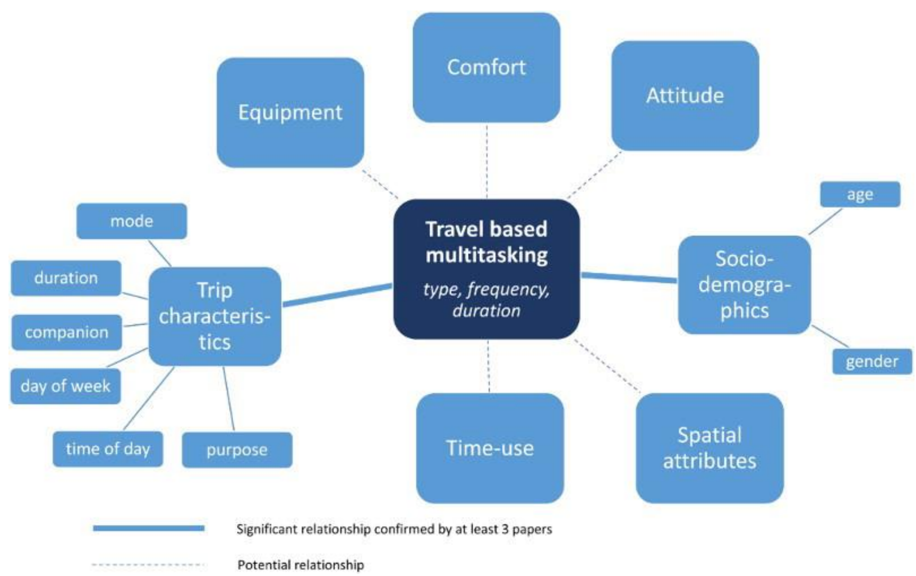


Multitasking activities in previous literature have been classified as 'passive' or 'active'. The difference in the level of these activities is the level of cognition required to perform the activities. Activities such as sleeping, relaxing, looking out of a window and people watching are considered passive while the activities such a typing emails, reading and operating vehicles has been considered active activities. In previous studies, passive activities have been considered unproductive and unhelpful to the increase in the value of time.

2.3 Factors Affecting Travel-based Multitasking

Literature analyzing travel-based multitasking (TBM) has been increasing in the last 15 years (Keseru & Macharis, 2018). This trends have come about after Mokhtarian and Salomon (2001) proposed the theory of positive utility of travel (PUT).

Figure 2-3. Relationship Between Travel Based Multittasking and Factors in Existing Literature



Keseru and Macharis (2018) identified 60 significant variables through review of 58 studies on multitasking behavior during travel. The variables are classified into 7 mutually exclusive categories (Figure 2-3):

- Socio-demographic variables
- Trip related variables
- Attitudinal variables

- Comfort related variables
- Equipment related variables
- Spatial attributes
- Time use related variables

Among they variables studied, a strong relationship was established between TBM and socio-demographic characteristics and trip related variables. However, this relationship is predominantly derived from literature on TBM from developed countries. There is a lack of studies in developing countries for the usage of travel time and the impact of various factors on it (Keseru & Macharis, Travel-based multitasking: review of the empirical evidence, 2018). The only studies found on multitasking in developing countries was on ICT use in Mumbai (Varghese & Jana, 2018) and travel time in Hong Kong (Tang, Zhen, Cao, & Mokhtarian, 2017).

There might be several reasons for a rider to multitask on while traveling on public transit. Firstly, as experienced through the unstructured interviews following the intercept questionnaire surveys, performing a multitasking activity might enable the rider to efficiently use time. For example, riders use ICT devices to perform work-related tasks of sending emails or taking calls (Ettema & Verschuren, 2007). On the other hand, the incidental activity might be conducted to make the activity of traveling more enjoyable. An example is purchasing a music player to cope with delays due commuter rail delays. In both cases, the value of time (VOT), which is derived purely from time and cost, changes. In the first case given above, the commuter would be less willing to spend money to avoid a delay since the work that is typically performed at the workplace can be done on-board the commuter train (Lyons & Urry, 2005). Similarly, in the second case, the travel is made more enjoyable by the number of ICT-related options available to use while traveling to keep the rider entertained. This might also lead to a decrease in the VOT leading to a higher value of travel time savings (VTTS) (Ettema & Verschuren, 2007).

Studies on TBM have been conducted on people's commutes across many developed countries: Belgium (Keseru, et al., 2015; Ton, T. D., 2016), Canada (Guo, Derian, & Zhao, 2014), England (Axtell, Hislop, & Whittaker, 2008; Lyons, Jain, & Holley, 2007), Japan (Ohmori & Harata, 2008), Netherlands (Ettema & Verschuren, 2007) and Norway (Gripsrud & Hjorthol, 2012) (Vilhelmson, Thulin, & Fahlén, 2011).

In a study of TBM activities in the Dutch Eindhoven region, Ettema and Verchuren (2007) found that VOT is 78% higher for riders of age 40 and younger and 53% higher for riders between 40 and 50 years of age. At the peak of their life, individuals who are younger than 40 years, are more likely to have greater household responsibilities putting a pressure on time allocation and results in higher values of VOTs (Ettema & Verschuren, 2007). This was particularly significant for individuals who were single parents. Findings suggest that individuals engaging in listening to music have a lower VOT than average and the individuals engaged in work related activities while traveling have higher a VOT than average. Multitasking behavior has an impact on VOT and may must be included in policy decision-making processes (Ettema & Verschuren, 2007).

Through a study on the Dutch-speaking population in Flanders, Belgium, Keseru, et al., (2015) highlighted that the frequent occurrence of activities that are passive such as listening to music or the radio was high. This, however, might be attributed to the low modal share of public transit in the region under study since public transit provides an opportunity to perform 'productive' activities when compared to modes that required active attention and higher cognitive resources such as driving.

The increase in use of the internet through ICT devices has enabled travelers to use their travel time more productively (Lyons & Urry, 2005). This is a trend that has been charted since the last two decades by TBM researchers –most research indicated the potential of ICT to change the paradigm of travel that considered travel time as lot or carrying negative utility. ICT behavior is influenced by several factors: type of transportation (Ton, 2016), degree of crowding, availability of seating, ride quality, temperature, noise level, ease of journey, travel time (Lyons & Urry, 2005), past travel experience and spatial patterns (Guo, Derian, & Zhao, 2014).

Guo, Derian and Zhao in 2014 established the importance of ICT-related multitasking during travel in buses in Vancouver, Canada. Smartphone usage is affected by comfort conditions, past travel experiences and spatial pattern depending on the direction of the trip (Guo, Derian, & Zhao, 2014).

The on-board travel time and the working hours of riders were significant predictors of multitasking behavior in a study done on passengers of the railway system in the Tokyo Metropolitan Region (Ohmori & Harata, 2008). In addition, according to the study, in a comparison between riders taking the crowded train and the uncrowded *Shinkansen*, it is found that travel with wider personal space and privacy induced riders to perform multitasking activities, for which there was higher willingness to pay.

On the other hand, TBM activities involving social interaction is significantly influenced by gender. According to (Keseru, et al., 2015), male riders less likely than their female counterparts to engage in conversation. This might be due to males tending to converse more in a formal context than an informal one (James & Drakich, 1993; Ton, 2016).

Beyond socio-economic and trip-related factors, multitasking, which contributes towards the overall travel experience plays a role in shaping the subjective well-being of the individual (Singleton, 2017). This is different across transportation modes and is also influenced by attitudinal factors (Singleton, 2017).

Among literature that looked at activity-travel patterns in developing countries, research by Dharmowijoyo, Susilo, & Karlström (2017) provides insight into variability of activities across ages. Students and workers tended to have higher variablity in activity-travel patterns which might be due to the higher frequency of discretionary activities. Beyond just individual characterstics, members of the household influence travel activity patterns. However, this research only explains multtiasking behavior and its relation to activity-travel pattens.

Varghese and Jana (2018) discussed the influence of various socio-demographic variables and ICT related characteristics of individuals such as possession of an ICT device and subscription to mobile internet on multitasking activities during trips – in all modes of transportation – from trip diary data collected from low-income households in the Mumbai Metropolitan Region. However, their analysis assumes a homogeneous and single TBM activity or the complete absence of multitasking activities during each trip. As seen in the on-board intercept survey, riders frequently engage in more than one multitasking activity during travel. This thesis overcomes this limitation when analyzing TBM on the MSR and the MM.

In summary, most literature that revolves around TBM has explored certain aspects of the TBM better than others. This thesis adds to it by exploring similar concepts through socio-economic and trip-data lenses in a developing country city. It contributes to the understanding of multitasking behavior in a cultural context that has not been explored and looks at TBM activities that are unique to the Mumbai Suburban Railway and Mumbai Metro.

3. The Mumbai Context

This chapter gives an introduction to TBM in the Mumbai Metropolitan Region and provides a background to its cultural context. It introduces the history of the Western line, upcoming Mumbai Metro lines, how mass transit is represented in the comprehensive mobility plan (CMP) and the cultural context associated with TBM on mass transit in the Mumbai Metropolitan Region.

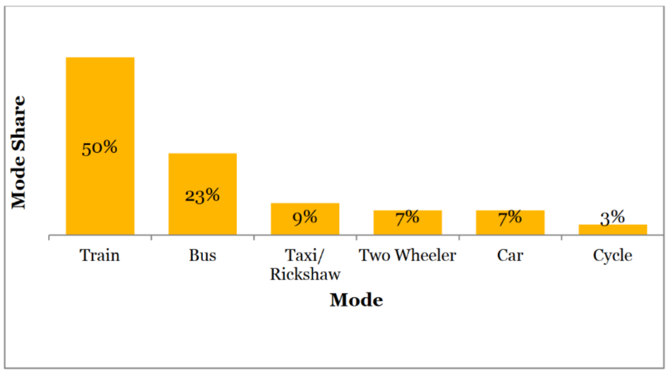
3.1 Introduction to the MMR's Public Transportation

The Mumbai Metropolitan Region has a population of 18,394,912 according to the Indian Census (2011) and includes the districts of Mumbai, Mumbai Suburban, Thane, Raigad and Palghar. 52% of the trips in the region are taken are on public modes of transportation (Pai, 2009). Riders taking public transit are divided among the BEST (Brihanmumbai Electric Supply & Transport Undertaking) buses and the mass transit modes of the Mumbai Suburban Railway, Monorail (which is currently not operational) and the Mumbai Metro.

Of the public transportation infrastructure that has been constructed in Mumbai, the Mumbai Suburban Railway has played an important role in shaping the urban fabric of the city. The urban form of Mumbai

Metropolitan Region (MMR) has been guided by the construction of the Western Line, Harbour Line and Central Lines resulting in the city's expansion along the north, northeast and east directions. State initiatives in the 1970s resulted in development of employment nodes along the lines of the Suburban Railway (Shirgaokar, 2014). Nodes of employment and housing extended the older core to points along the northern and western line of the Suburban Railway for a distance of 40-55 km (Shirgaokar, 2014).

Figure 3-1: Transportation Modal Split in the Mumbai Metropolitan Region Excluding Walking

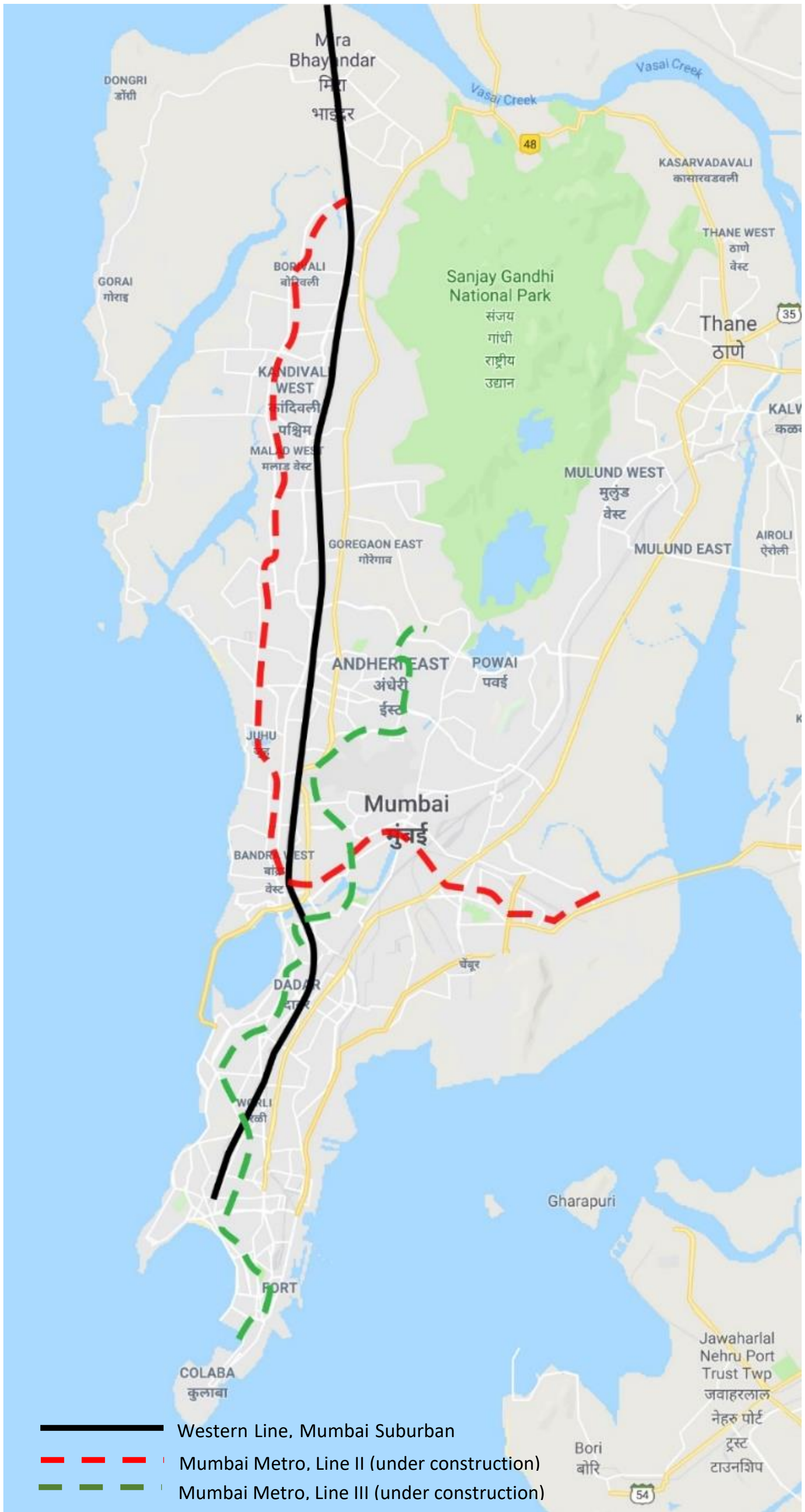


Source: Comprehensive Transportation Study (CST) for MMR ("TranSForm"), 2008

The Western Line of the Mumbai Suburban Railway was built in 1867 as a part of the long distance railroad from Mumbai to Baroda. The line, which connects Churchgate in downtown Mumbai to Dahanu Road in Palghar district through Suburban Mumbai, is operated by the Western Division of the Indian Railways. This commuter rail system runs at grade for the entire length of 123km.

The MSR operates two types of suburban train services along the Western Line – the fast and the slow trains. The fast service stops at selected stations while the slow service halts at all stations along its route on the Western Line. Andheri Junction, which forms the only multimodal interchange between the Western Line and the currently operational Line I of the Mumbai Metro, received the highest footfall among all stations in the MMR (Mumbai Metro One Pvt. Ltd., 2018). As a result, the Western Line faces severe overcrowding down to Churchgate during morning commute hours, from 8am to 12pm and up to Virar during evening commute hours, from 5pm to 9pm (Figure 3-2).

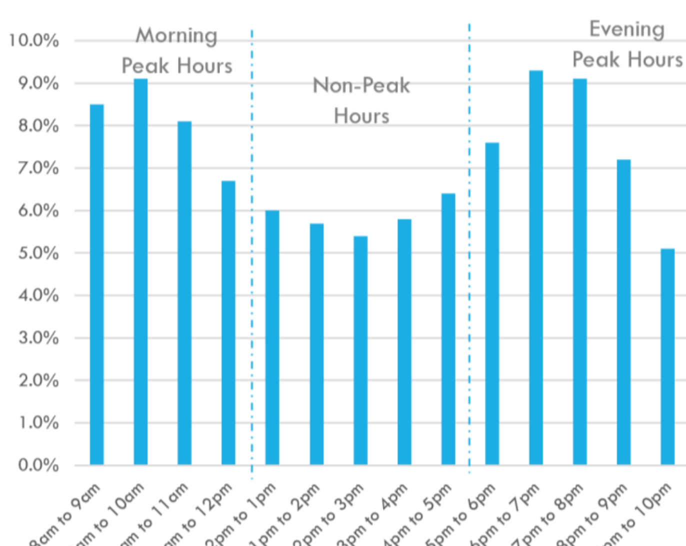
Figure 3-2: Map of the Mumbai Metropolitan Region Showing the Western Line of the Mumbai Suburban Railway and the Upcoming Mumbai Metro Line-II and Line-III



The Mumbai Suburban Railway has initiated a few policies to enhance rider experience. Most programs such as equipping selected railway stations with Wi-Fi hotspots have been implemented as a part of a larger scheme by Indian Railways. The Railwire program, rolled out in collaboration with Railtel and Google gives high speed and free Wi-Fi to passengers who have access to a phone number, for a period of one hour that can be renewed. According to Google's India blog in June, 2018, riders who connect to the Wi-Fi at Indian stations use 350MB of data on average. Also, for convenience of riders using the MSR network, a ticket booking app called UTS (Unreserved Ticketing System) was developed in 2016 to promote convenience of purchasing tickets without the hassles at the counter. It was part of an initiative by the Indian government to move towards a cashless economy. Beyond the initiatives mentioned above, the MSR was not engaged any strategies to directly address multitasking concerns on of riders on-board trains. Most facilities dealing with ICT such as charging have been provided only at railway stations; there is a dearth of facilities intended to help multitasking on-board Western Line trains despite a wide range of TBM activities that take place on board.

In addition to TBM activities listed by Lyons and Urry (2005) that commonly occur on commuter railway, there are certain activities that can be pointed as truly unique to the MSR such as the b*hajan mandalis* and lunch box delivery by *dabbawalas*. *bhajan mandalis* are small groups, usually of the Hindu religion, who sing hymns together in the Fast and Slow trains during commute hours on the MSR. These groups are formed by riders taking the same route regularly for their commute. In this thesis, the influence of the socio-economic and trip-related factors on group prayer is analyzed.

Figure 3-3: Temporal Distribution of Rider Entries and Exits on the Western Line Stations



3.2 Development of the Mumbai Metro

The Mumbai Metro Line I segment between Versova and Ghatkopar opened in 2014. It serves as a bridge between the Central and Western Lines of the MSR at the Andheri and Ghatkopar stations respectively. According to the Mumbai Metropolitan Regional Development Authority, the Mumbai Metro project was envisioned to solve the shortfall of the rail infrastructure development, which has not kept up with the rapid development of the city for 4-5 decades before 2014 and has led to the overcrowding on the MSR.

In view of increased ridership on the Mumbai Metro Line I, the Colaba-Seepz Line is slated to be constructed by December 2021. The Mumbai Metro Line III will run parallel to the Western line of the Suburban Railway. The Colaba to Bandra segment, which is planned to be completed in the first phase, will provide multimodal interchanges with the Suburban Railways at Mahalaxmi, Mumbai Central and Churchgate. The Mumbai Central to Bandra segment of the Western Line was selected due to this overlap so that the riders who take the questionnaire are able to reveal their perception of travelling on the Metro rail for their commute.

The unique parallel configuration of the Line II and Line III with the Western Line of the MSR provides a unique opportunity to explore the shift in ridership from the Western Line of the MSR. Since the metro project is aimed at reducing the load on the existing MSR system, it can be assumed that some riders currently taking the Western Line will change modes during their commutes to take the Metro instead. Looking at revealed and stated preferences and comparing these modes of mass transit will give insight into TBM activities that will happen on board Line II and III.

The Mumbai Metro(MM) Line I currently provides free Wi-Fi at all stations along the 11km line. However, similar to the Western Line, the train themselves do not provide Wi-Fi facilities. Upcoming lines on the MM network are not planned to include on-board Wi-Fi facilities.

Certain TBM activities such as the *bhajan mandalis*, that occur on the MSR are prohibited by law on the MM Line I. TBM activities that occur on-board on the MM conform more strictly to the activity space as mentioned by Lyons and Urry (2005).

Transit agencies have goals similar to most commuters' aim to minimize their travel time and cost. They may aim to reduce costs to increasing ridership and attracting riders to use public transit over other modes of transportation.

In summary, different conditions on the MSR and the MM provide opportunities to explore the difference in revealed multitasking activities that currently occur on the MSR and in stated multitasking preferences in the future on the Mumbai Metro.

4. Design and Implementation of the Intercept Survey

This chapter details the survey design and the implementation of the questionnaire survey used to gather primary data for quantitative analysis on revealed preference and stated preference of multitasking during travel. The primary data source for this thesis is derived from an on-board intercept questionnaire conducted during the last week of July, 2018, on the Western Line of the Mumbai Suburban Railway. The survey was aimed at collecting data to support the comparison of multitasking activities on two modes of mass transportation in the MMR.

4.1 Survey Design

Data used to analyze TBM can be collected from riders using multiple methods – each of which has advantages and disadvantages. In previous studies, quantitative data was collected through household surveys, intercept surveys, travel diaries, structured and passive observations and qualitative data was collected through focus group interviews and unstructured interviews. Keseru and Macharis (2018) noted that it is not possible to fully understand TBM activities in a certain setting without a combination of quantitative and qualitative methods due to limitations that are inherent to every method in exploring aspects of multitasking. Using different methods to approach the same problems can help address the multidimensional nature of TBM and explore the interrelationship between socio-economic, trip-related and psychological factors. Keseru and Macharis explained the advantages of certain survey methodologies:

> On the one hand, as Kenyon (2010) indicated, qualitative research can help to better define how respondents conceptualize multitasking episodes, which in turn could lead to a better definition of multitasking in surveys. Qualitative interviews can also provide more in-depth information on the personal motivations for and experiences of travel-based multitasking (Basmajian, 2010; Clayton et al., 2016). Specific methods such as travel ethnography can help to expand travel time use as a concept beyond utility and take non-economic benefits of travel into account (Lyons et al., 2008; Watts & Urry, 2008).
>
> On the other hand, structured observation has been found to provide large amounts of quantitative data on the nature of multitasking activities with the possibility of capturing such activities as they are happening, nevertheless with limited information about the experience and attitudes of travelers. Methods that can register multitasking activities while they are being carried out could improve the usefulness of data from structured observation. Smartphone apps that register movement (travel) could record activities on the smartphone (e.g. Internet browsing and using specific apps) at the same time.

Among quantitative methods, structured observations have been used frequently since they provide ease of collecting a large and accurate samples of data in a short period of time. It has advantages of being non-obtrusive since riders are observed in their 'natural setting', however, there might be some privacy concerns due to the observation of passengers over a long period of time (Ton, 2016). Passive observations do not record certain crucial factors that are needed to address questions related to socio-economic and trip-related variables.

A questionnaire survey has an advantage of gaining insights into a complete profile of the rider's trip that includes the socio-economic and trip-related characteristics, though it consumes more time than structured observations. The questionnaire asks the respondent to provide an activity-time summary of the TBM activities. A type of questionnaire – on-board intercept – avoids errors due to weak retrospective memory of activities and the length of their occurrences. Structured observations did not provide the time-activity detail in addition to individual characteristics necessary to address the research questions behind this thesis. Hence, the primary research method was an on-board intercept survey that targeted riders taking the Western Line of the MSR.

The on-board intercept questionnaire used for this thesis is short which helped to collect a large data sample in a short span of a week and to accommodate riders with short on-board travel time. Questions on socio-economic characteristic of the rider were shortened to a ‘fill-in-the-blank’ format for faster understanding and response. Since the study requires a deeper understanding individual rider characteristics without loss due to retrospective memory recollection, a questionnaire survey was chosen as the method of collecting primary data.

To supplement data in the questionnaire, follow-up interviews were done to add to the qualitative aspect of research as mentioned by Keseru and Macharis (2018). The follow-up interviews were short, unstructured and included questions relating to TBM on the MSR and the MM on the survey. Riders were asked the reasons behind their choice of multitasking activities. The qualitative dimension to analysis helps further analysis into the root causes behind choice of a certain TBM activities. The findings from quantitative model is interpreted to assist policy decisions through a qualitative analysis in Chapter 6.

The questionnaire used for the on-board survey is divided into four parts. The first part recorded the socio-economic characteristics of riders such as age, gender, household income and education. To improve response rate, choice of sensitive information such as household income was provided as brackets according to the household travel diary used by Varghese & Jana (2018).

Trip characteristics of origin station, destination station, modes of transportation used during the trip, perceived trip distance, perceived trip time and purpose of trip were recorded in the second part of the survey. Other modes that the respondent used during the trip were provided as options that could be circled among bus, auto-rickshaws, two-wheelers (motorcycles), four-wheelers (private cars), walking a distance greater than 800m, metro and taxis/TNCs (Ola or Uber). Respondents were given the option to choose multiple mode options for the journey.

The third part of the questionnaire consisted of revealed preference (RP) questions on multitasking behavior on the Suburban Railway during in-train travel. This part asked respondents to mention the percentage of time spent on each type of multitasking activity during their trip. The perception on the level of comfort and productivity was measured on a scale of 1 to 10.

The fourth part of the survey captures the stated preferences by asking the same questions in part 3 for a hypothetical replacement of the trip's Suburban Railway component with travel on the metro rail with similar crowding conditions.

Description of the TBM activities:

- No activity: Absence of multitasking activities
- Sleeping/snoozing: Activity of sleeping while seated
- Eating: Consumption of food on board the train. While doing the follow-up interviews, riders mentioned the savings in time when they have breakfast on board the train. However, lunch and dinner on the train was less common.
- Group prayers/ *'bhajans':* Participation in one of the '*bhajan mandalis'* – impromptu gathering on the train in the evenings – mostly on the fast suburban trains. Members are not fixed in these groups – riders who wished to participate aggregate together in a corner of the compartment and engage in singing. Participants donate to the organization leading the prayers at the end of the sessions.
- Music: Listening to music from a ICT device or a music player via headphones or earphones
- Videos: Watching videos on an ICT device
- Social media: Includes engaging in Facebook, messaging on instant messaging platforms such as WhatsApp or Facebook Messenger. This encompasses communication between people via digital media.
- Reading: Reading printed material

The questionnaire was designed as a paper based on-board intercept survey due to various reasons. First, the pen and paper version of the survey offered an opportunity to gather information simultaneously from various respondents on the train and increase the efficiency data collection. Digital entry methods such as phones and tablets were not preferred since some riders were not used to operating digital devices. An intercept and on-board survey provides an accurate depiction of the multitasking activities performed by riders in terms of reliability, accuracy and detail due to the immediacy of activities performed (Schaller, 2005). The accuracy of the data collected is due to clearer recall, which has been a problem in household surveys.

The survey was offered in Hindi and English. In case the randomly selected rider was unable to read or write, questions were asked verbally and the answers were recorded by the surveyors.

The survey intended to capture the multitasking behavior or riders who had destinations, origins or pass through the 36km long segment of the Western Line between Mumbai Central and Borivali. This specific segment was selected because the metro Line II and Line III lines run parallel to the Suburban Railway. Since they share interchanges, current riders of the Western line have the opportunity to use the Metro in 2021.

In this thesis, the multitasking activities recorded occur in sequence and happen only during on-board travel. There is no overlap between the incidental activities that the riders are engaged while traveling. While the analysis of multitasking can stretch between on-board travel time and waiting time, on-board travel time is considerably longer than waiting time on average.

4.2 Implementation of the Survey

Three local residents of the Dharavi neighborhood in Mumbai, who were employees of a survey company, assisted the author of the thesis in distributing written questionnaire to randomly selected passengers. Riders were selected with on the second class, first class and platforms to create a sample that is representative of the socio-demographic characteristics of the Greater Mumbai Metropolitan area.

Peak hour transit commuters were not surveyed due to the inability of performing multitasking activities in parcked conditions on the Suburban Railway. Women waiting on the platform were asked to participate on the survey to offset the skewed ratio of passengers on the general second class train compartments.

60 of the 196 survey respondents were asked to relate their experience commuting to and from work on the Mumbai Suburban Railway through unstructured follow-up interviews. Through the unstructured interviews, riders were asked questions regarding their perception of travel time, inconveniences to multitasking activities.

Figure 4-1: Map of the Mumbai Suburban Railway System

5. Interpretation of Multitasking Determinants

This chapter discusses the results of the exploration and interpretation of the on-board intercept survey through quantitative and qualitative analyses. The analyses establish connections between the factors affecting travel based multitasking both on the Mumbai Suburban Railway and the Mumbai Metro. First, multitasking determinants such as socio-economic and trip-related factors are used to develop discrete choice models through multinomial logistic (MNL) classifications, binomial logistic (BNL) classifications and decision trees. Next, the choice between ICT/ non-ICT and social/individual travel based multitasking is explored through BNL models. Finally, the chapter aggregates the results from the unstructured interviews and relates them to the results of the quantitative models.

5.1 Initial Findings

A comparison of the average time spent in multitasking activities during travel showed that the most common TBM activity on the Suburban Railway was listening to music (28.5% of travel time) and the highest proportion of travel time was spent without engaging in any activity on the Metro (28%). Riders of the Western line were more likely to engage in listening to music or reading on an ICT device by 7%. However, riders planned to spend nearly 12% more time not engaged in any multitasking activity on the Metro than they did on the suburban railway. Also, riders planned to spend slightly more time watching videos on their phone and talking on the Metro when compared to the Suburban Railway.

Figure 5-1: Frequency Distribution of Socio-demographic Variables in the Intercept Survey

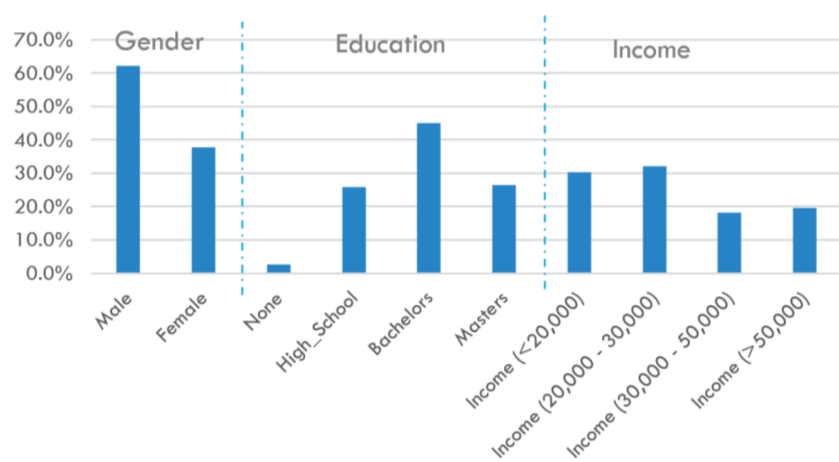


Figure 5-1 indicates the frequency distribution of the socio-economic variables in the intercept survey. The gender ratio is not close to 1 due to the relatively small number of female riders on the Suburban Railway. This gender ratio of the sample is different from the gender ratio of approximately 0.54:0.46 in the MMR, according to the 2011 Census of India. Among the 15 first and second class compartments on each train of the Mumbai Suburban Railway, three were reserved for ladies. Women preferred to travel in women-only carriages unless when traveling in groups. The ratio of riders with bachelor's degrees and income bracket 2 (₹20,000 - ₹30,000) was the highest. Among the respondents, 96% owned a smartphone device with internet data packs.

Figure 5-2: Percentage of Total Trip Time Spent on Travel Based Multitasking Activities

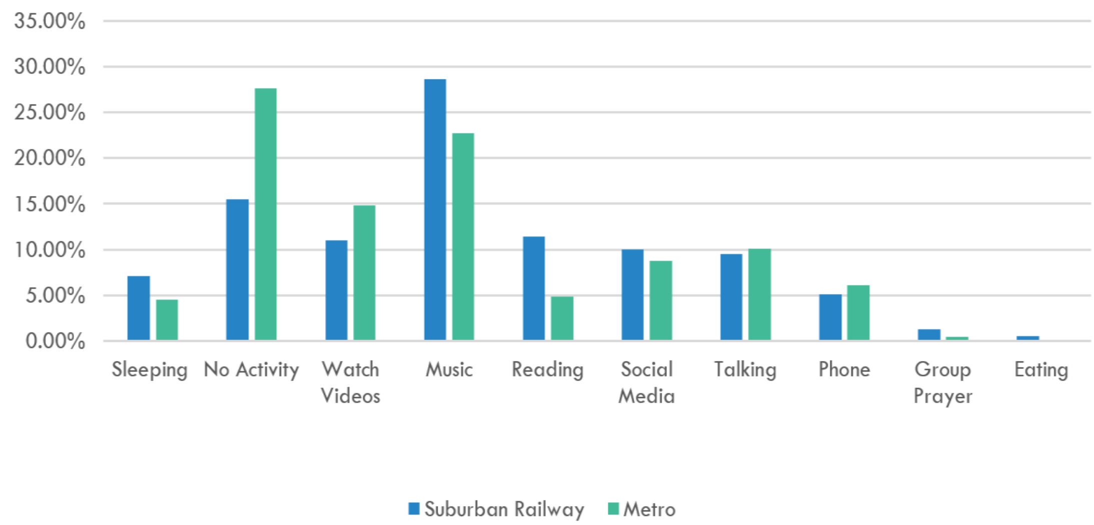
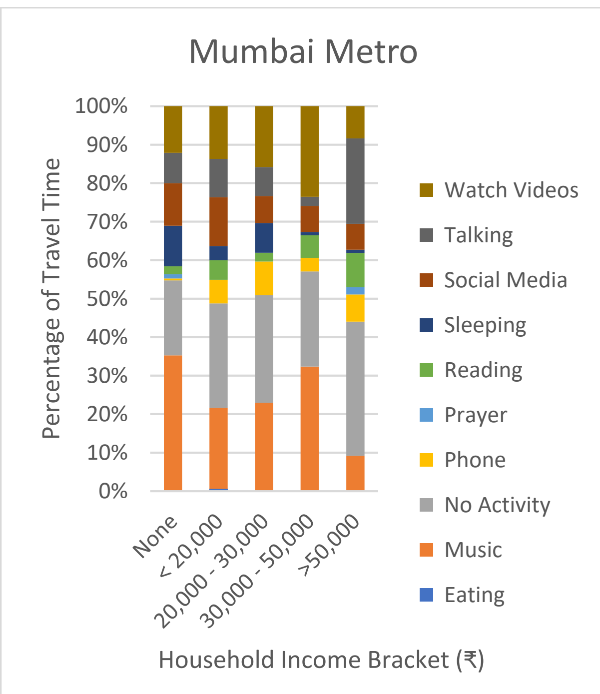


Figure 5-3: Distribution of Time Spent on Travel Based Multitasking Activities Controlled by Income Bracket



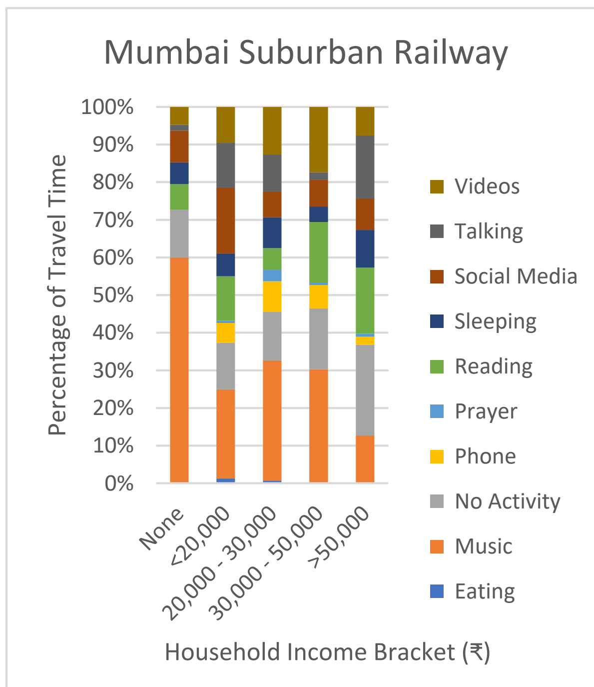
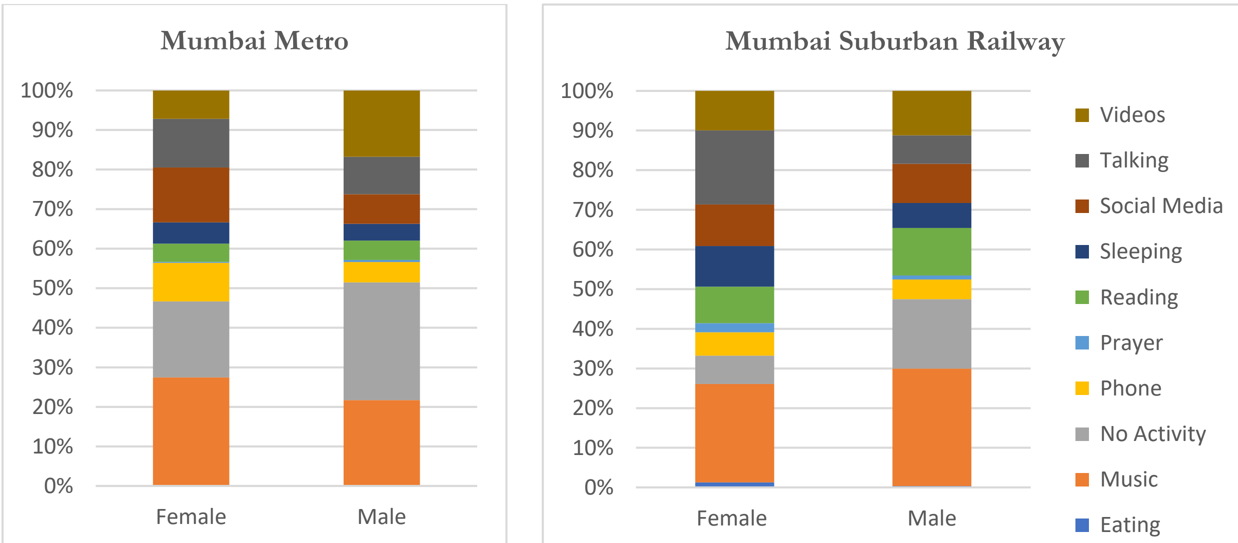


Figure 5-4: Distribution of Time Spent on Travel Based Multitasking Activities Controlled by Gender



Male riders had a greater tendency not to engage in any TBM activity when compared to female riders both on the MSR and the MM. Also, female riders showed a greater tendency to engage more in face-to-face conversations with co-passengers than male riders. When controlling for income brackets, as shown in Figure 5-3, there is no specific pattern noticeable among the passengers.

Among the different stations along the Western Line, the Borivali Station had the highest cumulative origin-destination samples. Andheri, which has the highest footfall among all the stations on the Western line (Mumbai Metro One Pvt. Ltd., 2018), had the second greatest number of samples as shown by Figure 5-5.

Figure 5-6 shows the influence of variables in predicting TBM activities through a random forest analysis. Age of the rider and the maximum willingness to pay (WTP) per minute on the Mumbai Metro were the strongest predictors of the TBM activity on which the rider chooses to spend the largest part of travel time.

Figure 5-5: Frequency of Rider Origins and Destinations by Station on the Suburban Railway

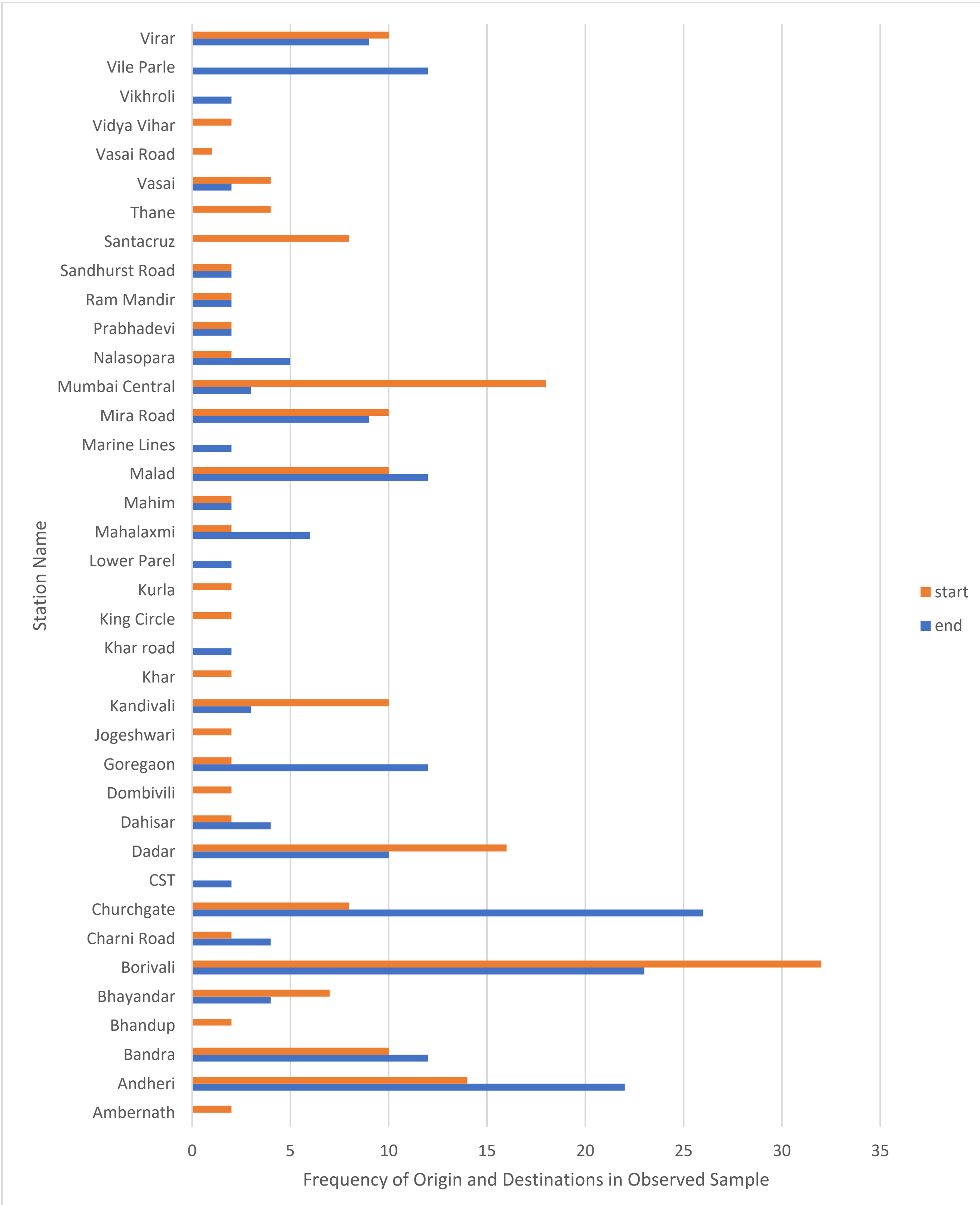
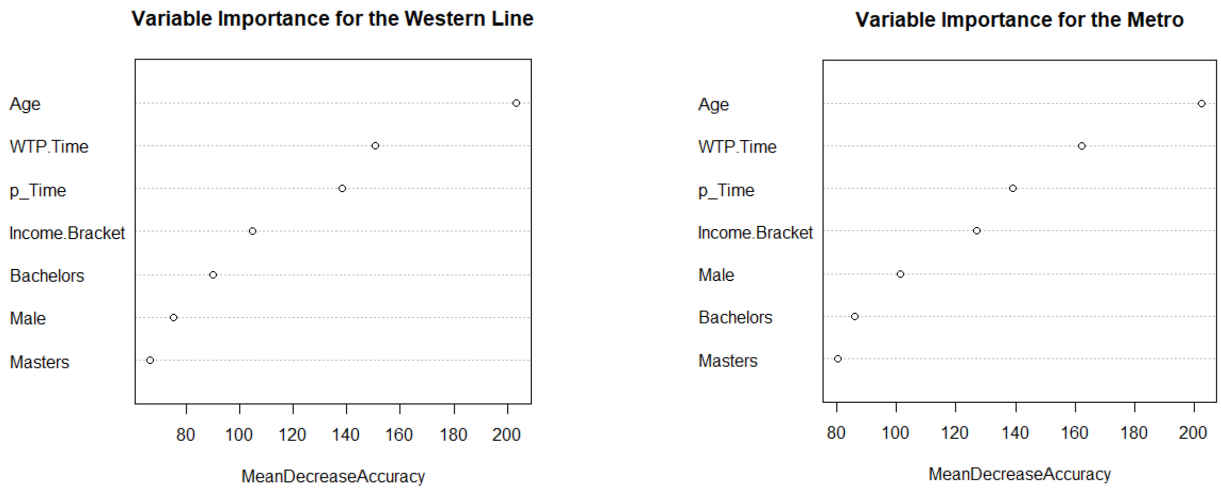


Figure 5-6: Random Forest Analysis to Determine Importance of Predictors



5.2 Models Relating Multitasking Determinants

Analytical methods used for analyzing both the socio-economic and trip-related factors on TBM are shown in Table 5-1. The analytical process begins with the multinomial logit (MNL) models on the longest TBM activity in each trip. Then, binomial logit (BNL) models are fitted on socio-economic and trip-related variables to capture the effect of the occurrence of each multitasking activity using a one-vs-rest approach (OVR). For better interpretability, activities which were performed for the longest duration for each trip are run through a classification tree. Finally, in order to answer the research questions pertaining to ICT and social activities, all the multitasking activities are classified based on their nature and run through four BNL models. Each of the approaches and the models used have advantages to understand the intercept survey in a rigorous way.

Table 5-1: Quantitative Models – Predictor Variables, Response Variable and Model Features

Model	Predictors	Response	Features
Random Forest (RF)	Continuous and ordinal Socio-economic and trip-related variables	Categorical variable – TBM activity on which the rider spent the greatest time during the trip	To identify the strongest predictors of TBM activities
Multinomial Logit (MNL)	Continuous and ordinal Socio-economic and trip-related variables	Categorical variable – TBM activity on which the rider spent the greatest time during the trip	Baseline model to compare to the findings by Varghese and Jana (2018)
Binomial Logit (BNL) – 14 models	Continuous and ordinal Socio-economic and trip-related variables	Binary variable – 0 or 1 depending on whether the TBM activity happened or not (one-vs-rest)	Factors affecting each TBM activity independent of other TBM activities
Decision Trees	Continuous and ordinal Socio-economic and trip-related variables	Categorical variable – TBM activity on which the rider spent the greatest time during the trip	To better visualize decision boundaries for different TBM activities
Binomial Logit (BNL) – 2 models	Continuous and ordinal Socio-economic and trip-related variables	Binary variable denoting the following – i. ICT-related or ii. Involving social interaction	Looking at features that affect different types of activities based on ICT usage and social interactions

The logit model was chosen for multivariate analyses and discrete choice analysis, both in the case of multinomial and binomial response variables. It stands out among other models when predicting discrete choice because it is easier to interpret and requires lesser assumptions when compared to linear models. Collinearity between the dependent and the independent variable and heteroscedasticity are not concerns in logit models.

While testing the null hypothesis, p = 0.15 was taken as the threshold. Since the sample size of the data set is small (196 trips), a p-value higher than the 0.05 was chosen.

Limitations due to the sample size also restricted the number of predictor variables that could be used for the models. According to Vapnik (1999) the ratio between predictors and the sample size cannot exceed 0.05. Hence, to ensure convergence of the models through maximum likelihood estimation (MLE) in the logit models, only some trip-related and socio-economic factors were selected as independent variables.

First, a discrete choice model is implemented through a MNL classification using socio-economic factors x_{ni} as independent variables and the occurrence of various multitasking activities as the dependent variables *ni* giving probability P_{ni} as described in equation 5.1. The probability is estimated through a sigmoid function based on a set of socio-demographic co-variates having coefficients β_{0-6} and a constant β_0 which are part of the common parameter vector β'. For each trip in the intercept survey, the multitasking activity selected was the one on which the rider spent the maximum percentage of time during the trip. In the MNL, the absence of multitasking activity was taken as the baseline for which the value of the β and its value of the loss function was taken to be zero. The utility associated with each multitasking state is given as a dot product of the coefficient matrix and the dependent variable matrix that consists on socio-demographic variables mentioned below. Equation 5.2 shows that the highest utility U_{ni} (sum of V – systematic utility and ε – random utility) is selected among the different multitasking activities performed by an individual.

$$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}}. \qquad \text{....................(5.1)}$$

$$\begin{aligned} P_{ni} &= Prob(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \ \forall j \neq i) \\ &= Prob(\varepsilon_{nj} < \varepsilon_{ni} + V_{ni} - V_{nj} \ \forall j \neq i) \end{aligned} \qquad \text{....................(5.2)}$$

An MNL model was fitted on socio-demographic variables of income bracket, gender, education level, travel time and maximum willingness to pay per minute for the trip. The dependent variable was a multinomial categorical variable representing the multitasking activity for which the largest proportion of time was spent in each trip. Group prayers or '*bhajans'* had a low sample size in the dataset and were omitted from the MNL model inputs.

Some variables such as age and willingness to pay per minute turned up as significant predictors for TBM both in suburban railway and the metro as shown through the results of the MNL shown in Table 5-2 and

5-3. Findings from the MNL model were corroborated by the earlier random forest analysis – age was found to be statistically significant for most of the multitasking activities on the Suburban Railway and the Metro. On the MM, age was weakly correlated with most activities except for engaging in social media, for which it was strongly negatively correlated. Similarly, increase in age implied a decrease in probability of spending time on multitasking activities on the MSR.

Contrary to the finding that WTP per minute was a strong predictor of TBM, the MNL model show that it is statistically significant only for ICT-related activities of listening to music and watching videos on the Suburban Railway and sleeping and speaking on the phone on the Metro. WTP per minute is strongly and positively correlated with listening to music and watching videos on the MSR. It is very strongly and negatively correlated with sleeping and speaking on the phone on the MM when compared to other TBM activities.

Perceived travel time was a weak predictor of TBM for all activities on the MM and the MSR despite being identified as the third strongest predictor in the random forest analysis. Income bracket of riders did not turn out to be significant for any TBM activity. Also, bachelor degree holders were likely to listen to music on the MSR when compared to riders of other levels of education. Being male was significant in talking to co-passengers and was strongly and negatively correlated on the MSR. However, male riders very strongly tended to engage in social media on the MM when compared to female riders.

Table 5-2: Multinomial Logit Model: Factors Influencing Multitasking Activity on the Mumbai Suburban Railway

Dep. Variable:	Activity	No. Observations:	195
Model:	MNLogit	Df Residuals:	146
Method:	MLE	Df Model:	42
Date:	Sat, 10 Nov 2018	Pseudo R-squ.:	0.1024
Time:	17:36:49	Log-Likelihood:	-324.06
converged:	True	LL-Null:	-361.01
		LLR p-value:	0.001711

Activity=Music	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.2028	0.203	-1.001	0.317	-0.600	0.194
Male	0.5425	0.635	0.854	0.393	-0.702	1.787
Bachelors	0.9100	0.523	1.739	0.082	-0.115	1.935
Masters	0.7395	0.632	1.170	0.242	-0.499	1.978
Age	-0.0655	0.020	-3.335	0.001	-0.104	-0.027
WTP-Time	0.8607	0.427	2.017	0.044	0.024	1.697
p_Time	0.0309	0.010	2.983	0.003	0.011	0.051

Activity=Phone	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.2552	0.394	-0.649	0.517	-1.027	0.516
Male	0.6340	1.275	0.497	0.619	-1.865	3.133
Bachelors	1.5467	1.221	1.267	0.205	-0.846	3.940
Masters	1.6730	1.495	1.119	0.263	-1.258	4.604
Age	-0.1001	0.064	-1.573	0.116	-0.225	0.025
WTP-Time	0.4331	0.826	0.524	0.600	-1.186	2.052
p_Time	-0.0139	0.027	-0.516	0.606	-0.067	0.039

Activity=Reading	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.0865	0.271	-0.319	0.749	-0.617	0.444
Male	-0.5309	0.768	-0.692	0.489	-2.035	0.973
Bachelors	-0.8918	0.731	-1.220	0.223	-2.325	0.541
Masters	0.5395	0.720	0.749	0.454	-0.872	1.951
Age	-0.0172	0.022	-0.793	0.428	-0.060	0.025
WTP-Time	-0.6312	0.752	-0.839	0.401	-2.105	0.843
p_Time	0.0225	0.012	1.857	0.063	-0.001	0.046

Activity=Sleeping	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.1242	0.281	-0.442	0.659	-0.676	0.427
Male	-0.8845	0.729	-1.213	0.225	-2.314	0.545
Bachelors	-0.1174	0.641	-0.183	0.855	-1.374	1.139
Masters	-0.3884	0.858	-0.452	0.651	-2.071	1.294
Age	-0.0376	0.023	-1.642	0.101	-0.082	0.007
WTP-Time	-0.1517	0.726	-0.209	0.835	-1.575	1.272
p_Time	0.0361	0.012	3.086	0.002	0.013	0.059

Activity=Social Media	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.3381	0.292	-1.158	0.247	-0.911	0.234
Male	0.6324	0.921	0.686	0.492	-1.173	2.438
Bachelors	0.0148	0.771	0.019	0.985	-1.496	1.526
Masters	0.8167	0.848	0.963	0.335	-0.845	2.478
Age	-0.0470	0.028	-1.649	0.099	-0.103	0.009
WTP-Time	-0.1904	0.706	-0.270	0.787	-1.575	1.194
p_Time	0.0134	0.015	0.912	0.362	-0.015	0.042

Activity=Talking	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	0.4012	0.312	1.285	0.199	-0.211	1.013
Male	-1.5844	0.815	-1.943	0.052	-3.183	0.014
Bachelors	-0.8971	0.750	-1.196	0.232	-2.368	0.573
Masters	-0.5757	0.834	-0.691	0.490	-2.210	1.058
Age	-0.0458	0.027	-1.705	0.088	-0.099	0.007
WTP-Time	0.7456	0.543	1.374	0.169	-0.318	1.809
p_Time	0.0184	0.014	1.320	0.187	-0.009	0.046

Activity=Watch Videos	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	0.2622	0.270	0.971	0.331	-0.267	0.791
Male	-0.3179	0.790	-0.402	0.687	-1.866	1.230
Bachelors	0.4149	0.697	0.595	0.552	-0.952	1.781
Masters	-0.1130	0.934	-0.121	0.904	-1.944	1.718
Age	-0.1233	0.036	-3.453	0.001	-0.193	-0.053
WTP-Time	1.2358	0.567	2.180	0.029	0.125	2.347
p_Time	0.0351	0.012	2.839	0.005	0.011	0.059

Table 5-3: Multinomial Logit Model: Factors Influencing Multitasking Activity on the Mumbai Metro

Dep. Variable:	Activitym	No. Observations:	196
Model:	MNLogit	Df Residuals:	147
Method:	MLE	Df Model:	42
Date:	Sat, 10 Nov 2018	Pseudo R-squ.:	0.1269
Time:	17:21:03	Log-Likelihood:	-301.74
converged:	True	LL-Null:	-345.61
		LLR p-value:	4.529e-05

Activitym=Music	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.0589	0.175	-0.336	0.737	-0.402	0.284
Male	-0.1360	0.497	-0.274	0.784	-1.109	0.837
Bachelors	0.6358	0.435	1.461	0.144	-0.217	1.489
Masters	0.5860	0.562	1.043	0.297	-0.515	1.687
Age	-0.0346	0.017	-1.999	0.046	-0.068	-0.001
WTP-Time	0.1967	0.352	0.559	0.576	-0.493	0.887
p_Time	0.0091	0.007	1.282	0.200	-0.005	0.023

Activitym=Phone	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	0.1561	0.382	0.408	0.683	-0.593	0.906
Male	-1.2436	0.839	-1.482	0.138	-2.888	0.401
Bachelors	1.1450	1.014	1.129	0.259	-0.842	3.132
Masters	1.3917	1.274	1.092	0.275	-1.105	3.889
Age	-0.0550	0.042	-1.312	0.189	-0.137	0.027
WTP-Time	-3.1122	1.868	-1.666	0.096	-6.773	0.548
p_Time	0.0087	0.013	0.651	0.515	-0.018	0.035

Activitym=Reading	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	0.3773	0.398	0.947	0.344	-0.404	1.158
Male	-1.4968	1.246	-1.201	0.230	-3.939	0.945
Bachelors	1.0298	1.340	0.769	0.442	-1.596	3.656
Masters	2.4427	1.482	1.649	0.099	-0.461	5.347
Age	-0.0247	0.049	-0.505	0.613	-0.121	0.071
WTP-Time	-0.4781	0.697	-0.686	0.493	-1.845	0.888
p_Time	-0.0692	0.030	-2.281	0.023	-0.129	-0.010

Activitym=Sleepingm	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.5246	0.380	-1.381	0.167	-1.269	0.220
Male	1.3557	1.213	1.118	0.264	-1.022	3.733
Bachelors	-0.4124	0.881	-0.468	0.640	-2.140	1.315
Masters	0.7726	1.059	0.730	0.466	-1.303	2.848
Age	-0.0298	0.033	-0.898	0.369	-0.095	0.035
WTP-Time	-3.1626	1.813	-1.744	0.081	-6.716	0.391
p_Time	0.0008	0.014	0.059	0.953	-0.027	0.028

Activitym=Social Media	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	-0.2231	0.295	-0.756	0.450	-0.801	0.355
Male	-0.3245	0.771	-0.421	0.674	-1.837	1.188
Bachelors	1.1768	1.029	1.143	0.253	-0.840	3.194
Masters	3.0602	1.118	2.738	0.006	0.869	5.251
Age	-0.1368	0.056	-2.450	0.014	-0.246	-0.027
WTP-Time	0.1433	0.831	0.172	0.863	-1.486	1.773
p_Time	0.0195	0.012	1.565	0.118	-0.005	0.044

Activitym=Talkingm	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	0.4545	0.275	1.653	0.098	-0.084	0.993
Male	-1.1565	0.782	-1.479	0.139	-2.689	0.376
Bachelors	-0.8406	0.662	-1.269	0.204	-2.139	0.458
Masters	-0.5525	0.735	-0.752	0.452	-1.992	0.887
Age	0.0373	0.021	1.796	0.072	-0.003	0.078
WTP-Time	-0.5863	0.449	-1.306	0.191	-1.466	0.293
p_Time	-0.0483	0.016	-2.996	0.003	-0.080	-0.017

Activitym=Watch Videos	coef	std err	z	P>|z|	[0.025	0.975]
Income Bracket	0.0589	0.213	0.276	0.782	-0.359	0.477
Male	1.3004	0.780	1.667	0.096	-0.229	2.830
Bachelors	-0.0274	0.522	-0.052	0.958	-1.051	0.996
Masters	-0.6070	0.787	-0.772	0.440	-2.149	0.935
Age	-0.0610	0.024	-2.503	0.012	-0.109	-0.013
WTP-Time	-0.3396	0.482	-0.705	0.481	-1.284	0.605
p_Time	-0.0026	0.009	-0.269	0.788	-0.021	0.016

A similar approach was taken by Varghese and Jana (2018) while establishing the relationship between socio-economic factors and multitasking behavior on all modes of transportation in the Mumbai Metropolitan Region. However, the MNL model is limiting due to the assumption that the riders perform a single homogeneous activity throughout their trip. Since the on-board survey data has greater detail of the division of time between multitasking activities during travel, further models can be used to exploit the granularity of the multitasking data and visualize the relationship between the occurrence of TBM activities and socio-economic factors.

To further leverage details in the collected data, a BNL approach was run for each TBM option in the survey, resulting in 7 separate models. The results are summarized in Table 5-4 and Table 5-5. To gain more insight by capturing the information of the percentage of time spent on each trip, occurrence of each multitasking activity was considered as separate dependent variables and the response variables took the value 0 or 1 depending on whether any time was spent on that TBM activity (on-vs-rest method). Eating was omitted due to its sparse occurrence.

Age turned to be statistically significant again in the prediction of ICT-related activities of watching video and listening to music. Similar to the results from the MNL model, it was negatively and strongly correlated with the occurrence of watching videos and listening to music both on the MM and MSR. However, the strength of the coefficients on the MSR was slightly low for the occurrence of ICT-related activities – that is, age does not influence the ICT related TBM as strongly on the MM. The binomial model also showed that age is statistically significant and positively correlated with the 'no activity' state, which was a disadvantage of the MNL model where 'no activity' was assumed as the baseline dependent variable.

Table 5-4: Binomial Logit Model: Factors Influencing Stated Multitasking Activity on the Mumbai Metro

	Dependent variable:						
	Sleeping	No Activity	Videos	Music	Emails	Social Media	Talking
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income Level	-0.389	0.048	0.145	-0.047	-0.151	-0.440**	0.025
	(0.262)	(0.145)	(0.151)	(0.142)	(0.207)	(0.171)	(0.163)
Male	-0.368	-0.028	1.136**	-0.309	-0.443	-0.203	-0.210
	(0.547)	(0.429)	(0.475)	(0.386)	(0.531)	(0.416)	(0.455)
Undergraduate	-1.525**	0.128	-0.550	0.300	-0.430	-0.142	-1.242***
	(0.597)	(0.383)	(0.405)	(0.370)	(0.555)	(0.420)	(0.432)
Graduate	-0.575	0.052	0.091	0.117	0.827	0.803*	-0.346
	(0.628)	(0.440)	(0.454)	(0.435)	(0.564)	(0.476)	(0.442)
Age	-0.197	0.539***	-0.903***	-0.508**	-0.297	-0.341	0.099
	(0.289)	(0.173)	(0.251)	(0.198)	(0.297)	(0.219)	(0.184)
WTP/Time	-2.749**	0.801**	-0.651	0.096	0.176	-0.174	0.215
	(1.253)	(0.395)	(0.428)	(0.385)	(0.490)	(0.467)	(0.431)
Travel Time	-0.184	0.283	-0.307	0.111	-0.695*	0.383*	0.028
	(0.344)	(0.211)	(0.221)	(0.202)	(0.393)	(0.221)	(0.235)
Official	-0.508	0.684*	-0.141	-0.046	-0.349	-0.350	0.148
	(0.619)	(0.375)	(0.400)	(0.372)	(0.561)	(0.430)	(0.416)
Constant	1.228	-1.542***	-1.466**	-0.400	-1.481**	-0.041	-0.732
	(0.895)	(0.565)	(0.612)	(0.534)	(0.724)	(0.592)	(0.575)
Observations	196	196	196	196	196	196	196
Log Likelihood	-57.968	-117.742	-110.201	-123.929	-72.433	-101.709	-99.992
Akaike Inf. Crit.	133.935	253.484	238.401	265.859	162.865	221.418	217.983
Note:					*p<0.1; **p<0.05; ***p<0.01		

Among other statistically significant variables, WTP per minute is strongly and negatively correlated with sleeping during travel on both the MM and the MSR. However, WTP per minute gives the opposite effect with watching videos where it is negatively correlated on the MM and strongly and positively correlated on the MSR.

Certain factors such as the duration of travel, level of education, levels of income and gender were significant for certain TBM activities in the BNL. The effect of these variables on occurrence of multitasking activities is explained in Chapter 6 by providing supporting evidence from follow-up interviews of the surveyed riders.

Table 5-5: Binomial Logit Model: Factors Influencing Stated Multitasking Activity on the Mumbai Suburban Railway

	Dependent variable:						
	Sleeping	No Activity	Videos	Music	Emails	Social Media	Talking
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income Level	0.065	0.161	0.055	-0.263*	-0.044	-0.148	0.297*
	(0.180)	(0.175)	(0.162)	(0.148)	(0.152)	(0.159)	(0.166)
Male	-0.756	0.810	0.495	0.298	-0.039	-0.052	-0.968**
	(0.483)	(0.681)	(0.446)	(0.405)	(0.447)	(0.420)	(0.451)
Undergraduate	0.964*	-0.256	0.641	0.682*	0.610	0.700	-0.408
	(0.520)	(0.469)	(0.440)	(0.382)	(0.446)	(0.432)	(0.424)
Graduate	0.455	-0.396	0.719	0.029	1.459***	1.032**	-0.276
	(0.618)	(0.537)	(0.515)	(0.442)	(0.483)	(0.497)	(0.474)
Age	0.096	0.696***	-1.049***	-0.839***	0.017	-0.624**	0.245
	(0.203)	(0.189)	(0.291)	(0.212)	(0.182)	(0.248)	(0.179)
WTP/Time	-0.590	0.223	1.057**	-0.179	0.463	-0.024	0.727*
	(0.748)	(0.469)	(0.415)	(0.400)	(0.430)	(0.425)	(0.429)
Travel Time	0.476*	-0.075	0.627***	0.090	0.491**	0.175	0.227
	(0.254)	(0.273)	(0.234)	(0.211)	(0.220)	(0.219)	(0.230)
Official	0.655	0.588	-1.238**	-0.051	0.494	-0.721	0.224
	(0.448)	(0.450)	(0.485)	(0.391)	(0.395)	(0.446)	(0.425)
Constant	-1.633**	-2.687***	-2.454***	0.136	-2.047***	-1.140*	-1.460**
	(0.757)	(0.799)	(0.665)	(0.543)	(0.630)	(0.614)	(0.586)
Observations	196	196	196	196	196	196	196
Log Likelihood	-81.332	-84.858	-102.512	-116.380	-106.930	-106.790	-99.371
Akaike Inf. Crit.	180.663	187.715	223.024	250.761	231.859	231.581	216.742

Note: *p<0.1; **p<0.05; ***p<0.01

A decision tree was run to better visualize and interpret the different ICT activities, non-ICT activities, social activities and individual activities. Figures 5-7 and 5-8 provide the structure of the decision trees. Decision trees of depth 4 and Gini impurity were used to build the partition trees. Gini impurity is used to measure the degree of inequality of distribution of different TBM activities. A Gini impurity of 0 denotes a perfectly equal distribution.

In the boxes, the percentage indicates the total number of data samples that conform to the split condition at each node. The percentage of the total number of riders engaged in each activity at each node is denoted as a decimal. Each node is colored according to the most common activity.

Similar to the previous models and the random forest analysis, age and WTP per minute were the strongest predictors. However, a pattern of separation by applying decision boundaries through these two variables is observed in this model. For the MSR, the distinction is clear: an age below 34 years and a WTP per minute of more than 1.3 rupees leads to the highest probability of the occurrence of ICT related activities such as watching videos and sleeping. However, this type of clear division is not observed on the classification tree for the MM, where the only an age over 29 years and a WTP per minutes of more than 0.30 rupees is observed.

Figure 5-7: Decision Tree for Travel Based Multitasking on the Western Line, Mumbai Suburban Railway

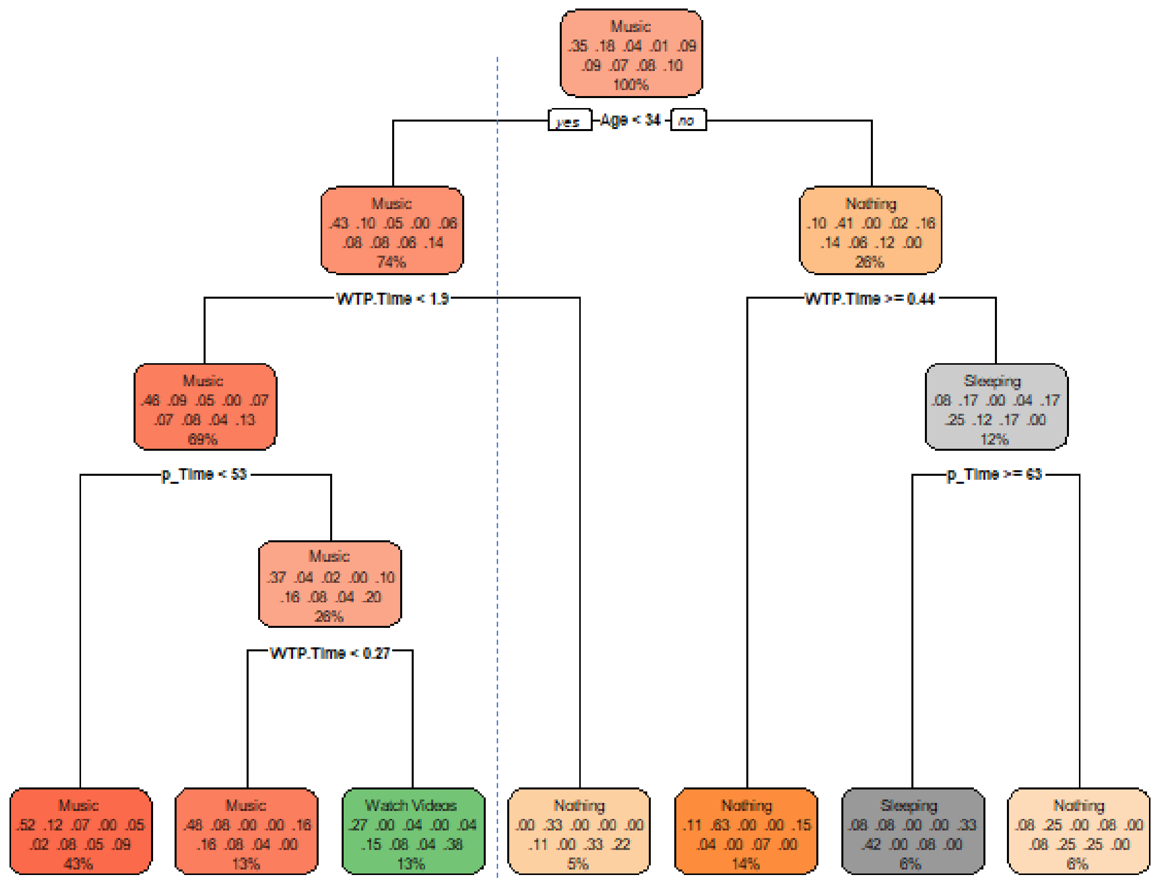
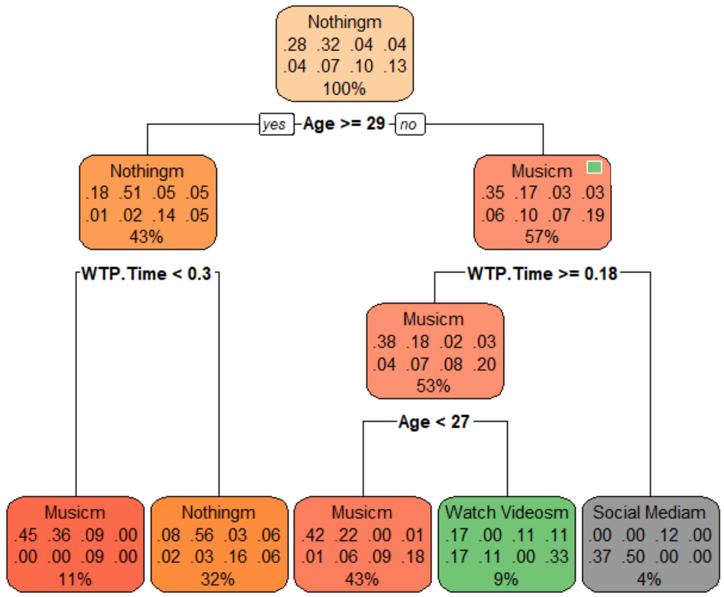


Figure 5-8: Decision Tree for Stated Travel Based Multitasking on the Mumbai Metro



To better understand this clear distinction and also develop a model that directly addresses the questions of TBM involving the use of ICT and TBM involving social and interactive activities, BNL models were run again on socio-economic and certain trip related variables.

Two binomial models were used TBM activities with types of TBM activities as response: the first models classified activities into two types depending on whether the activities were ICT-related and the second model classified response activities based on whether the activity involved social interaction or not as shown in Table 5-6. The dependent variable in the first model takes the value 0 or 1, indicating whether the TBM activities that the rider was engaged in were non-ICT based or ICT based. The second model worked on the same structure for TBM involving social interaction.

The results of the classified BNL model is summarized in Table 5-7. Again, age is strongly and negatively correlated with ICT-related TBM both on the MM and the MSR. Strong negative correlation also occurred between social interaction and being male or having an undergraduate degree.

Table 5-6: Classification Buckets for BNL Models on ICT-related and Social Activities

ICT Based Classification

ICT
- Talking over the phone
- Watching videos
- Emails/Messaging

Non-ICT
- No Activity
- Group Prayer
- Sleeping
- Face-to-face talking
- Eating

Social Interaction Based Classification

Int
- Emails/ Messaging
- Face-to-face talking
- Group prayer
- Talking over the phone

Non-Int
- No activity
- Sleeping
- Eating
- Watching Videos

Table 5-7: Factors Affecting ICT-related and Social Travel Based Multitasking

	Dependent variable:			
	ICT (1)	Int (2)	ICTm (3)	Intm (4)
Income Bracket 2	0.175 (0.415)	-0.325 (0.474)	-0.078 (0.402)	0.573 (0.465)
Income Bracket 3	0.733 (0.529)	-1.396^{*} (0.807)	0.935^{*} (0.514)	-1.078 (0.824)
Income Bracket 4	-0.851 (0.524)	0.109 (0.577)	-0.839 (0.523)	0.718 (0.562)
Male	0.739^{*} (0.418)	-0.834^{*} (0.450)	0.093 (0.407)	-0.986^{**} (0.454)
Undergraduate	0.312 (0.394)	-1.047^{**} (0.468)	0.101 (0.386)	-0.182 (0.474)
Graduate	0.397 (0.463)	-0.309 (0.495)	0.234 (0.452)	0.695 (0.493)
Age	-1.065^{***} (0.229)	-0.076 (0.213)	-0.859^{***} (0.211)	0.175 (0.191)
WTP/Time	-0.570 (0.394)	-0.231 (0.511)	-0.763^{*} (0.410)	-0.254 (0.514)
Travel Time	-0.307 (0.218)	-0.203 (0.265)	0.056 (0.212)	-0.043 (0.248)
Constant	-0.269 (0.514)	0.058 (0.551)	0.357 (0.507)	-0.760 (0.577)
Observations	196	196	196	196
Log Likelihood	-110.733	-87.479	-115.321	-91.476
Akaike Inf. Crit.	241.467	194.958	250.642	202.952
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

5.3 Discussion

Among socio-economic variables studied in the quantitative models, certain factors stood out more than others; some of the correlations were expected and some were surprising. Corroboration with insights from unstructured interviews gave some insight into the root causes behind certain anomalous TBM behavior.

Comparing the results from models described in Section 5.2, it is safe to summarize that age and WTP per minute were the strongest predictors of specific multitasking activities in which a rider would engage. Gender had a greater effect on the TBM for MM riders when compared to MSR.

Both on the MSR and on the MM, WTP per minute was positively correlated with listening to music. This might indicate that riders who are willing to pay more per minute for their travel time tend to listen to music during travel or vice versa. Several passengers mentioned that listening to music cancelled loud noises experienced by passengers due to open windows and doors on the MSR. Also, riders' WTP estimates seemed to be have a proxy to the fare that they paid for their trip on the Suburban Railway.

Correlation between age and multitasking behavior was not surprising. ICT-related activities decrease with the increase in the age of the rider both on commuter rail and on metro trains (Bjørner, 2016; Gamberini et al., 2013; Lyons et al., 2016). This might be due to higher WTP by younger riders when comparted to older people. The effect of age on ICT usage was marginally higher on the MSR than the MM. Several of the riders interviewed, who were older than 34 years, stated that there the absence of prayer groups on the MM would nudge them to perform ICT related activities – such as watching videos or listening to music. This occurrence of organized groups for prayer might be a direct effect of length of travel time since the prayer groups were seen more often on fast train, where riders tend to take longer journeys, when compared to slow trains, where riders travel shorter distances.

Gender was strongly positively correlated with occurrence of social behavior on the train. This result does not seem surprising on the surface since it has been observed in previous literature in Belgium (Keseru, et al., 2015), Britain (Lyons, Jain, & Weir, 2016) and New Zealand (Russell, et al., 2011). Studies have indicated the tendency of females to socialize more in informal contexts than in formal contexts (James & Drakich, 1993; Ton, 2016). Most women traveled in groups and with male companions in general compartments since they felt insecure. However, this was not the case in ladies' compartments where women felt safe and frequently traveled alone. Performing ICT related activities increased the feeling of insecurity in crowded situations according to some female riders.

Income brackets for a rider was positively correlated only with TBM activities involving social interaction on the MSR and was insignificant in predicting most other activities. It was negatively correlated to talking and music on the MSR and social media usage on the MM. No significant conclusions could be made for the influence of income on TBM activities through interviews with riders. However, there was a sense of general reluctance when asked to comment about incomes, which was expected, despite the questionnaire asking for a bracket rather than an exact income.

6. Infrastructure and Policy Implications

The analysis of multitasking activities through the quantitative models have brought out some issues that the MMR and mass transportation systems in India face as a whole. This chapter outlines possible issues influencing TBM and proposes policies and infrastructure recommendations to address them.

6.1 Policy Interventions

Understanding multitasking behavior before conducting the cost-benefit analysis for planning transportation infrastructure such as the Mumbai Metro can benefit the business strategies, service design and vehicle design for the operation of the metro. During the final stage of planning, when facilities on trains and stations are decided for the MM Lines in the future, analysis used in this thesis can be leveraged to understand TBM activities. It can also be instrumental to understand the behavior of different socio-economic groups of riders and hence strive for incorporating equity in facilities intended to assist multitasking.

Quantitative analysis of the TBM activities involving social interaction has surprisingly shed light on a very important issue that the current MSR and MM transit agencies are dealing with – safety of female riders. On the MSR and the MM, male riders have a lower tendency to engage in socially interactive activities when compared to females. Through interviews with female passengers, the cause of this can be traced to women's sense of security while travelling. Some of the interviewed female riders felt uncomfortable travelling along in general coaches and preferred to travel in ladies' coaches when alone. Women travelling in general coaches were observed to be travelling in groups that included one or more male members, with whom they tended to socialize and which might have led to the correlation with gender.

Several female passengers also raised the concern of not being able to engage in ICT-related activity on general coaches due to a sense of insecurity both on the MSR and the MM. This ability to multitask, or in this case, comfortably perform TBM activities, has a direct implication on the health of the rider due to the inability of performing a TBM routine during a daily commute (Olsson, Gärling, Ettema, Friman, & Fujii, 2012) and loss in productivity (Gripsrud & Hjorthol, 2012).

From quantitative analysis in the previous chapter, two socio-economic variables – gender and age – greatly influence social and ICT-related TBM behavior. As shown above, while addressing the difference in social interaction among riders of different genders, it points to a potential flaw in the configuration of the train and the women-only compartment. Analysis performed in this thesis points to a possibility of reforming gender segregation policies on the MSR and the proposed MM trains. However, to completely address policies in this section, deeper understanding of the gender divide is needed, which can be analyzed through qualitative analysis of rider experience on both of these modes of mass transit. As mentioned before, providing Wi-Fi hotspots on the trains will be a step to reduce the inequity, especially among people who own smartphones but who do not subscribe to a mobile internet service. Not all riders interviewed possessed an internet pack that they felt would be sufficient to stream videos during on-board travel. Wi-Fi facilities on board will ensure that ICT related TBM can be carried out either to fulfil work-related or communication requirements. Specifically, the beneficiaries of this service can be students who mentioned the absence of data packs on their phones due to high charges.

A scheme of discriminating in charging different types of riders for Wi-Fi services based on age is a possibility to consider. While the WTP per minute varies by age, riders who have higher WTP – the working and middle age group – can be charged for their usage, while the younger student riders can be provided with free internet on-board trains.

Since the trips surveyed occurred during non-commute hours, extreme crowding was not a deterrent according to interviews. Respondents who return late in the evening stated that levels of crowding were so high that 'it is a very aggressive fight to enter the compartment, especially at intermediate stations where the train arrive already fully saturated'. Passengers did not listen to music or watch videos since there was a high chance of losing earphones and mobiles in the crowd. During the commute hours, respondents would not perform any activity and wait for the trains to reach their stations. Respondents also stated that the only TBM activity that happened during the peak hours was group prayers. However, most of riders engaging in the *bhajan mandalis* exclusively boarded train at its origin station and had a higher chance of obtaining a seat for their journey.

According to the Mumbai Metro Master Plan, if the presence of the metro reduces demand for the Western Line, peak commute hours might witness less crowding and thus give greater opportunity to perform TBM activities during peak commute hours. Riders who mentioned frequently traveling on the MSR and the MM Line I during peak hours mentioned the high stress associated with boarding and getting off the train. This was reflected in the passenger behavior during the non-peak hours also.

Finally, there arises a question of what TBM activities are appropriate for each mode of transportation. Among the activities that currently happen on board, the *bhajan mandalis* received both support and opposition from riders interviewed. Riders stated that the activity was part of the cultural fabric of the city and felt that it represented a core value of being a resident of Mumbai. Many mentioned that the prayers, though mostly Hindu hymns, provided a way to bond with fellow passengers regardless of socio-economic group. However, the Indian Railways has been enforcing rules and charging those involved in the organization of prayers on the grounds of it being a nuisance to fellow passengers. This sentiment was reflected by some riders, who felt that the *mandalis* added to the already noisy interiors of the MSR train.

In summary, research and interpretations from this thesis can be used to promote gender equity, public health, ICT usage during on-board travel and indirectly address the most pertinent issues that the Indian Railways and the Mumbai Metro are dealing with.

7. Conclusions

This thesis analyzed travel based multitasking (TBM) behavior in the context of the Mumbai Metropolitan Region's Suburban Railway and the Mumbai Metro through three objectives:

First, it aimed to find the TBM activities in which riders of mass transit in the MMR engage. Second, it aimed to find the influence of socio-economic and trip-related variables on the occurrence of TBM activities. Third, this thesis aimed to provide policy recommendations to the MSR and the MM that directly address on-board TBM.

7.1 Summary of Findings

Several socio-economic factors stood out in their influence of TBM in the MSR and MM. Among them age and willingness to pay per minute of travel time had the strongest influence on the type of TBM activity in which the rider was engaged. The analysis of multitasking among females has led to certain critical issues that mass transit systems have been facing in the MMR. Perception of safety, especially among female riders greatly influenced the choice of multitasking activity in which the rider was involved. Female riders had a higher chance of interacting social during on-board travel, both on the MSR and the MM. ICT usage was higher among younger riders, while riders above the age of 34 preferred to participate in group prayers or *'bhajans'* on the MSR. The thesis recommends providing Wi-Fi facilities on-board both the MSR and the upcoming MM lines. Also, in order to provide equitable opportunity to multitask on-board the thesis recommends a revision of the ladies' compartment policy on mass transportation modes in the MMR.

7.2 Limitations and Future Work

Biases on the SP survey were avoided through a screening question for all riders. Respondents were asked if they have experienced travel on the Mumbai Metro. All riders who answered in the negative to the question were omitted from the survey. However, biases on the stated preference (SP) part of the questionnaire might have occurred due to the following reasons:

- Benefits associated to each TBM activities that the rider proposes to perform on board the metro
- Difference in fares and time associated with performing the same trip on the metro.
- Ambiguity in language used to set the hypothetical situation for the SP survey.

Future work into the field of Travel Based Multitasking (TBM) can offer great opportunities to understand the needs of riders using mass transit transportation systems in the Mumbai Metropolitan Region (MMR). In this thesis, a small sample of rider trip and socio-demographic information was collected over a certain period of time. This can be extended into a more extensive survey that captures greater number of trips across different metro and suburban railway corridors. Future surveys can be imagined as a combination of household, structured observations and on-board intercept surveys. The combination can address the missing latent rider base of the metro that was not covered in this thesis and also can avoid the loss or inaccuracy in reporting TBM activities due to recall.

In this thesis, only the effect of socio-economic and trip-related variables were considered. Considering attitudinal characteristics such as risk taking behavior of riders can give a very enriched view to understanding how attitudes influence ICT-related and social interactions in different settings. Behavioral economic principles can be used to interpret attitudes of riders and find avenues to nudge riders to take mass transit options. Also, needs of different types of riders based on trip purpose, gender and age can be identified and can be leveraged to nudge the rider towards mass transit usage in the MMR. Catering to specific needs can increase the utility and benefits derived from multitasking and will lead to a quality and positive travel experience.

In order to translate and quantify the effects of multitasking positive utility, a VTTS model can be derived from more granular survey questions. The VTTS factor used to calculate benefits for riders can be modified to incorporate TBM by adding a multitasking activity term to utility, which is a function of time and cost. VTTS can be calculated for different TBM activities and the need for a rider to engage in a particular activity must be measured and incorporated simultaneously. This can be done by giving hypothetical scenarios and asking the riders their willingness to pay if a single TBM activity is carried out for the entire trip.

The classification of the TBM activities as ICT-related or involving social interaction can be further broken down into whether or not it involves smart phones and internet. This disaggregation can give robust model and unearth several insights into different dependencies on equipment to perform TBM activities.

Finally, extending TBM to multitasking can provide a revised framework to approach transportation mode choice among the residents of the MMR and predict the ridership of the upcoming MM lines. The environmental and traffic implication of this line of work are numerous.

Considering all limitations and possibility of future work, this thesis hopes to provide a starting point for research on TBM in the MMR and assist MM and MSR decision-makers on TBM related policies.

Appendices

8.1 Structure of the Data from the On-board Intercept Questionnaire

Survey A (sample size: 196 trips): (On board intercept survey on the Suburban Railway Western Line in 2018)

Variables:

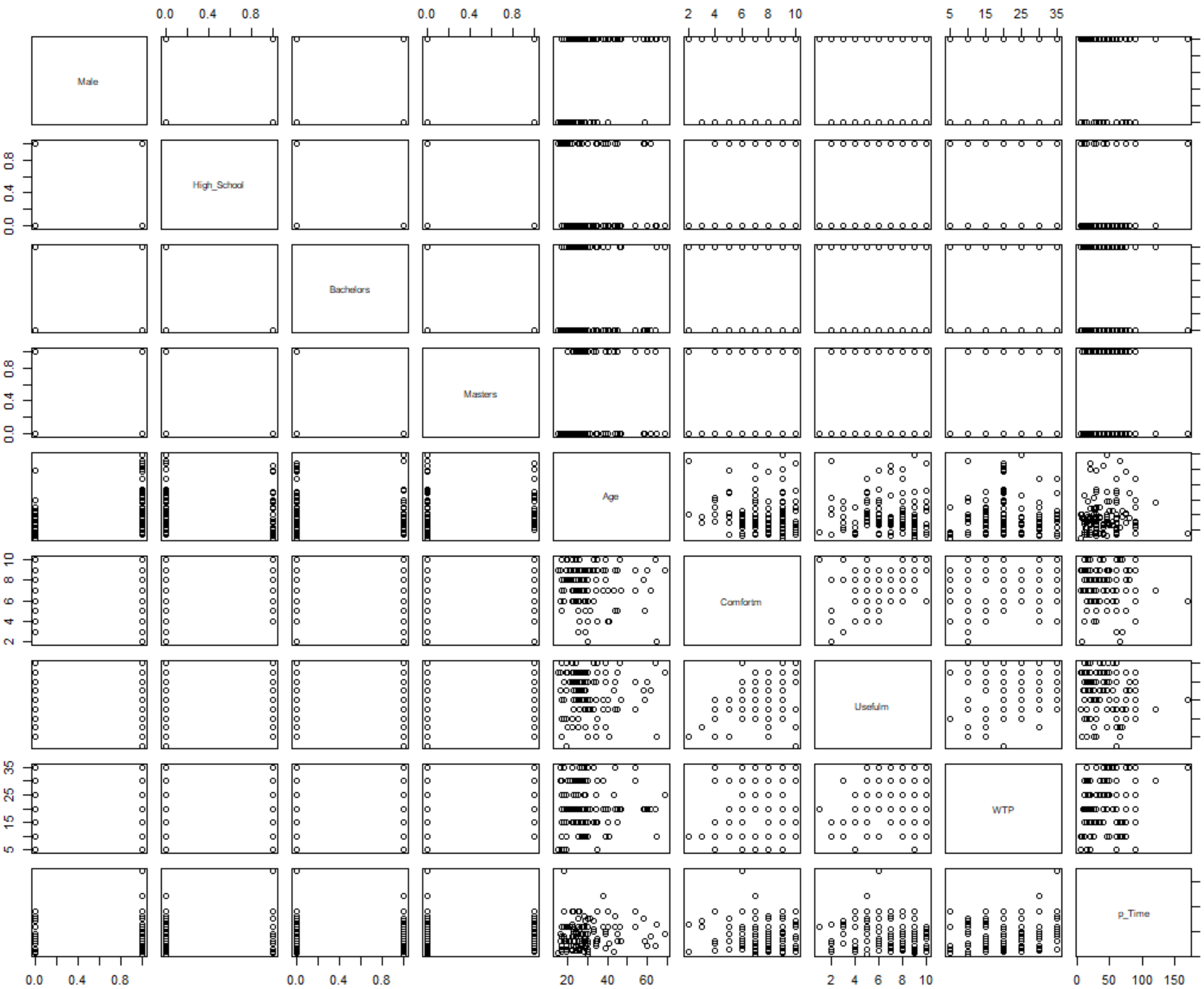
- Socio-demographic characteristics:
  - Income Bracket: (0,1,2,3,4)
    - 0 – No household income
    - 1- 0 to 20,000 INR
    - 2 – 20,000 – 30,000 INR
    - 3 – 30,000 – 50,000 INR
    - 4 - >50,000 INR
  - Age: (0-100)
  - Gender: (M,F)
  - Education: (0,1,2,3)
    - 0 – No education
    - 1 –High School
    - 2 – Bachelors degree
    - 3 – Masters degree
- Trip characteristics:
  - Origin Station:
  - Destination Station:
  - Other modes used for trip:
    - Private car: (Y,N)
    - Two-wheeler: (Y.N)
    - Auto rickshaw: (Y,N)
    - Public Bus: (Y,N)
    - Walking > 800m: (Y,N)
    - Uber/Ola: (Y,N)

        - Metro: (Y/N)
        - Cycle: (Y/N)
    - Purpose of trip: (Official, Non-official)
- Ownership of smartphone: (Y,N)
- Revealed preference (for travel on the suburban railway Western Line):
    - Multitasking activity (percentage time spent on each activity – sums to 100%):
        - No activity: %
        - Sleeping: %
        - Reading on device: %
        - Speaking with copassengers: %
        - Listing to music: %
        - Watching video on device: %
        - Social media on device: %
        - Speaking on the phone: %
    - Comfort during travel: (Scale of 1 to 10)
    - Productivity during travel: (Scale of 1 to 10)
- Stated preference (for travel on the Metro Line 3 under similar crowding conditions):
    - Multitasking activity (percentage time spent on each activity – sums to 100%):
        - No activity: %
        - Sleeping: %
        - Reading on device: %
        - Speaking with copassengers: %
        - Listing to music: %
        - Watching video on device: %
        - Social media on device: %
        - Speaking on the phone: %
    - Comfort during travel: (Scale of 1 to 10)
    - Productivity during travel: (Scale of 1 to 10)
    - Willingness to pay for the same trip on the metro: (in Rupees)
    - Perceived time: (rounded to the nearest minute)

8.2 Descriptive statistics for RP and SP survey

Statistic	N	Mean	St. Dev.	Min	Max
S.no	196	98.500	56.724	1	196
Male	196	0.801	0.400	0	1
Female	196	0.199	0.400	0	1
None	196	0.026	0.158	0	1
High_School	196	0.255	0.437	0	1
Bachelors	196	0.444	0.498	0	1
Masters	196	0.260	0.440	0	1
Age	196	-0.000	1.000	-1.269	3.510
Purpose	196	0.250	0.434	0	1
WTP	196	0.000	1.000	-1.905	1.737
WTP.Time	196	0.681	0.539	0.056	2.609
Income.Bracket	196	2.107	1.250	0	4
Income_1	196	0.250	0.434	0	1
Income_2	196	0.291	0.455	0	1
Income_3	196	0.173	0.380	0	1
Income_4	196	0.189	0.392	0	1
p_Time	196	0.000	1.000	-1.413	4.411
Car	196	0.051	0.221	0	1
Bus	196	0.179	0.384	0	1
Metro	196	0.087	0.282	0	1
Two.Wheeler	196	0.133	0.340	0	1
Taxi	196	0.133	0.340	0	1
Auto	196	0.179	0.384	0	1
Walking..8km	196	0.276	0.448	0	1
Cycling	196	0.015	0.123	0	1
Sleeping_d	196	0.179	0.384	0	1
Nothing_d	196	0.199	0.400	0	1
Watch.Videos_d	196	0.316	0.466	0	1
Music_d	196	0.510	0.501	0	1
Reading_d	196	0.270	0.445	0	1
Social.Media_d	196	0.276	0.448	0	1
Talking_d	196	0.230	0.422	0	1
Phone_d	196	0.250	0.434	0	1
Prayer_d	196	0.056	0.231	0	1
Eating_d	196	0.041	0.198	0	1
Sleeping	196	0.071	0.182	0	1
Nothing	196	0.155	0.331	0	1
Watch.Videos	196	0.110	0.212	0	1
Music	196	0.287	0.348	0.000	1.000
Reading	196	0.114	0.256	0	1
Social.Media	196	0.100	0.213	0	1
Talking	196	0.095	0.236	0.000	1.000
Phone	196	0.051	0.133	0.000	1.000
Prayer	196	0.013	0.062	0	1
Eating	196	0.005	0.032	0	0
ICT	196	0.556	0.498	0	1
nonICT	196	0.444	0.498	0	1
Int	196	0.194	0.396	0	1
nonInt	196	0.806	0.396	0	1
Useful	196	-0.000	1.000	-2.217	1.917
Comfortable	196	-0.000	1.000	-2.235	2.339
Sleepingm_d	196	0.112	0.316	0	1
Nothingm_d	196	0.347	0.477	0	1
Watch.Videosm_d	196	0.311	0.464	0	1
Musicm_d	196	0.383	0.487	0	1
Readingm_d	196	0.148	0.356	0	1
Social.Mediam_d	196	0.260	0.440	0	1
Talkingm_d	196	0.230	0.422	0	1
Phonem_d	196	0.245	0.431	0	1
Prayerm_d	196	0.020	0.142	0	1
Eatingm_d	196	0.010	0.101	0	1
Sleepingm	196	0.045	0.157	0	1
Nothingm	196	0.277	0.408	0	1
Watch.Videosm	196	0.148	0.288	0.000	1.000
Musicm	196	0.227	0.333	0.000	1.000
Readingm	196	0.048	0.162	0.000	1.000
Social.Mediam	196	0.087	0.195	0	1
Talkingm	196	0.101	0.234	0.000	1.000
Phonem	196	0.061	0.157	0.000	1.000
Prayerm	196	0.005	0.037	0	0
Eatingm	196	0.002	0.016	0	0
ICTm	196	0.510	0.501	0	1
nonICTm	196	0.490	0.501	0	1
Intm	196	0.214	0.411	0	1
nonIntm	196	0.786	0.411	0	1
Usefulm	196	0.000	1.000	-2.569	1.517
Comfortm	196	0.000	1.000	-2.932	1.369
Sm.Ph	196	0.959	0.198	0	1

8.3 Correlation table between socio-economic and trip variables



8.4 BNL with Choice of Mode for riders with Multimodal Trips

BNL with Trip Characteristics for the Metro

	Dependent variable:						
	Sleeping	No Activity	Videos	Music	Emails	Social Media	Talking
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Car	-16.823	0.989	0.962	-1.527^{*}	-16.399	-0.742	-16.086
	(1,981.565)	(0.791)	(0.762)	(0.887)	(1,183.378)	(0.801)	(1,245.821)
Bus	0.313	0.062	0.243	0.264	-0.102	-0.077	0.589
	(0.621)	(0.419)	(0.419)	(0.404)	(0.584)	(0.484)	(0.439)
Metro	-16.757	1.194^{**}	-0.608	-0.936	0.924	-0.740	-0.861
	(1,542.610)	(0.563)	(0.629)	(0.634)	(0.639)	(0.699)	(0.808)
Two Wheeler	-0.185	-1.780^{**}	0.578	0.452	-0.449	1.165^{**}	-0.311
	(0.795)	(0.693)	(0.455)	(0.458)	(0.793)	(0.472)	(0.596)
Taxi	0.650	-0.115	-0.704	1.011^{**}	1.057^{*}	1.256^{**}	-0.095
	(0.714)	(0.506)	(0.573)	(0.492)	(0.579)	(0.500)	(0.613)
Three Wheeler	-0.071	1.149^{***}	-0.826^{*}	0.362	-0.095	0.037	0.601
	(0.609)	(0.413)	(0.472)	(0.395)	(0.610)	(0.457)	(0.427)
Walking .8km	0.535	0.355	-0.460	-0.086	0.886^{*}	0.504	0.248
	(0.514)	(0.361)	(0.376)	(0.357)	(0.460)	(0.388)	(0.407)
Constant	-2.166^{***}	-0.946^{***}	-0.591^{**}	-0.629^{**}	-2.162^{***}	-1.462^{***}	-1.356^{***}
	(0.397)	(0.260)	(0.248)	(0.249)	(0.376)	(0.294)	(0.295)
Observations	196	196	196	196	196	196	196
Log Likelihood	-64.538	-116.278	-116.152	-125.437	-75.572	-106.306	-99.972
Akaike Inf. Crit.	145.076	248.556	248.304	266.874	167.145	228.612	215.944
Note:							*p<0.1; **p<0.05; ***p<0.01

8.5 Codes for developing models using the RP and SP data

```
#installing packages
install.packages('caret')
install.packages('e1071')
install.packages("PerformanceAnalytics")
install.packages("corrplot")
install.packages('Amelia')
install.packages("mlogit")
install.packages("XLConnect")
install.packages("stargazer")
install.packages('rpart')
install.packages('randomForest')
```

```
#installing libraries
library(Amelia)
library(caret)
library(mlogit)
library(XLConnect)
library(stargazer)

#reading files
multi = read.csv(file="test.csv")
my_data <- multi

#checking columns
sapply(my_data, class)
pairs(my_data[,c('Male','High_School','Bachelors','Masters','Age','Comfortm','Usefulm','WTP','p_Time')])
my_data


my_data[c('Age','Comfortable','Comfortm','Useful','Usefulm','WTP','p_Time')] <-
lapply(my_data[c('Age','Comfortable','Comfortm','Useful','Usefulm','WTP','p_Time')], function(x)
c(scale(x)))
summary(my_data)

#binomial models for the metro
mylogit1 = glm(Sleepingm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age +  WTP.Time + p_Time, data=my_data, family='binomial')
mylogit2 = glm(Nothingm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit3 = glm(Watch.Videosm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit4 = glm(Musicm_d ~  Income.Bracket +Male + +Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit5 = glm(Readingm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit6 = glm(Social.Mediam_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit7 = glm(Talkingm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit8 = glm(Phonem_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit9 = glm(Prayerm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit10 = glm(Eatingm_d ~ Income.Bracket + Male + Bachelors
        + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')


stargazer(title = "Logit Model: Factors influencing multitasking activity on the Mumbai Metro Line III",
```

```
	header= FALSE  ,  covariate.labels = c('Income Bracket 1', 'Income Bracket 2','Income Bracket 3', 'Income Bracket 4', 'Male',  'Undergraduate', 'Graduate','Age', 'WTP/Time', 'Travel Time','Constant' ),
	mylogit1, mylogit2,mylogit3, mylogit4, mylogit5, mylogit6, mylogit7,  type="html", no.space = FALSE, single.row=FALSE, out='models_s.htm',
	dep.var.labels = c("Sleeping", "No Activity" , "Videos", "Music" , "Emails" , "Social Media","Talking"))



#binomial models for suburban trains
mylogit1 = glm(Sleeping_d ~ Income.Bracket + Male+Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit2 = glm(Nothing_d ~ Income.Bracket + Male  +Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit3 = glm(Watch.Videos_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit4 = glm(Music_d ~  Income.Bracket +Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit5 = glm(Reading_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit6 = glm(Social.Media_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit7 = glm(Talking_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit8 = glm(Phone_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit9 = glm(Prayer_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit10 = glm(Eating_d ~ Income.Bracket + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')

mylogit1
#summary tables
stargazer(title = "Logit Model: Factor multitasking activity on the Suburban Railway Western Line ",
	header= FALSE  ,  covariate.labels = c('Income Bracket 1', 'Income Bracket 2','Income Bracket 3', 'Income Bracket 4', 'Male',  'Undergraduate', 'Graduate','Age', 'WTP/Time', 'Travel Time','Constant' ),
	mylogit1, mylogit2,mylogit3, mylogit4, mylogit5, mylogit6, mylogit7,  type="html", no.space = TRUE, single.row=FALSE, out='models_m.htm',
	dep.var.labels = c("Sleeping", "No Activity" , "Videos", "Music" , "Emails" , "Social Media","Talking"))


#ICT and Interaction models
mylogit1 = glm(ICT ~Income_2 + Income_3 + Income_4+ Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit2 = glm(Int ~ Income_2 + Income_3 + Income_4 + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit3 = glm(ICTm ~ Income_2 + Income_3 + Income_4 + Male + Bachelors
	+ Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
```

```
mylogit4 = glm(Intm ~ Income_2 + Income_3 + Income_4+ Male + Bachelors
           + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')


#summary table
stargazer(title = "Logit Model: Factors affecting multitasking categories",
       header= FALSE, covariate.labels = c( 'Income Bracket 2','Income Bracket 3', 'Income Bracket 4',
'Male',  'Undergraduate', 'Graduate','Age', 'WTP/Time', 'Travel Time','Constant' ),
       mylogit1, mylogit2,mylogit3, mylogit4,    type="html", no.space = TRUE, single.row=TRUE,
out='buckets_s.htm')



for (i in c(1,2,3,4,5,6,7,8,9)){
cm = confusionMatrix(table(as.numeric(pred4 >= i/10),
                as.numeric(my_data[,c("High_School")] == 1)))
print(cm$overall['Accuracy'])
}

library(rpart)
library(rpart.plot)
library(rattle)

install.packages("rpart.plot")
install.packages("rattle")


#Full Dataset
fitclass_col_fd1 <- rpart(Activity ~ Income.Bracket + Male + Bachelors
                  + Masters + Age +  WTP.Time + p_Time
                  , data = my_data,
                  cp = 0.001, method="class", control = rpart.control(maxdepth = 4), minsplit = 2)
fitclass_col_fd2 <- rpart(Activitym ~ Income.Bracket + Male + Bachelors
                  + Masters + Age +  WTP.Time + p_Time
                  , data = my_data,
                  cp = 0.001, method="class", control = rpart.control(maxdepth = 4), minsplit = 1)
fitclass_col_fd3 <- rpart(Activity ~ Income.Bracket + Male + Bachelors
                  + Masters + Age +  WTP.Time + p_Time
                  , data = my_data,
                  cp = 0.001, method="class", control = rpart.control(maxdepth = 4), minsplit = 1)
fitclass_col_fd4 <- rpart(Activity ~ Income.Bracket + Male + Bachelors
                  + Masters + Age +  WTP.Time + p_Time
                  , data = my_data,
                  cp = 0.001, method="class", control = rpart.control(maxdepth = 4), minsplit = 1)
summary(fitclass_col_fd)
plotcp(fitclass_col_fd)
prp(fitclass_col_fd, type = 1, extra = 1, under = TRUE, split.font = 12, varlen = -10)
```

```
fancyRpartPlot(fitclass_col_fd)
rpart.plot(fitclass_col_fd1,main='Classification Tree for Multitasking Activities: Suburban Railway, Western Line')
rpart.plot(fitclass_col_fd2,main='Classification Tree for Multitasking Activities: Metro Line III')
rpart.plot(fitclass_col_fd3)
rpart.plot(fitclass_col_fd1)

library(randomForest)
randomfuni_1= randomForest(Activity ~ Income.Bracket + Male + Bachelors
                    + Masters + Age +  WTP.Time + p_Time
                    , data = my_data, ntree= 10000, importance = TRUE)
randomfuni_2= randomForest(Activitym ~ Income.Bracket + Male + Bachelors
                    + Masters + Age +  WTP.Time + p_Time
                    , data = my_data, ntree= 10000, importance = TRUE)

#Plotting Importance
varImpPlot(randomfuni_1, type = 1,main='Variable Importance for the Western Line')
varImpPlot(randomfuni_2, type = 1,main='Variable Importance for the Line II and Line III')

#View(randomfuni_1$importance)
summary(randomfuni_1)


#binomial models for the metro
mylogit1 = glm(Sleepingm ~ Income.Bracket + Male + Bachelors
          + Masters + Age +  WTP.Time + p_Time, data=my_data, family='binomial')
mylogit2 = glm(Nothingm ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit3 = glm(Watch.Videosm ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit4 = glm(Musicm ~  Income.Bracket +Male + +Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit5 = glm(Readingm ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit6 = glm(Social.Mediam ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit7 = glm(Talkingm ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit8 = glm(Phonem ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit9 = glm(Prayerm ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
mylogit10 = glm(Eatingm ~ Income.Bracket + Male + Bachelors
           + Masters + Age + WTP.Time + p_Time, data=my_data, family='binomial')
```

```
stargazer(title = "Logit Model: Factors influencing multitasking activity on the Mumbai Metro Line III",
        header= FALSE   ,   covariate.labels = c('Income Bracket 1', 'Income Bracket 2','Income Bracket 3',
'Income Bracket 4', 'Male',  'Undergraduate', 'Graduate','Age', 'WTP/Time', 'Travel Time','Constant' ),
        mylogit1,  mylogit2,mylogit3,  mylogit4,  mylogit5,  mylogit6,  mylogit7,    type="html",  no.space  =
FALSE, single.row=FALSE, out='models_s_p.htm',
        dep.var.labels = c("Sleeping", "No Activity" , "Videos", "Music" , "Emails" , "Social Media","Talking"))



#binomial models for suburban trains
mylogit1 = glm(Sleeping_d ~ Income.Bracket + Male+Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit2 = glm(Nothing_d ~ Income.Bracket + Male  +Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit3 = glm(Watch.Videos_d ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit4 = glm(Music_d ~  Income.Bracket +Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit5 = glm(Reading_d ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit6 = glm(Social.Media_d ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit7 = glm(Talking_d ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit8 = glm(Phone_d ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit9 = glm(Prayer_d ~ Income.Bracket + Male + Bachelors
          + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')
mylogit10 = glm(Eating_d ~ Income.Bracket + Male + Bachelors
           + Masters + Age + WTP.Time + p_Time, data=my_data, family='quasibinomial')

mylogit1
#summary tables
stargazer(title = "Logit Model: Factor multitasking activity on the Suburban Railway Western Line ",
        header= FALSE   ,   covariate.labels = c('Income Bracket 1', 'Income Bracket 2','Income Bracket 3',
'Income Bracket 4', 'Male',  'Undergraduate', 'Graduate','Age', 'WTP/Time', 'Travel Time','Constant' ),
        mylogit1, mylogit2,mylogit3, mylogit4, mylogit5, mylogit6, mylogit7,  type="html", no.space = TRUE,
single.row=FALSE, out='models_m_p.htm',
        dep.var.labels = c("Sleeping", "No Activity" , "Videos", "Music" , "Emails" , "Social Media","Talking"))


View(stargazer(my_data, type = 'html', out='summary.htm', omit.summary.stat = 'p25','p75'))
```

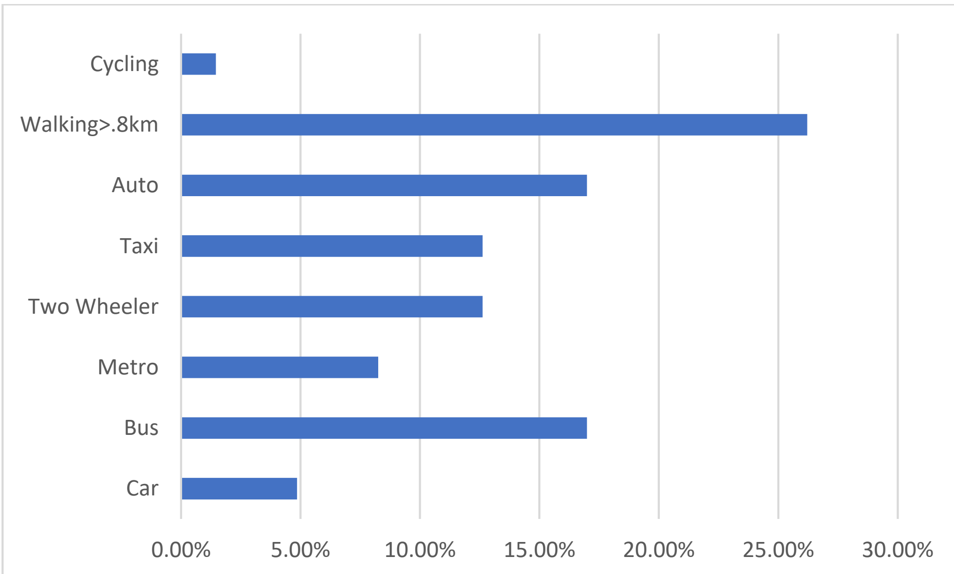
Python code:

```
%matplotlib inline
```

```
import statsmodels.api as st

import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
sns.set()

df = pd.read_csv('test.csv')
df = df[df['Activity'] != 'Prayer']
df['Activity'] = df['Activity'].replace({"Nothing": "A"})

x=df[['Income Bracket','Male','Bachelors','Masters','Age','WTP-Time','p_Time']]
y=df['Activity']

df = pd.read_csv('test.csv')
df = df[df['Activitym'] != 'Prayer']
df['Activitym'] = df['Activitym'].replace({"Nothingm": "A"})

x=df[['Income Bracket','Male','Bachelors','Masters','Age','WTP-Time','p_Time']]
y=df['Activitym']
logisr = LogisticRegression().fit(x,y)

df = pd.read_csv('test.csv')
df = df[df['Activitym'] != 'Prayer']
df['Activitym'] = df['Activitym'].replace({"Nothingm": "A"})

x=df[['Income Bracket','Male','Bachelors','Masters','Age','WTP-Time','p_Time']]
y=df['Activitym']
logisr = LogisticRegression().fit(x,y)

df = pd.read_csv('test.csv')
df = df[df['Activitym'] != 'Prayer']
df['Activitym'] = df['Activitym'].replace({"Nothingm": "A"})

x=df[['Income Bracket','Male','Bachelors','Masters','Age','WTP-Time','p_Time']]
y=df['Activitym']
logisr = LogisticRegression().fit(x,y)

df = pd.read_csv('test.csv')
df = df[df['Activitym'] != 'Prayer']
df['Activitym'] = df['Activitym'].replace({"Nothingm": "A"})
```

```
x=df[['Income Bracket','Male','Bachelors','Masters','Age','WTP-Time','p_Time']]
y=df['Activitym']
logisr = LogisticRegression().fit(x,y)
```

8.6 Modal Share for the Secondary Mode of Travel (Intercept Survey)



8.7 Predicted value from Multitasking Activities on the Mumbai Metro Line III

BNL with Trip Characteristics for the Suburban Railway

	Dependent variable:						
	Sleeping	No Activity	Videos	Music	Emails	Social Media	Talking
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Car	-0.135	-15.310	0.617	-0.463	-0.814	0.153	0.109
	(0.841)	(1,123.544)	(0.759)	(0.867)	(0.904)	(0.743)	(0.960)
Bus	-0.021	-1.351^{**}	0.606	1.139^{***}	1.207^{***}	0.625	0.410
	(0.567)	(0.636)	(0.416)	(0.420)	(0.427)	(0.441)	(0.437)
Metro	-0.333	2.434^{***}	0.233	-0.891	-0.733	-0.648	0.991^{*}
	(0.718)	(0.674)	(0.569)	(0.605)	(0.664)	(0.660)	(0.570)
Two Wheeler	0.022	-0.230	-0.374	0.661	0.143	1.068^{**}	0.266
	(0.619)	(0.606)	(0.534)	(0.471)	(0.532)	(0.475)	(0.519)
Taxi	1.311^{**}	-2.438^{**}	0.801^{*}	2.615^{***}	0.769	1.458^{***}	-0.913
	(0.548)	(1.120)	(0.485)	(0.687)	(0.524)	(0.495)	(0.694)
Three Wheeler	-1.280^{*}	0.862^{*}	0.107	-0.536	-0.165	0.212	0.231
	(0.777)	(0.471)	(0.438)	(0.421)	(0.468)	(0.446)	(0.471)
Walking .8km	0.874^{**}	-0.208	0.912^{**}	0.057	0.988^{***}	0.606	0.525
	(0.420)	(0.453)	(0.360)	(0.352)	(0.378)	(0.387)	(0.391)
Constant	-1.858^{***}	-1.341^{***}	-1.308^{***}	-0.348	-1.551^{***}	-1.647^{***}	-1.542^{***}
	(0.337)	(0.304)	(0.277)	(0.243)	(0.299)	(0.302)	(0.298)
Observations	196	196	196	196	196	196	196
Log Likelihood	-84.555	-83.889	-115.764	-120.849	-107.143	-107.683	-101.154
Akaike Inf. Crit.	185.109	183.778	247.527	257.699	230.286	231.367	218.308

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

8.8 Questionnaire used for the SP and RP surveys

MULTITASKING BEHAVIOR SURVEY

Socio-demographic questions:

1. **Name** ____
2. **Gender** ☐ Male ☐ Female
3. **Education** ☐ None ☐ Senior secondary school ☐ Bachelors degree ☐ Master/ Post Grad/PhD
4. **Age** ________
5. **Household income:**

☐ <Rs. 20,000 ☐ Rs.20,000-Rs.30,000

☐ Rs.30,000-Rs.50,000 ☐ >Rs,50,000

---

6. **What is your origin?** ☐ Home ☐ Workplace ☐ (other)________________
7. **What is your destination?** ☐ Home ☐ Workplace ☐ (other)________________
8. **Trip Start station on the Suburban network:** ______________________
9. **Trip End station on the Suburban network:** ______________________
10. **Transfer stations (if applicable):** ____________________
11. **Travel distance on the Suburban Rail:** _______________km (round to the nearest minute)
12. **Travel time on the Suburban Rail:** _______________minutes (round to the nearest minute)
13. **What is the purpose of your trip:** ☐ Official ☐ Personal

14. **Types of transportation between office and home during commute (please tick):**

- ☐ Car/ private four wheeler
- ☐ Local bus/ company bus
- ☐ Metro
- ☐ Walking more than 800m
- ☐ Taxi/Uber/Ola
- ☐ Cycling/ electric cycle
- ☐ Bike/ Two-wheeler
- ☐ Auto/ Three wheeler

15. **What activities do you do while traveling on the suburban train? (percentage of time spent)**

- ☐ Sleeping
- ☐ No Activity
- ☐ Watch Video
- ☐ Listen to Music
- ☐ Reading
- ☐ Social Media like FB
- ☐ Talking to others
- ☐ Phone calls
- ☐ Prayer/ bhajan
- ☐ Eating/drinking

16. **Do you own a smartphone?** ☐ Yes ☐ No

17. **On a scale of 1 to 10, how useful is your travel time on the local train (circle one)?**

1(lowest) 2 3 4 5 6 7 8 9 10(highest)

18. **On a scale of 1 to 10, how comfortable do you feel while traveling on the local train (circle one)?**

1(lowest) 2 3 4 5 6 7 8 9 10(highest)

19. **What activities do you do while traveling on the metro train? (percentage of time spent)**

- ☐ Sleeping
- ☐ No Activity
- ☐ Watch Videos
- ☐ Listen to Music
- ☐ Emails
- ☐ Social Media like FB
- ☐ Talking to others
- ☐ Phone calls
- ☐ Prayer/ Bhajans
- ☐ Eating/drinking

20. **Have you travelled on the metro?** ☐ Yes ☐ No

21. **On a scale of 1 to 10, how useful is your travel time on the local train (circle one)?**

1(low) 2 3 4 5 6 7 8 9 10(high)

22. **On a scale of 1 to 10, how comfortable do you feel while traveling on the metro (circle one)?**

1(low) 2 3 4 5 6 7 8 9 10(high)

23. **How much are you willing to pay from home to work on the metro (for a single trip if there exists a connection)?**

☐ Rs. 5 ☐ Rs.10 ☐ Rs. 15 ☐ Rs. 20 ☐ Rs. 25 ☐ Rs.30 ☐ Rs.35

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