Identifying Commuting Behavior Segments for TDM Program Design: University Case Study

By

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Submitted to the Department of Urban Studies and Planning
in partial fulfillment of the requirements for the degree of

Master in City Planning

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2020

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ABSTRACT

Cities and larger employers provide transportation services to diverse users with widely different commuting behavior patterns. Although it may introduce complexities in policy design and implementation to treat different users in various ways, the knowledge of the heterogeneity among them offers us new potentials in optimizing service design and improving user experience.

In this research, the case of the Massachusetts Institute of Technology (MIT) has been utilized as an example to explore the potentials of identifying commuting behavior segments and offering actionable policy recommendations. In order to understand the conditions of MIT transportation services, the mid-term impacts of the AccessMIT program are evaluated using the MIT Commuting Surveys conducted in 2014, 2016, and 2018. Then, this research investigates the discrepancy between self-reported commuting diaries and actual commuting behavior utilizing both active and passive mobility data. Finally, this thesis applies emerging methodologies to segment commuting behavior clusters using a longitudinal representation of multi-year passive mobility data and applies the proposed methodology to a sample of MIT employees.

This research reveals three key findings. First, the impact of the AccessMIT program launched by MIT in 2016 has sustained itself and had a positive mid-term impact on changing employees' commuting mode choices and improving their satisfaction rates. Yet this impact varied across different employee groups. For example, the decrease in the *single-occupancy vehicle* (SOV) mode choices of administration, service, and medical staff happened immediately after the launch of AccessMIT in 2016, but that of faculty happened much slower. Second, the discrepancy between self-reported and actual commuting behavior is not substantial when examining all MIT employees in the aggregate. However, it varies largely among different groups of employees (e.g., different employee types). Third, the application of the up-to-date clustering methodologies identifies 9 commuting behavior clusters. These 9 clusters carry distinct temporal commuting patterns. For example, *aspiring meanderers* saw an apparent decrease in the parking frequency while *determined riders* had a high transit frequency and a very low parking frequency, which have been both steady. Moreover, to offer actionable policy recommendations for next-stage *transportation demand management* (TDM) at MIT, this thesis supplements the empirical analysis with a comprehensive profiling process using both active and passive mobility data and socio-demographic characteristics.

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Acknowledgments

This research would not have been possible without the intellectual inputs, invaluable insights, and generous support from the fantastic humans I have met at MIT and the the continuous support from my family.

Jinhua, your passion and rigor towards research always motivate me to break through my limit. I have felt so grateful that you invited me into the JTL family, The seminars, DL4T course, and our meetings have led me into the world of research. Elena, your support, trust, and brilliant suggestions have helped me to reach a higher level. John, you sharp and knowledgeable comments have tremendously enriched my understanding of this research and my thinking.

Julie, Derek, Joseph, Stu, this research cannot be accomplished without the strong support and cheer from you and all the lovely human beings in MITOS. I miss the days we sat together in the office, talking and eating.

Anne, I appreciate so much your guidance and termless help. You inspired me to come to DUSP, gave me my first RA-ship, and treat me as not only a student but also a close friend.

Weiyi, I always feel blessed to have you on my side. These two years at Cambridge would have been much less colorful and enjoyable without you accompanying, supporting, and love. ♥

Contents

Chapter 1

Introduction

Transportation demand management (TDM), also known as *travel demand management*, refers to a collection of strategies and tools that offer travelers with maximum choices (U.S. Department of Transportation [USDOT], 2020). As the purposes of TDM have gradually evolved from mitigating environmental and development challenges to offering reliable and efficient traveling options (Federal Highway Administration [FHWA], 2004), the approaches towards TDM are also diversifying. The development of novel TDM approaches such as awareness campaigns and targeted TDM programs and the emergence of new transportation modes, including electric vehicles (EV) and autonomous vehicles (AV), has been rapidly changing the landscape of TDM.

However, both these emerging transportation modes and the already widely used transportation services such as public transits serve widely diverse users who have distinct socio-demographic and attitudinal attributes. They, therefore, have heterogeneous patterns of travel behavior (travel time, travel frequency, and travel locations). When cities and employers design new TDM programs or modify their existing services, it is essential to treat different users in various ways since they are sensitive to different factors (Anable, 2005). Although this process may introduce extra complexities in policy design and implementation, the knowledge of the diversity among transportation users offers new potentials in optimizing system performance and improving user experience (Goulet-Langlois, Koutsopoulos, & Zhao, 2016).

This thesis builds on previous research that identified travel behavior segments and applies up-to-date methodologies to capture heterogeneity among transportation service users and segment meaningful commuting behavior clusters utilizing a longitudinal representation of multi-year commuting activities. By applying the proposed methodology on a sample of the employees of MIT, we identify clusters having apparent similarity within each one and distinct heterogeneity between different clusters.

In order to contextualize the research, this thesis first evaluates the mid-term impacts of the AccessMIT program using the biennial MIT Commuting Survey 2014, 2016, and 2018. As one of the primary data sources available to researchers and university decision-makers, the biennial MIT Commuting Survey has been widely studied (Block-Schachter, 2009; Rosenfield, 2018) and used for designing TDM programs at MIT. Inspired by the differences between self-reported and actual travel behavior introduced by Rosenfield (2019), this thesis assesses the discrepancy between survey-elicited travel behavior and actual travel behavior derived from passive mobility data by focusing on the weekly parking and public transit frequency. The findings help us determine the applicability of these two sets of mobility data under different scenarios. Finally, through an application of the clustering methodology and a profiling process using both active and passive data available to this research, we offer targeted policy recommendations for each commuting behavior cluster to inform future TDM program design at MIT.

1.1 Motivations

TDM was first introduced to the United States as a way to mitigate many environmental challenges, including heavy air pollution caused by the ascending car usage (Meyer, 1999), and it has become a frequently studied topic in the transportation field. After being long utilized to alleviate environmental and planning issues, TDM's focuses have gradually evolved to providing reliable and effective options for users of transportation services (FHWA, 2004). Thus, approaches including structural and psychological interventions have been introduced and experimented by researchers and practitioners (Fujii, Gärling, & Kitamura, 2001; Thaler & Sunstein, 2008), improving the impacts of TDM systems and design. As the transportation services and TDM programs of dense cities and large employers serve widely diverse users, considerable efforts have been made to capture the heterogeneity among these users, which has the potential to inform better service design and improve user experience. A number of studies have used attitudinal characteristics, self-reported travel diaries, and passive mobility data to understand the heterogeneity and identify travel behavior segments (Anable, 2005; Goulet-Langlois et al., 2016; Ortega-Tong, 2013; Jiang, Ferreira, & González, 2012).

Similar to other large employers in the U.S., MIT has been facing substantial commuting-related challenges. While being troubled by the difficulties of providing extra heavily subsidized parking facilities, the university is also perplexed by the tremendous cost of renewing old parking lots and systems. Also, the goal of taking more responsibilities in mitigating regional congestion and making positive environmental impacts motivates the university to propose new approaches to better manage the commuting behavior of its employees. On the other hand, MIT employees are facing issues, including longer commute time and frequent congestion.

In order to improve this situation, MIT has implemented TDM programs such as AccessMIT, which offers free, unrestricted use of the MBTA subway and local bus systems and several other benefits for eligible employees. These programs have achieved sound impacts in shifting people's commuting mode choices (Rosenfield, 2018) and promoting mode shifts. Moving TDM at MIT towards the next stage, the university and researchers have also been exploring ways to influence employee's mode choices using more diverse approaches, including the randomized controlled trial (RCT) experiments by Rosenfield, Attanucci, and Zhao (2019). However, the heterogeneity among the users of MIT transportation services has not been carefully studied even though MIT, as a large employer, has a diverse employee cohort. Also, the majority of the existing TDM programs at MIT are designed and implemented based on the results from the biennial MIT Commuting Survey, which provides a comprehensive set of commuting-related information of MIT employees. The surveys have the advantage of comprehensiveness and simplicity, yet they have been less attractive in understanding accurate individual-level travel behavior due to its integrated bias, including social desirability bias (Fisher, 1949), self-images (Heider, 1958), and misreporting. Although the Commuting Survey conducted by MIT are explicitly designed and well organized to capture employees' real commuting behavior and attitude, the survey results have clear disparities with the actual travel behavior derived from passive mobility data, such as parking records and public transit tap-ins (Rosenfield, 2018; Rosenfield et al., 2019). Moreover, these disparities may introduce uncertainty in designing TDM programs using these results.

1.2 Research Objectives and Approaches

Given the above motivations, this thesis has three main objectives.

First, this thesis evaluates the mid-term impacts of MIT TDM programs--notably AccessMIT--through the analysis of the results of the biennial MIT Commuting Survey conducted in 2014, 2016, and 2018. While the responses of commuting related questions such as primary mode choices and mode shifts are used for quantitative analysis on commuting behavior trends, attitudinal information including awareness, participation, and the willingness to participate in new programs offers us perspectives towards employee’s decision making. Moreover, in order to investigate the durability of the impacts of AccessMIT, which was introduced by Rosenfield (2018), this thesis builds on the previous research (Rosenfield, 2018) and studies the evolution of the commuting-related properties across the three surveys.

Second, the research aims to reveal the discrepancy between self-reported commuting diaries and actual commuting behavior using both active mobility data from the surveys and passive mobility data such as gated parking records and public transit tap-ins. A group of indices has been introduced to represent the discrepancy in weekly parking frequency and transit uses. Furthermore, the potential associations between the identified discrepancy and socio-demographic, attitudinal, and commuting related attributes have been explored through a series of multivariate linear regressions.

Finally, to identify meaningful and actionable commuting behavior segments among MIT employees, we propose a longitudinal representation of individual commuting behavior and apply it to a sample of MIT employees. Then, a clustering and profiling process is conducted to offer feasible policy recommendations.

This research employs quantitative analysis on both active and passive mobility data sources. In particular, primary analysis methods includes multivariate linear regression (Chapter 5), commuting behavior representation and *k-means* clustering algorithms via *principal component analysis* (PCA) (Chapter 6), and other analytical approaches such as spatial autocorrelation and multinomial logistic regression (Chapter 6).

The MIT Commuting Survey is our primary active mobility data source. It includes a comprehensive set of attributes related to employees' commuting behavior, such as primary commuting modes, mode shifts, and weekly commuting diaries. Passive mobility data sources include the records of entering and exiting MIT parking facilities collected originally from the Parking Department of MIT and public transit tap-ins collected via the collaboration between the Massachusetts Bay Transportation Authority (MBTA) and

MIT. These datasets are made available to this research by the MIT Office of Sustainability (MITOS). Socio-demographic data (HR data), including ages, genders, and affiliations, is collected and made available for this research by MITOS from the Human Resources Department of MIT. In order to protect the privacy of MIT employees, all the collected data is anonymized.

1.3 Thesis Organization

This thesis is organized into seven Chapters. Chapter 2 provides an overview of the development of TDM, the relationship between TDM and the behavioral science, TDM at MIT, and the approaches of travel behavior segmentation by reviewing related theories and work. Chapter 3 introduces the data and the methodology employed in this research. Chapter 4 evaluates the mid-term impacts of the AccessMIT program by investigating results from the MIT Commuting Survey. Chapter 5 focuses on the discrepancy between self-reported and actual commuting behavior and explores potential factors correlated with the discrepancy. Chapter 6 implements the proposed commuting behavior representation and a *k-means* clustering process via PCA, whose resulting clusters are then profiled and matched with policy recommendations. Finally, Chapter 7 offers a summary of this research, together with some takeaways and some potential future directions.

Chapter 2

Literature Review

Commuting related issues have effects on multiple stakeholders, including employees, employers, transit agencies, and municipalities. Employees are influenced by the increasing commute time and cost; employers are no longer able (or do not want) to provide more highly subsidized parking facilities; transit agencies are concerned about revenue growth; municipalities are becoming less attractive due to regional congestion and environmental issues. To tackle these urgent issues, researchers and practitioners have attempted and implemented a wide range of TDM approaches, including structural and psychological interventions (Fujii et al., 2001; Thaler & Sunstein, 2008), awareness campaigns (Rose & Ampt, 2001), the combination of financial and social "nudges" (Gates, 2015), and randomized controlled trial (RCT) experiments (Rosenfield, 2018). Some of these efforts have had sound impacts on reshaping people's travel mode choices and promoting more sustainable mode choices other than the single-occupancy vehicle (SOV). Even if some other approaches are more in the experimenting or piloting stages and have not attained promising effects, they provide valuable insights towards people's mode choices and the reasons behind them. However, as new data and methodology emerge in the field of intelligent transportation systems, more possibilities and uncertainties are introduced.

Building on the previous research on TDM, commuting conditions at MIT and travel behavior clustering, this research takes advantage of both active data sources such as survey data and HR data and passive mobility data to explore the possibilities of employing ad hoc clustering algorithms to identify commuting behavior segments and offering actionable policy options.

In this Chapter, we first introduce some background of TDM, including the transportation management area in the U.S., hard and soft approaches of TDM, and the metrics applied to evaluate the impacts of TDM programs. Then, we outline the development of TDM programs at MIT, including some history and recent efforts such as AccessMIT to provide the proper context for this research. Moreover, to investigate and compare the performance of both self-reported commuting diaries and passive mobility data, the relevant literature on the relationship between behavioral science and transportation is reviewed. Finally, previous research of travel behavior segments in the transportation area is introduced, including attitudes-based clustering, survey-based clustering, and clustering approaches using passive mobility data, which supports the clustering process deployed in Chapter 6.

2.1 Transportation Demand Management (TDM)

Tools and methods available to employers and municipalities to change people's travel mode choices have evolved since the concept of TDM was first introduced into the U.S. as a way to reduce air pollution in the 1970s (Meyer, 1999; Rosenfield, 2018). After the "building more road" approach had been proved neither effective nor environmentally friendly, structural, and psychological interventions were introduced (Fujii et al., 2001; Thaler & Sunstein, 2008). As argued by Ariely (2010) from a behavioral economics perspective, social norms and the forces that keep them on (Pentland, 2014) are usually both cheaper and effective than monetary means in influencing people's mode choices.

This Section first focuses on the emerging trend of soft TDM approaches and then summarizes some of the research that evaluates the impacts of TDM programs.

2.1.1 Hard and Soft Approaches for TDM

Usually featuring monetary incentives or strict regulations, hard TDM approaches have been used as a norm in managing employer-based travel demands and have been proved to be effective practically and theoretically. For example, Block-Schachter (2009) examined whether a Mobility Pass program, which offered drivers low-cost access to public transit, could be effective at MIT. He simulated and predicted the potential effects of the pass, and his findings argued that the scenario of offering the pass would be promising. Then, after the implementation of an actual MIT/MBTA Mobility Pass Pilot experiment, another study by Gates (2015) has corroborated that the proposal by Block-Schachter (2009) to be practical and useful.

Cashing out employer-paid parking also exemplified the fact that hard TDM approaches influence employees' choice-making (Shoup, 1997). The analysis of eight firms suggested a 17 percent decrease in the number of solo drivers, while a 50 percent increase in transit riders, after the introduction of the cashing out policy.

However, the expensive costs of hard TDM approaches make employers and municipalities hesitant to implement such programs. For example, even though the benefit/cost ratio achieved 4/1 and higher in the cashing out program mentioned by Shoup (1997), the $2 increase in individual subsidy per month accumulated to a large amount. Moreover, when the groups with the highest switchability have already changed their commuting behavior, it costs more to influence the rest. Also, there are limited options in the toolbox of hard TDM approaches. All of these reasons urge researchers and practitioners to propose more economical options, one of which are soft TDM approaches.

Inspired by behavioral science, including behavioral economics, soft TDM approaches, which are informed by the socio-demographic nuance behind people's choices of travel behavior and modes, create new possibilities for employers and municipalities (Zhao, 2009). Zhao (2009) suggested that capturing and incorporating social and psychological factors of transportation choice makers can inform better planning practice and answer the preferences of transportation service users.

Another effective approach is to propagate existing TDM programs to make more users aware of them, the process of which is called an *awareness campaign*. Metcalfe and Dolan argued that the barriers of sufficient information was one of the key factors associated with the market failures of transportation services (2002). Practically, *Travel Blending*, the TDM program proposed to reduce car uses in Australia, saw a 10% reduction in car driving distance by sending the individuals suggestions on how to reduce car uses (Rose & Ampt, 2001). Rosenfield (2019) conducted an RCT experiment at MIT with a larger sample following a similar fashion of awareness campaigns.

2.1.2 TDM Program Evaluation

While the efforts to reduce car use and promote sustainable travel modes vary from hard approaches such as money incentives and regulations to soft approaches such as awareness campaigns, evaluations of the impacts of these programs are limited (Rosenfield, 2019). Some work has been done before implementing TDM programs to provide enough information about the possible scenarios for decision-makers (Block-Schachter, 2009; Gates, 2015), yet much less research assesses the effects of the implemented programs.

The Federal Highway Administration (FHWA) released a white paper in 2016 to introduce TDM programs implemented by six universities including MIT; Stanford University; the University of

California, Berkeley (UC Berkeley); the University of California, Los Angeles (UCLA); the University of Washington, Seattle; and Yale University. This white paper reviewed the TDM programs by each university and compared the university-wide commuting patterns with the regional patterns. More information about this report is included in the next Section. Yet, since the primary purpose of this report was to summarize the "Innovative Policies and Technologies" that each university employed, less attention was given to test the relationship between the changes in travel behavior and the implemented programs.

More recently, Rosenfield (2018) has evaluated the TDM programs at MIT such as AccessMIT by adopting the first three principles introduced by the Transit Cooperative Research Program Report 107 in 2005: awareness, participation, and behavior change. He reported positive short-term impacts of the AccessMIT program, including an increase in the percentages of employees who chose public transit as their primary commuting modes (Rosenfield, 2018). Also, randomized control trials (RCT) have recently been used to evaluate newly proposed TDM programs. These trials assigned different groups to different interventions (awareness campaigns, monetary incentives, and both) and measured the outcomes in these groups against a control group that did not receive any TDM incentives (Rosenfield, 2019). Building on previous research, we evaluate the mid-term impacts of the AccessMIT program utilizing more comprehensive datasets, which is introduced in Chapter 4.

2.2 Travel Demand Management at MIT

2.2.1 Employer-Based TDM and University Campus Programs

Also known as site-based programs, employer-based TDM programs are usually implemented by only one or several employers. They have a specific target population, the employees. Thus, they share a unique capacity to shape and reshape their target population's travel behavior. Although some of the early employer-based programs are required by the governments back to the 1990s, most recent ones are initiated by employers to nudge their employees' travel behavior to a more sustainable level, with monetary, environmental, and behavioral motivations.

Employers have been considered ideal venues for testing and implementing new TDM programs due to their centralized administrative resources and their specific target population (Dill & Wardell, 2007; Hendricks, 2005; Rosefield 2018). Employees of the same employers often share similar travel destinations and humankind, despite the heterogeneity among their commuting behavior. As a result, employer-based TDM programs have the potential to achieve "win-win" scenarios for both employers and employees.

As typically one of the largest employers in municipalities and regions, universities share most of the same advantages other employers have, other than a more diverse spread of populations. Regardless of students, there are still branches of employees in a university workplace who share significantly different travel patterns. For example, a group of service staff may have to arrive at the campus before 6:00 am every day, while some research scientists only visit the campus 2-3 times a week with flexibilities in working time (MIT Commuting Survey, 2018).

The white paper released by FHWA (2016) described the employer-based TDM efforts of six universities to address the commuting issues of their employees. We select two examples from this report and review them.

Well-served by public transit, the primary TDM programs implemented by UC Berkeley were to offer students free passes on AC transit and discount passes on Bay Area Rapid Transit (BART). The costs of the passes mainly came from student fees, parking permit sales, daily parking revenue, and faculty and staff transit pass sales.

On the contrary, Stanford University has developed an extensive and free shuttle bus system (i.e., Marguerite) that covered all the critical spots on campus and some frequently visited places off-campus, including shopping, dining, and recreation destinations. Also, eligible affiliates of the university enjoyed free transit passes for bus, light rail, and commuter rail, while others could purchase pre-tax transit passes. Other TDM programs implemented by Stanford included the bicycle program and free assistance on commute planning.

2.2.2 History and Context of TDM at MIT and AccessMIT

Like other universities and large employers, researchers and university decision-makers at MIT have made a continuous effort to evaluate and improve the commuting patterns of the MIT community. More specifically, much research has been done to reduce car use and push or nudge employees towards more sustainable commute modes, including public transit, carpooling, biking, walking, and telecommuting.

Block-Schachter (2009) tested how subsidized transportation programs implemented by employers could benefit both the employer and employee and lead to a more sustainable future. The research argued that the multimodal commuters, who had the potential to travel more sustainably, had not been well served by existing TDM programs at MIT. As a result, he proposed a Mobility Pass program and predicted the potential benefits: how it might lead to an "everyone wins" scenario. Also, the research introduced how the proposal scenario could be feasible through pre-tax programs. Block-Schachter's research was later used as one of the references for designing the AccessMIT program.

To elaborate on the benefits for multiple stakeholders, Kamfonik (2013) showed that a mobility pass program could help employers better manage transportation demands, increase the convenience of employees, raise ridership for transit agencies (e.g., MBTA), and introduce financial benefits for each group. The research focused on evaluating the effects of the MBTA Corporate Pass Program, which has proved to have a positive impact on the development of travel agencies.

Evolving from simulations and empirical studies to more actionable recommendations, Gates (2015) suggested a series of modifications to the existing TDM programs at MIT. In order to shift employees' mode choices from SOV to more sustainable modes, she recommended financial and social incentives, which could be incorporated into the TDM program design. Many of the programs proposed in this research such as universal transit passes, daily parking charges, and a commuter dashboard had later served as essential parts of the AccessMIT program introduced in 2016 by MIT. Figure 2.1 illustrates the proposed dashboard by Gates (2015), and Figure 2.2 shows the implemented dashboard in the AccessMIT program.

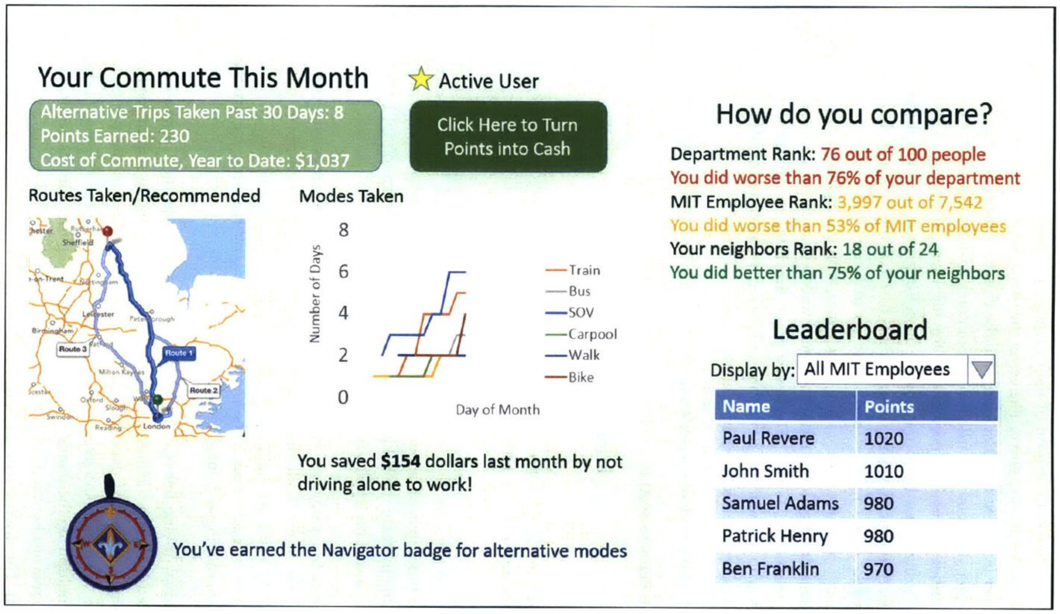

Figure 2.1 Proposed Commuting Dashboard (Gates, 2015)

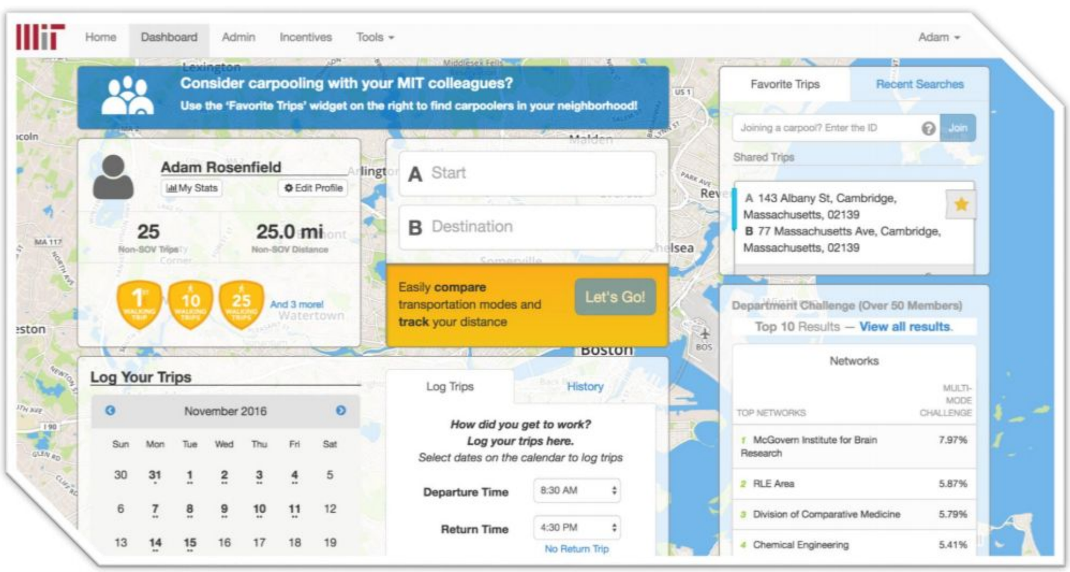

Figure 2.2 The AccessMyCommute dashboard accompanying AccessMIT

Right before the introduction of AccessMIT, Hartnett (2016) conducted a study based on the MIT Commuting Survey. It analyzed the survey results from 2004 to 2014 to identify the historical trends of commuting behavior at MIT and the reasons behind these trends. The research argued that financial incentives had played an influential role in changing employee's travel behavior, and it suggests future use of similar approaches.

As the final step of a series of efforts of TDM programs, MIT launched the AccessMIT program in 2016, which represented a progressive vision for reducing SOV commuting and promoted more sustainable commuting modes (MIT Department of Facilities, 2020). The benefits introduced by this program include:

- Free, unrestricted use of the MBTA subway and local bus systems for benefits-eligible Cambridge campus MIT faculty and staff with the AccessMIT pass;
- A 50-60% commuter rail subsidy for students, faculty, and staff;
- A 50% subsidy for parking at MBTA stations, up to $100 per month;
- Reimbursement for up to 50% of private transit commuting costs, up to $255 per month;
- A daily rate parking program that gives commuters the flexibility to choose different transportation modes on different days (MIT Department of Facilities, 2020).

Also, a public awareness campaign (Figure 2.3) and a commuter dashboard (Figure 2.2) has accompanied the commuting benefits introduced by AccessMIT. Rosenfield (2018) showed the positive short-term impacts of AccessMIT, such as shifting employees' commuting mode choices, by investigating the 2016 Commuting Survey, which was conducted right after the launch of the program. Also, MIT Office of Sustainability (2020) has reported that the AccessMIT program has contributed to the 15 percent reduction in on-campus parking demand, as well as the ascending public transit uses.

Figure 2.3 Promotional posters of the AccessMIT program

Based on the sound short-term impacts of AccessMIT, researchers and decision-makers at MIT and beyond have started to think about the next-stage TDM programs at MIT, which is informally named AccessMIT 2.0. These programs include targeted TDM programs, soft TDM approaches, and other intelligent transportation solutions. For example, Rosenfield (2018) and Rosenfield et al. (2019) have explored the potential effects of monetary rewards, awareness campaigns, and combinations of these two approaches via an RCT experiment on a sample of 2023 MIT employees. Although there was no significant difference between the actual commuting behavior of treatment groups and that of the control group, this research attained two valuable insights for later research: 1) the approaches resulted in an increase in the awareness rates and the stated reduction of car use; and 2) the disparity between self-reported travel behavior and the actual commuting patterns derived from passive mobility data indicated the limitation of survey-based self-reported travel behavior (Rosenfield et al., 2019).

This research builds on these previous studies, notably Block-Schachter (2009), Gates (2015), Rosenfield (2018), and Rosenfield et al. (2019), and evaluates the mid-term impacts of the AccessMIT program and identify commuting behavior segments for next-stage TDM at MIT.

2.3 Relations to Behavioral Science

As mentioned in the last section, behavioral science has informed TDM program design and implementation while providing new insights about people's reasons for making decisions. Previous research argued that individuals' behavior is significantly affected by attitudes, social norms, and controls (Ajzen, 1991; Ariely, 2010; Pentland, 2014). For example, individuals' attitudes towards incentives had a significant impact on how they make decisions and choose from different behavioral modes (Ariely, 2010). Taking advantage of the underlying relationship between attitudes and behavior, Anable (2015) clustered 6 meaningful travel behavior segments such as complacent car addicts and aspiring environmentalists. Her research also suggested that these segments' attitudinal and socio-demographic characteristics could be used to offer targeted policy options.

Although the attitudinal factors are useful to profile individuals conducting commuting activities and can be effective in segmenting travel behavior clusters, their value can be diluted because of the bias of self-reporting. Any survey-based research might introduce social desirability bias, self-serving bias, or even purely misreporting bias even when the survey was well designed. For example, individuals surveyed might state a mode shift to please the surveyors while there was no statistically significant change in actual travel behavior (Rosenfield et al., 2019).

On the other hand, Gärling, Fujii, and Boe (2001) described how habits could be treated as indicators for future behavior. Goulet-Langlois et al. (2016) explored how multi-week activity sequences indicating travel habits could be used to identify the difference between distinct travel behavior segments. These different behavioral segments could be utilized to design targeted TDM programs and recommend transportations policies (Anable, 2005; Rosenfield et al., 2019).

2.4 Travel Behavior Segmentation

2.4.1 Self-Reported and Actual Travel Behavior

Other than attitudinal attributes, self-reported travel behavior has also been widely used in transportation modeling and TDM program design. It primarily comes from general transportation surveys such as the MIT Commuting Survey and more detailed activity questionnaires such as the International Physical Activity Questionnaire (IPAQ). Since self-reported travel behavior is usually collected via structured questions, it has the advantage of usability and comprehensiveness. However, similar to other survey-based results, bias such as social desirability bias and self-images might be introduced in this active mobility data.

On the other hand, the advances in urban sensing technology and computational methods have enabled researchers to take better advantage of passive mobility data, which carries accurate information about travel behavior. Passive mobility data, including both extrinsic mobility data (e.g., mobile phone network data, GPS data, and accelerometer data) and intrinsic mobility data (e.g., transit smart card data and parking records), has been used in recent years to study travel behavior and inform TDM program design (Forsyth, Hearst, Oakes, & Schmitz, 2008; Zhao, Koutsopoulos, & Zhao, 2018). For example, Forsyth et al. (2008) used both active mobility data such as IPAQ and travel diaries and passive data such as accelerometer data to study the potential associations between the intensity of physical activities and build environment features. Rosenfield et al. (2019) used intrinsic passive mobility data, including gated parking records and public transit tap-ins, to evaluate the effects of an RCT experiment at MIT.

This research formally assesses the discrepancy between self-reported travel behavior extracted from active mobility data sources, notably surveys, and actual travel behavior derived from passive mobility data sources to suggest different scenarios where the two sets of data are suitable for.

2.4.2 Segmenting Travel Behavior Clusters

There are a variety of benefits for understanding the heterogeneity of transportation service users and incorporating their diversity into the TDM program design (Anable, 2005; Lathia, Froehlich, & Capra, 2010). Other than using attitudinal attributes as introduced in Section 2.3, mobility data (both active and passive) has been utilized to identify meaningful and actionable travel behavior segments.

Some studies focused on the basic transportation variables such as travel frequency, journey time, and OD pairs to cluster travel behavior groups (Ortega-Tong, 2013). These three variables and the other 17 variables helped Ortega-Tong (2013) identify 8 distinct travel behavior groups. Noticeably, the research introduced methods to investigate the spatial distribution of the resulting clusters. Similar efforts have been made by Ma, Wu, Wang, Chen, and Liu (2013) and Kieu, Bhaskar, and Chung (2014) by measuring spatial and temporal regularity during a short period.

Although some general travel behavior patterns were captured in these earlier studies, important information like longitudinal travel habits has been lost (Goulet-Langlois et al., 2016). Incorporating travel habits, which have proved to have large influences on travel decisions (Metcalfe and Dolan, 2012), into the travel behavior segmentation could help to keep more information than basic statistics such as weekly parking, or primary mode choices.

To incorporate finer-grained travel behavior, Jiang et al. (2012) identified travel behavior segments using data derived from an activity-based travel survey covering more than 30,000 individuals and 10,552 households in the Chicago Metropolitan Area. This research employed PCA, which was first introduced into human mobility studies by Eagle and Pentland (2009), to identify eigen activities, i.e., the latent patterns behind the high-dimension travel behavior data. They then employed k-*means* clustering algorithms to identify the distinct clusters for both weekdays and weekends (Jiang et al., 2012). The research captured much richer information than only using basic statistics. Yet, it was still troubled by two drawbacks mentioned before: the self-reporting bias and the loss of longitudinal travel behavior patterns.

More recently, Goulet-Langlois et al. (2016) proposed a method to represent longitudinal travel sequences by defining user areas and inferring user activities. Travel behavior across a period of 29 days was derived from the Transportation for London (TfL) smart card data, and the travel sequences were inferred from the methods they introduced. A PCA process similar to the one used by Jiang et al. (2012), a *k-means* clustering, and a cluster stability test were employed respectively for dimension reduction, clustering via PCA, and confirming the quality of the clustering methods. Finally, 11 clusters have been identified in this research, including four working day clusters, four homebound clusters, one complex activity pattern cluster, and two interrupted pattern clusters.

In line with the objectives to identify the longitudinal commuting behavior clusters, our research builds on the work of Jiang et al. (2012), Ortega-Tong (2013), and Goulet-Langlois et al. (2016). We propose a methodology in Chapter 3 to retrieve and infer commuting activity sequences from multiple data sources, to determine the eigen sequences, and to segment commuting behavior clusters.

Chapter 3

Data and Methodology

This Chapter introduces the data used for each of our research objectives and the methodologies employed.

3.1 Data Collection, Preprocessing, and Confidentiality

3.1.1 MIT Commuting Surveys

MIT, every two years since 2002, administers the MIT Commuting Survey to all employees (i.e., faculty and staff) and students to learn about how they commute to the MIT campus and how the existing TDM programs perform. The implementation processes are overseen by the Institutional Research department (IR) of MIT, and the data is shared with the State of Massachusetts and the City of Cambridge. Figure 3.1 shows a welcome page of the 2018 MIT Commuting Survey, and comprehensive information about the surveys can be found at *http://ir.mit.edu/commuting-to-mit*.

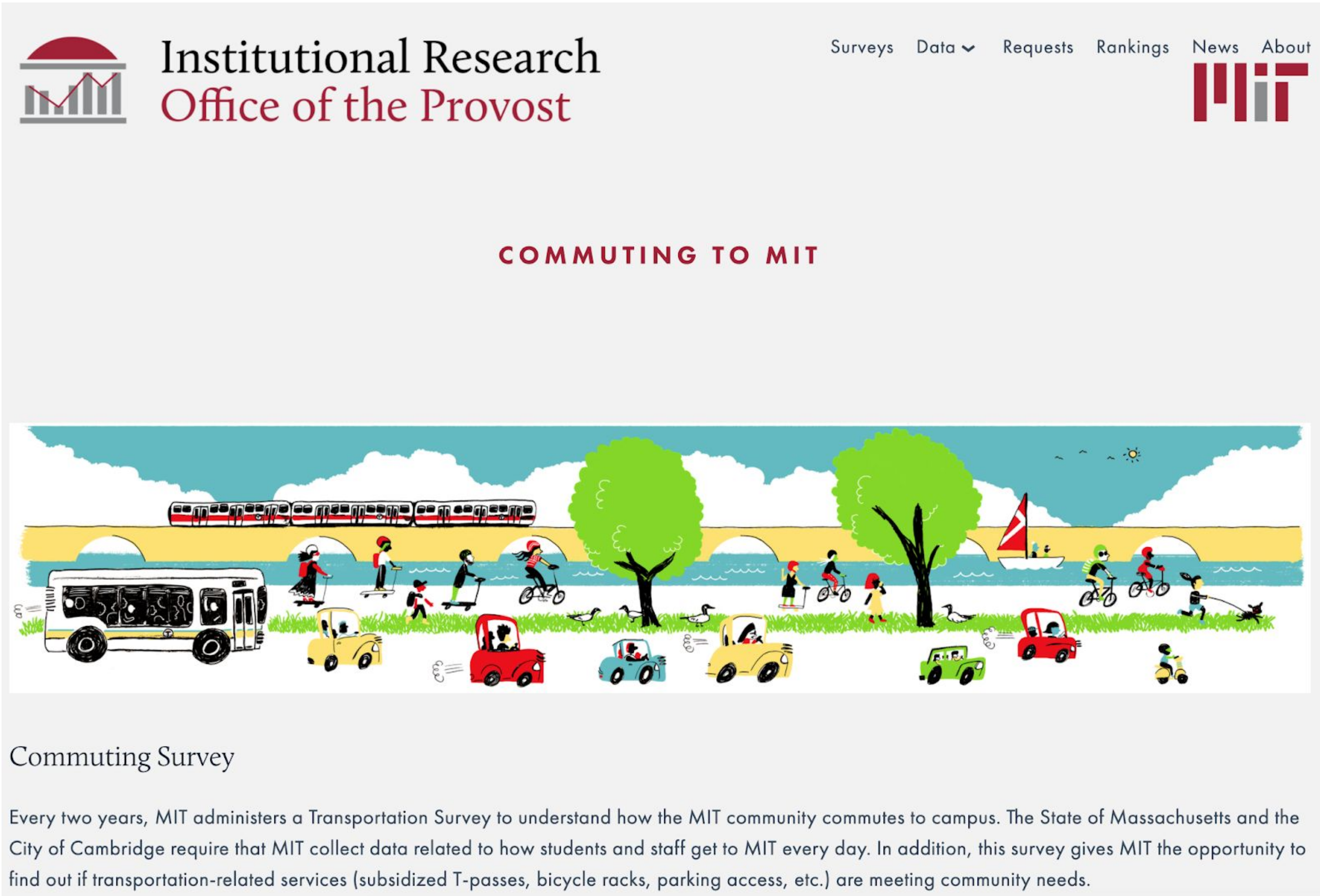

Figure 3.1 The welcome page of the 2018 MIT Commuting Survey

Other than attaining a better sense of how the MIT community is traveling, the surveys are also supposed to assess whether the transportation services provided by MIT meet the needs of its employees and students, as well as to identify any potential improvement for existing services and better managing transportation demands.

In this research, we review the 2014, 2016, and 2018 MIT Commuting Surveys, focusing on employees. These surveys are used as a source to study the trends of commuting mode choices, to provide active mobility data, and to profile commuting behavior segments.

To be specific, primary mode choices, mode shifts, reasons for mode shifts, awareness and participation rates, and satisfaction rates are aggregated in Chapter 4 to evaluate transportation services at MIT. Then, weekly gated parking frequencies and public transit uses are derived from the self-reported travel diaries collected by the latest survey. These self-reported commuting frequencies are then compared with the actual commuting frequencies elicited from passive mobility data in Chapter 5. Moreover, the survey answers are used to profile the resulting commuting behavior clusters in Chapter 6.

3.1.2 Passive Mobility Data

The primary passive mobility datasets available for this research is the records of MIT gated parking (i.e., parking activities on MIT parking facilities) and the public transit tap-ins of sampled MIT employees.

MIT gated parking records: we collect MIT gated parking records from MITOS, who receive the data from the Department of Facilities at MIT. This department controls and oversees all the on-campus parking facilities of MIT, either gated or ungated, yet only the parking activities occurring in the gated facilities are recorded in our data. Every time a registered user enters a gated parking facility at MIT, one record is created to document that activity. Every record in the raw data includes a unique university ID, a parking lot name, entry time, and whether the activity is allowed or not. The raw data is then preprocessed into a more structured format for modeling by an in-house data science team at MITOS. Noticeably, if an employee has more than one gated parking record on a particular day, only the first one is kept since we care more about whether he/she parks on a specific day rather than how many times he/she parks on that day.

Public transit tap-ins (MBTA Charlie card tap-ins): MIT receives public transit use data at the individual level and aggregated level through the collaboration with MBTA, and we access this data via MITOS as well. As mentioned in Chapter 2, the AccessMIT program has offered each eligible employee a free transit pass. Every time he/she rides on public transit, one record is created. The raw data has a unique ID associated with the university ID and a timestamp. The transit tap-in data is preprocessed following a similar manner as for the gated parking data.

To protect the privacy of the employees, all the passive mobility data we received is anonymized.

3.1.3 Socio-Demographic Characteristics

The Human Resources department at MIT collects socio-demographic information (HR data), including ages, genders, affiliations, and living addresses, from employees yearly. With privacy concerns, we receive data with only census block groups that living addresses are located in, rather than the exact addresses. Moreover, the socio-demographic characteristics are also anonymized, and we do not report any of them at the individual level.

3.2 Methodology

3.2.1 Commuting Discrepancy Indices

To study the discrepancy between self-reported and actual commuting behavior derived, we employ the 2018 Commuting Survey and two passive datasets, including gated parking records and transit tap-ins.

The survey is used as an active mobility data source to extract the self-reported commuting behavior. To be specific, employees were asked to report their weekly commuting diaries by choosing commuting modes for the week before they answered the survey. The set of commuting modes they could choose from is illustrated in Table 3.1, and the answers are collected on a daily basis.

Table 3.1 The list of commuting modes in the 2018 Commuting Survey

Commuting mode categories	Commute method
SOV	Drove alone the entire way
Public Transit	Drove alone, then took public transportation
	Walked, then took public transportation
	Shared ride/dropped off, then took public transportation
	Bicycled and took public transportation
Carpool/Vanpool/Private Shuttle	Rode in a private car with 1-4 commuters
	Rode in a vanpool (5+ commuters) or private shuttle (e.g. TechShuttle, SafeRide)
Bicycle	Bicycled
Walk	Walked
Others	Worked at home or other remote location
	Dropped off at work
	Out of office (e.g., sick, vacation, jury duty, business trip)
	Took a taxi or ride service (e.g., Uber, Lyft)
	Other
Scheduled Day off	Scheduled day off (e.g., weekend)

This research proposes a parking discrepancy index (PDI) and a transit discrepancy index (TDI) to represent the disparity between self-reported and actual commuting behavior, and we here introduce the process of constructing these indices.

Self-reported commuting activities are aggregated into weekly parking days and weekly transit days. Simultaneously, to construct the dataset indicating actual commuting behavior from passive mobility data, multi-week gated parking records and transit tap-ins are also aggregated into weekly frequencies (days). Then, the median of the aggregated weekly commuting days is used to better represent the actual commuting behavior. Finally, self-reported parking behavior and actual parking behavior are merged based on the unique user ID we generate. Table 3.2 exemplifies the dataset we build via these steps.

Table 3.2 Example self-reported and actual parking days

User ID	Median of actual weekly parking counts	Self-reported weekly parking counts
********	3.5	3
********	3	4

After the discrepancy matrix is constructed, we represent PDI as being denoted in Eq. (1), where $\Delta p, m$ denotes the PDI for given employee *m*, Ap, m denotes the median of actual weekly parking days, and Sp, m denotes the self-reported weekly parking days. Similarly, we have Eq. (2) for the TDI representation, where $\Delta t, m$ denotes the TDI for given employee *m*, At, m denotes the median of actual weekly transit days, and Sp, m denotes the self-reported weekly transit days.

$$\Delta p, m \ = \ Ap, m \ - Sp, m \tag{1}$$

$$\Delta t, m \ = \ At, m \ - St, m \tag{2}$$

3.2.2 Multivariate Linear Regression (MLR)

To identify the potential associations between the discrepancy indices--PDI and TDI--and the socio-demographic, attitudinal, and commuting related attributes, we build on the work of Goulet-Langlois (2016) and Ortega-Tong (2013) employ a series of multivariate linear regression (MLR) models denoted by Eq. (3).

$$DI = \beta 0 + \beta 1 X_{Socio-demographics} + \beta 2 X_{Mode\ choices} + \beta 3 X_{Attitudes} + \beta 4 X_{Actual\ frequency} + \varepsilon \quad (3)$$
$$\varepsilon \sim N(0,\ \sigma^2)$$

DI in Eq. (3) denotes the commuting discrepancy index PDI or TDI. Socio-demographics attributes $X_{Socio-demographics}$ are extracted from the HR data and tested as potential correlates. Mode choice attributes $X_{Mode\ choices}$ and attitudinal attributes $X_{Attitudes}$ are extracted from the 2018 Commuting Survey. In addition, the actual commuting frequency $X_{Actual\ frequency}$ derived from passive mobility data is included as well. Details about the variables are introduced in Chapter 5.

3.2.3 A Longitudinal Representation of Multi-Year Commuting Behavior

Central to the clustering methods in this research is to represent each employee's multi-year commute behavior. We introduce in this Section a methodology to represent longitudinal commuting behavior sequences using multiple passive mobility datasets. To represent both the commuting activities and the sequences of them, each employee is encoded as a time-ordered chain of commute activities inferred from multi-year gated parking records and transit tap-ins.

As gated parking records and transit tap-ins only provide us information about these two mode choices (SOV and public transit) and no information about other modes including biking or carpooling, we are only enabled to partially reconstruct the longitudinal commuting sequences for each employee. Although SOV and transit occupy a dominant percentage of primary mode choices of MIT employees (MIT Commuting Survey, 2018), this partial representation has limitations of not incorporating specific types of commuting activities such as biking and walking. Potential approaches to improve this representation in future research is discussed in Chapter 7.

The steps of representation are listed below:

1. Defining commute mode "buckets": Mentioned before, it only allows us to partially reconstruct the commuting sequences using the data. Thus, modified commuting mode categories are created based on the categories used in the surveys. we keep "driving alone" (SOV), "transit", and "others", and we add another category--"both"--to denote the occasion that the two modes are used on the same day. Carpooling, biking, and walking are classified into "others", while gated parking records are used as a proximity to reflect driving along activities.
2. Inferring longitudinal activity sequences: Commuting activities completed by each employee are ordered by days and used to encode an activity sequence matrix following the method introduced by Goulet-Langlois et al. (2016).
    - If the user had one or more than one gated parking record (i.e., MIT parking facility entries) and no transit tap-in on a particular day, then the user only drove to campus or back that day.
    - If the user had one or more than one transit tap-in and no gated parking record on a particular day, then the user only took public transit to campus or back that day.
    - If the user had both one or more than one gated parking record and one or more than one transit tap-in on a particular day, then the user took both commuting modes to campus or back that day.
    - If the user had neither gated parking record nor transit tap-in on a particular day, then the user took other commuting modes or did not travel that day.
3. Encoding the longitudinal activity sequences: Encoding the commute sequence of each individual and all the employees as images (Goulet-Langlois et al., 2016) is used in this research, where each pixel and the color covering it indicate the commuting mode chosen by an individual on a

particular day. The high-dimension encoded commuting sequences are visualized following Table 3.3 and prepared for PCA in the Section.

Table 3.3 Commuting statues summary

Activity status	Commute activities	Color code
-1	User drives that day	Red
0	User takes other commuting modes or does not travel on that day	Grey
1	User drives and takes public transit on that day	Yellow
2	User takes public transit that day	Green

3.2.4 Principal Component Analysis (PCA) / Eigen Decomposition for Commuting Patterns

As a dimension reduction approach widely utilized in the machine learning and computer vision area, *principal component analysis* (PCA) was first introduced to study human mobility patterns by Eagle and Pentland (2009). Then, PCA has been employed as an effective means to deal with high-dimension travel behavior patterns (Jiang et al., 2012; Goulet-Langlois et al., 2016). In this research, we use PCA to unveil the underlying structure of the multi-year commuting activity sequences represented from passive mobility data using the method introduced in the last Section.

First, the representing matrix is constructed based on the encoded commuting activities. For a time period of d days, the commuting activity of each user is denoted by a vector of d activity statuses, and values of the activity statuses are assigned following Table 3.3. Each factor is then transformed into xd binary vectors, where x indicates the number of total commuting statuses, four in this research. All vectors occupy a $N * xd$ matrix, where N is the size of the sample. The matrix is standardized by subtracting the mean of each column.

Second, the processed matrix is fed into a PCA process, which returns the eigenvectors and the eigenvalue of each vector. These eigenvector-eigenvalue pairs are then used to calculate the principal components (PC) of the matrix. Finally, the performance of different numbers of PCs is evaluated to determine the optimal number of PCs to reconstruct the commuting sequences. The explicit criteria employed for the case study is introduced in Chapter 6.

3.2.5 Clustering Travel Behavior Segments by K-Means Clustering Algorithm via PCA

As discussed previously in Section 3.2.4, the representing matrix with xd dimensions of N employees acts as our primary matrix for commuting behavior segmentation. To dealing with high-dimensional categorical variables, applying *k-means* clustering algorithms via PCA has been proved to be a effective and much more efficient approach since it asks for much less computational power because of a smaller dimensional scale (Goulet-Langlois et al., 2016; Jiang et al., 2012). According to the criteria for selecting PCs, the original matrix is reconstructed with fewer PCs, which are uncorrelated and independent. The reconstructed matrix is fed into a *k-means* clustering algorithm to segment distinct commuting behavior clusters.

One of the key problems in the clustering process is to determine the optimal k to better capture the latent patterns of the data. As discussed by Jiang et al. (2012), external criteria, internal criteria, and relative criteria are commonly used to optimize the clustering process. Since we do not have a external or relative source to reference, we propose to use internal criteria. To be specific, we use the Silhouette index (Rousseeuw, 1987) and the DB index (Davies and Bouldin, 1979) to measure, respectively, the compactness of clusters and the ratio of within cluster distances to across cluster distances, and to find the optimal k value.

Chapter 4

Mid-Term Impacts of AccessMIT

Rosenfield (2018) assessed the short-term impacts of the AccessMIT program by utilizing data from the 2016 MIT Commuting Survey, which was conducted right after the launch of the program. Some of the outcomes he evaluated included changes in employees' commuting mode choices and improvement of their satisfaction rates. A significant increase in the proportion of employees who chose public transit as their primary commuting mode and a drop in that of employees who chose was observed in the 2016 survey, compared to the results from the 2014 survey. Moreover, MIT commuter benefits was listed as the second most common reason for commuting mode shifts in the 2016 survey. In addition, Rosenfield (2018) described an increase in the overall satisfaction rate of employees from 2014 to 2016, which also indicates the positive short-term impacts of the program. How strong, though, has the impact of the AccessMIT program sustained?

In this Chapter, we use successive commuting surveys of 2012, 2014, and 2016 to evaluate whether this program has sustained impacts in influencing employees' commuting mode choices and boosting their satisfaction rate. These evaluations build on the early efforts on improving MIT transportation services by Block-Schachter (2009), Gates (2015), and Rosenfield (2018). We also propose some recommendations for policy making at MIT and a few suggestions for future survey design.

4.1 MIT Commuting Survey and Survey Representation

In order to evaluate how employees and students of MIT are utilizing the transportation services provided by the university and their attitudes towards potential new programs, MIT conducts the MIT Commuting Survey every two years. These surveys include questions about the choices of commuting modes, the shifts of commuting modes, the attitudes towards transportation services provided by MIT, and many other commuting-related aspects. A complete list of questions from the 2018 Commuting Survey can be found in Appendix A.

Table 4.1 provides the sample representation of the 2014, 2016, and 2018 Commuting Surveys among MIT employees. As can be seen, the response rates of these three surveys are around 50% - 60%, which results in 5500 - 6500 respondents. Socio-demographic attributes such as employee types and ages collected from the HR Department enable us to profile the 2016 and the 2018 survey respondents. We can see that the proportion of different genders, different age groups, and different employee types of the 2018 survey respondents aligns with that of the 2016 survey respondents. We then use these three surveys to investigate the mid-term impacts of AccessMIT in the following Sections.

Table 4.1: Survey Representation

		2014 Survey	2016 Survey	2018 Survey
Response rates		60.00%	54.00%	57.00%
N (Answered)		6386	5700	5827
Female		-	52.10%	52.20%
Age	< 40	-	46.80%	45.60%
	40-59	-	37.50%	37.80%
	60+	-	15.70%	16.60%
employees type	Faculty	-	7.60%	8.60%
	Research	-	36.60%	34.40%
	Admin, service, and medical	-	37.60%	39.30%
	Support	-	18.20%	17.60%

4.2 Choices of Primary Commuting Modes

4.2.1 Overall Choices of Primary Commuting Modes

The surveys have asked employees to report the commuting modes they choose to use in the current year. Despite the fact there may be a confounding effect of new employees behaving slightly differently from the existing ones, the results offer us a straightforward way to understand the overall trends of commuting at MIT. Also, a comparison between the results of different surveys can provide insights about how the trends evolve. Moreover, this comparison for different employee groups offers us more insight about heterogeneity among MIT transportation users, which is introduced in Section 4.2.2.

In surveys until 2014, only the primary modes of commuting were inquired about. Employees could choose from a comprehensive set of commuting modes such as “Drive alone the entire way” and “Walk, then take public transportation", which are denoted by the "Commuting mode" column in Table 4.2. Then, starting from the 2016 survey, the secondary commuting modes have also been asked in the survey, where employees could report the modes they used occasionally. The primary and secondary modes are inquired about with the following question: "What are your CURRENT commuting method(s) to MIT? Select your primary method, and if applicable, a secondary method (e.g. during nice weather, flexible hours, etc.)." Respondents are supposed to choose from the same list of commuting modes as that of the earlier surveys.

A comprehensive analysis of the choices of the primary and secondary commuting modes is available in Appendix B, which includes information about the proportion of each commuting mode in the 2014, 2016, and 2018 surveys. In order to investigate the broader trends of commuting behavior at MIT and their connections with TDM programs, we basically employ the principles of aggregating different commuting modes used by the survey and modify it to better fit our research objectives. Thus, the commuting modes are classified in Table 4.2.

Table 4.2 Classification of Commuting Modes

Commuting mode category	Commuting mode
SOV	Drive alone the entire way
Public transit	Bicycle and take public transportation
	Drive alone, then take public transportation
	Share ride/dropped off, then take public transportation
	Walk, then take public transportation
Bicycle	Bicycle
Walk	Walk
Carpool/Vanpool/Private Shuttle	Ride in a private car with another person
	Ride in a private car with 2-4 commuters
	Ride in a vanpool (5 or more commuters) or private shuttle (e.g., TechShuttle, SafeRide)
Others	Work at home (or other remote location)
	Dropped off at work
	Take a taxi or ride service (e.g., Uber, Lyft)
	Other

These classification principles allow us to aggregate similar commuting modes into larger categories, and enable us to aggregate the survey results. By aggregating the proportions of each commuting mode extracted from different surveys into 6 commuting mode categories (i.e. SOV, public transit, bicycle, walk, carpool/vanpool/private shuttle, & others), we are able to track the evolution of the mode choices more clearly.

Table 4.3 indicates the proportion of each commuting category stated in the 2014, 2016, and 2018 survey. To compare the evolution of mode choices across the three surveys, only primary modes are summarized and aggregated into Table 4.3 since the secondary modes were not asked in the 2014 survey. Similarly, Figure 4.1 indicates how the shares of each mode category changed since the 2014 survey, where the horizontal axis denotes the years while the vertical axis indicates the percentages of mode categories. Before we investigate the changes across successive surveys, we can see that SOV took up 25-30% of all mode categories, while public transit took up around 40-50%. Active modes such as bicycle and walk were reported as the primary mode categories by a relatively small proportion of the respondents.

Then, as can be seen from the upper green line in the graph, there was an increase in the proportion of employees who chose public transit as the primary mode category from 42% to 47% right after the launch of the AccessMIT program in 2016. This fact was also reported by Rosenfield (2018) as the results of the incentives introduced by the program. And, more meaningful, the proportion who choose public transit as the primary mode category has sustained at this high level in the 2018 survey and this is likely due to the long lasting effects of AccessMIT. A similar trend can be seen from the proportions of employees choosing SOV, which dropped from 28% in the 2014 survey to 24% in the 2016 survey, and then has stayed steady.

Hence, based on these results, the AccessMIT program has a sustained impact on changing employees ' commuting mode choices towards more sustainable modes, notably public transit. A more detailed investigation of this trend among different employee types is offered in the next section.

Table 4.3 Proportions of different commuting mode categories reported in the 2014, 2016, and 2018 surveys

Commuting category	2014 Survey	2016 Survey	2018 Survey
N	6335	5563	5766
SOV	28.00%	24.00%	24.50%
Public transit	42.00%	47.00%	49.00%
Bicycle	9.00%	11.00%	9.80%
Walk	9.00%	10.00%	9.30%
Carpool/Vanpool/Private Shuttle	6.50%	6.00%	4.30%
Others	5.70%	2.70%	3.10%

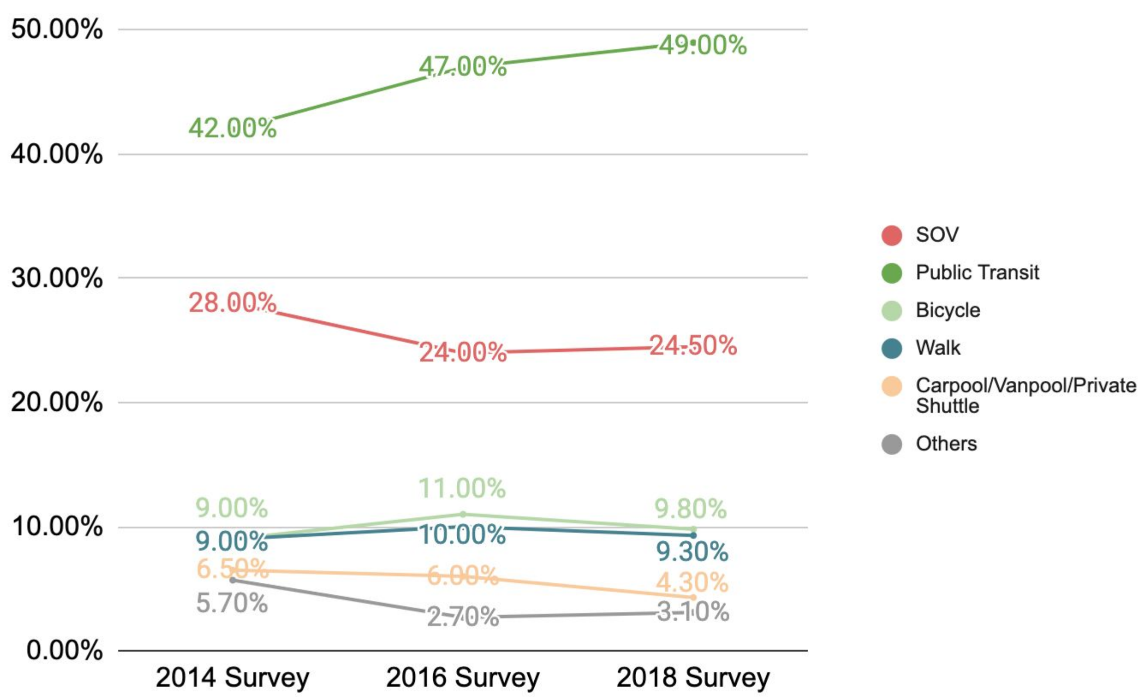

Figure 4.1 Proportions of different commuting categories reported in the 2014, 2016, and 2018 surveys

4.2.1 Choices of Primary Commuting Modes by Employee Types

At the same time, we summarize the evolution of commuting mode choices of different employee types across these three surveys and report some interesting findings. The results of faculty; research staff; administration, service, and medical staff; and support staff are indicated in Table 4.4, 4.5, 4.6, and 4.7 respectively. As can be seen from these tables, all of the four employee types have experienced an decreased choice of SOV mode and an increased choice of public transit, which aligns with our conclusion from the last Section. However, their changing patterns varied largely among different types.

The reduction of the proportion of faculty who chose SOV as their primary commuting mode happened in two steps, from 2014 to 2016 (5.74%) and from 2016 to 2018 (4.85). Other three types of employees experienced an apparent decrease from 2014 to 2016 and then stayed relatively steady. The disparity of behavioral changes between faculty and staff can be also found in the transit mode choices. The proportion of faculty choosing transit in the 2016 survey did not see a substantial change, yet this percentage growed by 4.37%. All other three types of employees saw immediate increases in the percentages of transit mode in the 2016 survey, right after the launch of AccessMIT. In addition, we can observe the different extents to which the decrease and increase happened. For example, faculty had the largest decrease by 10.59% of the SOV share across the three surveys, while administration, service, and medical staff saw the most significant increase in transit mode share by 9.57%.

These results offer us some key takeaways. Different employee types reacted to the same TDM incentives in different ways, including speed and intensity. For example, some specific groups of employees (e.g. administration, service, & medical staff) were more sensitive to the incentives than others and this might be associated with their socio-demographic and attitudinal characteristics.

Table 4.4 Proportions of different commuting mode categories reported in the 2014, 2016, and 2018 surveys (faculty only)

Commuting category	2014 Survey	2016 Survey	2018 Survey
N	492	422	489
SOV	39.63%	33.89%	29.04%
Public transit	25.61%	26.30%	30.67%
Bicycle	11.59%	17.54%	14.72%
Walk	9.76%	11.85%	14.11%
Carpool/Vanpool/Private Shuttle	8.33%	5.45%	7.98%
Others	5.08%	4.98%	3.48%

Table 4.5 Proportions of different commuting mode categories reported in the 2014, 2016, and 2018 surveys (research staff only)

Commuting category	2014 Survey	2016 Survey	2018 Survey
N	2,624	2,098	1,987
SOV	17.57%	15.59%	15.90%
Public transit	43.10%	47.33%	49.12%
Bicycle	14.52%	16.06%	16.00%
Walk	13.07%	12.87%	13.14%
Carpool/Vanpool/Private Shuttle	5.03%	4.34%	3.27%
Others	6.71%	3.81%	2.57%

Table 4.6 Proportions of different commuting mode categories reported in the 2014, 2016, and 2018 surveys (Administration, service, and medical staff only)

Commuting category	2014 Survey	2016 Survey	2018 Survey
N	2,071	2,100	2,281
SOV	39.58%	33.90%	33.63%
Public transit	37.60%	43.10%	47.17%
Bicycle	4.15%	5.48%	5.22%
Walk	4.83%	6.76%	6.40%
Carpool/Vanpool/Private Shuttle	8.20%	6.71%	4.65%
Others	5.60%	4.05%	2.94%

Table 4.7 Proportions of different commuting mode categories reported in the 2014, 2016, and 2018 surveys (Support staff only)

Commuting category	2014 Survey	2016 Survey	2018 Survey
N	1,132	1,026	1,009
SOV	22.97%	17.15%	18.83%
Public transit	53.45%	59.36%	61.65%
Bicycle	4.77%	6.04%	5.75%
Walk	5.48%	7.12%	5.95%
Carpool/Vanpool/Private Shuttle	6.18%	5.36%	3.96%
Others	7.16%	4.97%	3.87%

4.3 Commuting Mode Shifts and Reasons

The information about the shifts between different commuting modes was also collected by the Commuting Surveys, together with the questions about general commuting modes. In addition, employees were asked to report the reasons why they changed their commuting modes. This Section summarizes the mode shifts extracted from the 2018 survey and compared with that of the 2016 survey.

According to the 2018 survey, 586 employees stated mode shifts, i.e. different commuting modes in the previous year (2017), taking up 12% of the survey respondents. The Sankey diagram in Figure 4.2 shows how they shifted between different modes. Similarly, a Sankey diagram indicating the stated mode shifts from 2015 to 2016 is presented by Figure 4.3, which is extracted from Rosenfield (2018).

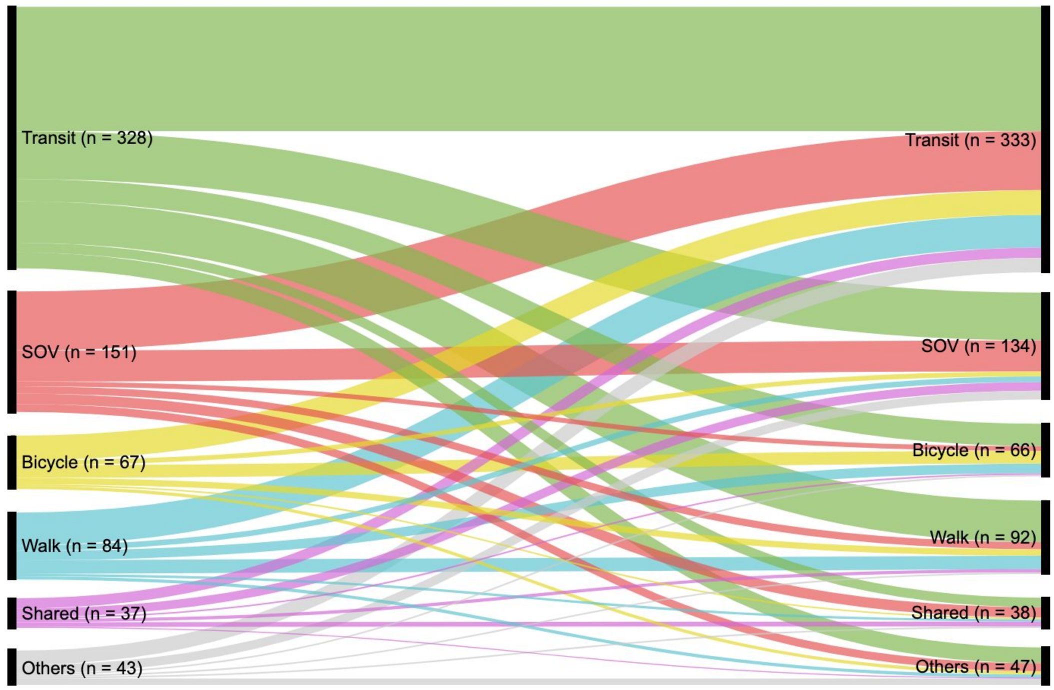

Figure 4.2 Stated mode shifts from 2017 (left) to 2018 (right) among respondents who reported changing modes. The continuity of the same mode implies the choice of a new secondary mode.

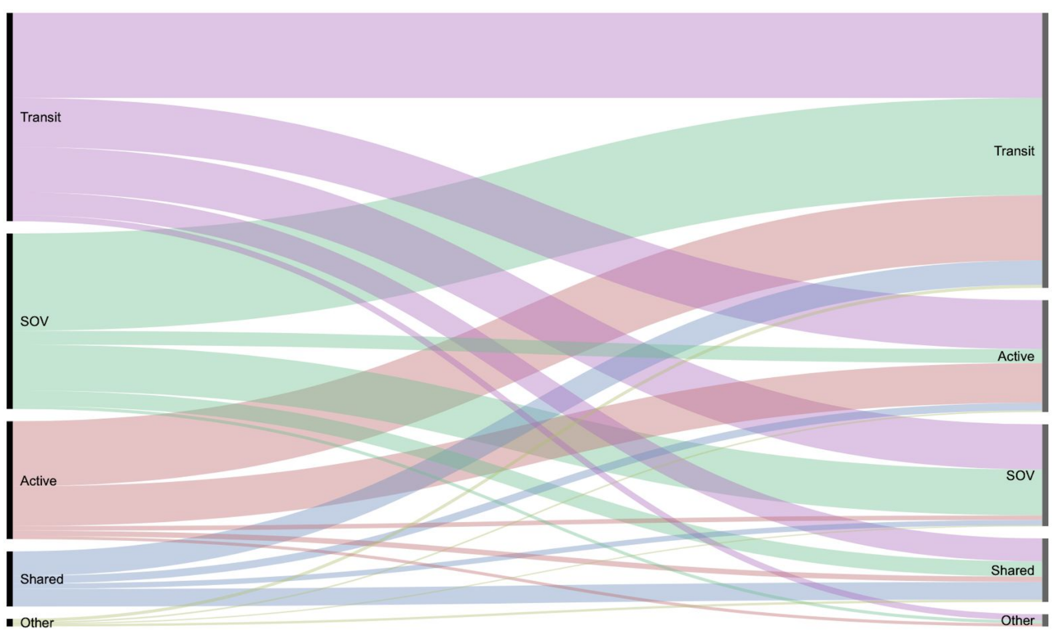

Figure 4.3 Stated mode shifts from 2015 (left) to 2016 (right) among respondents who reported changing modes. The continuity of the same mode implies the choice of a new secondary mode. (Rosenfield, 2018)

First of all, we can notice a clear trend of shifting from SOV to public transit stated in the 2016 survey, which resulted in a higher proportion of public transit in 2016, compared to that of 2015. This was likely contributed by the impacts of the AccessMIT program (Rosenfield, 2018).

However, despite the fact that a group of respondents also stated they shifted from SOV to public transit in the 2018 survey, the proportion of public transit does not see a significant difference, with 46% in 2017 and 47% in 2018. The reason for this phenomenon was the "net gain" of public transit. From 2015 to 2016, a large group of employees reported shifting from SOV to public transit while a much smaller group reported shifting backwards, yet, from 2017 to 2018, these two groups had similar size. Yet, this complements the sustained impact of AccessMIT.

Table 4.4 Stated Reasons for Mode Shifts*

Reason for mode shift	**2016**	**2018**
Moved place of residence	37.00%	43.00%
Changed jobs and/or hours	7.00%	7.00%
Life event (e.g. family structure)	18.00%	17.00%
Availability of a vehicle (e.g. purchased a car)	7.00%	7.00%
MIT commuter benefits	24.00%	14.00%
Other	26.00%	29.00%
* Percentages add up beyond 100% due to multiple selections		

Employees who stated shifting their modes were also asked to report the reasons for their mode shifts. The proportion of different reasons is summarized in Table 4.4. As can be seen, "moved place of residence" was the primary reason for shifting between different commuting modes. It is likely because the change of home locations influences many factors associated with commuting behavior, including accessibility to public transit, travel time of different modes, and social norms.

It is interesting to notice that the proportion of employees choosing “MIT commuter benefits” was 24% in 2016, the second highest, which was just lower than “moved place of residence”. This was probably because the significant incentives introduced by AccessMIT in 2016 had shifted a group of employees in between different modes. Noticeably, this number dropped by 10% to 14% in 2018, lower than “moved place of residence” (43%) and “life event” (17%). Despite this drop, the commuter benefits were still impactful in contributing to employees’ mode shifts, especially when we consider the fact that no significant new incentives have been introduced after the launch of AccessMIT in 2016.

4.4 Satisfication

In evaluating the impacts of TDM programs, another essential factor of concern is the user experience. This research measures this factor utilizing the overall satisfaction rates towards MIT’s transportation services collected by the 2014, 2016, and 2018 Commuting Surveys.

As can be seen from Figure 4.4, which indicates the employee satisfaction rate, a large increase occurred in the proportion of satisfied employees, from 76% in 2014 to 84% in 2016, while a drop happened for the proportion of “neither satisfied nor dissatisfied” employees, and the trend lasted till the 2018 survey. This improvement of user perception was likely due to the sustained impacts of the AccessMIT program, notably the subsidies including free MBTA passes. Then, for all these three surveys, 5% of the respondents for each survey reported that they were somewhat or very dissatisfied with MIT’s transportation service. This fact suggested that the needs of a particular group of employees have not been met by the existing services. In addition, the satisfaction rate of different employees groups are shown in Table 4.5.

Moreover, another fact that we realize is the substantial difference between the improvement of satisfaction rates for only employees and that of satisfaction rates for employees and students together. To be specific, when combining the employees and students, 77 percent said they are satisfied, indicated by Figure 4.5, and this proportion has stayed steady in the following two surveys, which is largely different from the trend of employees satisfaction rates. Notably, an increased dissatisfaction rate for the whole sample is observed in 2016. As the dissatisfaction rate of employees stayed steady. Figure 4.6 indicates that this increase of dissatisfaction was contributed by students, which was likely due to the fact that most of the AccessMIT benefits were only for employees.

Therefore, while confirming the positive impacts of AccessMIT on improving employees satisfaction rates, we recommend giving more focus on the commuter benefits for students. More implications about how to learn about the interests and needs of students at MIT are discussed in Section 4.7.

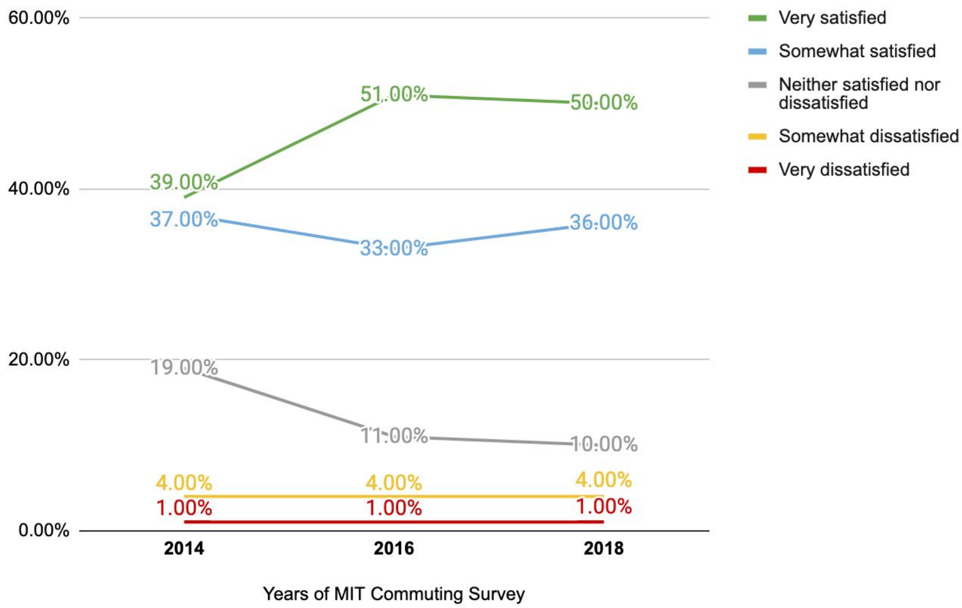

Figure 4.4 Overall satisfaction rates towards MIT's transportation services (employees only)

Table 4.5 Satisfaction rates across different employee types and primary commuting modes

	2014	2016	2018
Employee types			
Faculty	69.66%	80.82%	86.17%
Research staff	73.04%	85.29%	87.07%
Administration, service, and medical staff	79.47%	84.05%	85.06%
Support staff	78.68%	85.74%	85.87%
Primary commuting modes			
SOV	67.75%	71.65%	71.92%
Public transit	82.93%	91.00%	92.38%
Bicycle	77.72%	85.66%	86.87%
Walk	69.87%	89.30%	88.78%
Carpool/Vanpool/Private Shuttle	72.48%	78.72%	81.25%
Others	74.27%	80.81%	82.50%

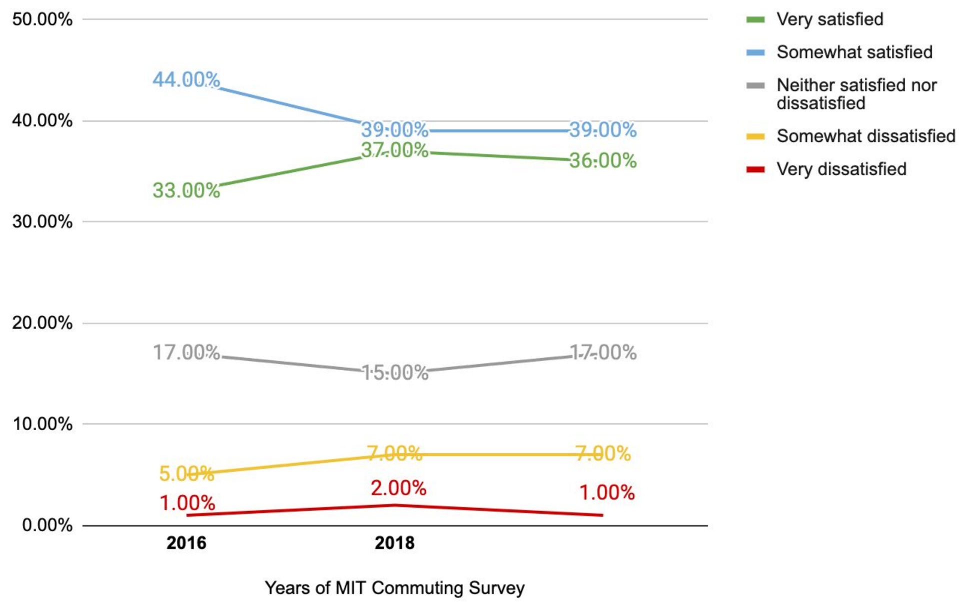

Figure 4.5 Overall satisfaction rates towards MIT's transportation services (employees and students)

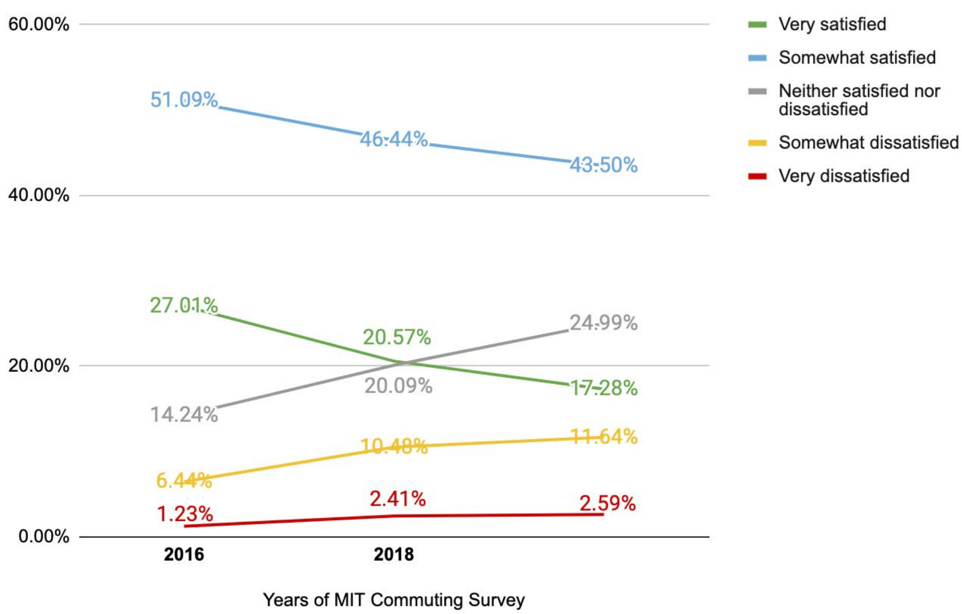

Figure 4.6 Overall satisfaction rates towards MIT's transportation services (students only)

4.5 Awareness and Participation of MIT's Traranportation Services

Other than the AccessMIT program launched by MIT in 2016, which mainly offers transit-related subsidies, MIT provides a comprehensive set of transportation services related to driving, public transit, bicycle, carpooling, and job flexibility.

In order to understand how these services meet the needs of the MIT community and how employees perceive them, the awareness and the participation in each service was also asked in the surveys. After cleaning and aggregating a long list of results of these questions, we generated a comprehensive dataset covering the awareness and participation in these services.

Since a majority of the public transit related services were introduced by the AccessMIT program in 2016, the service structure of the 2016 and 2018 survey varied largely from that of the 2014 survey. Therefore, we only include results from the 2016 and 2018 survey in this Section. The awareness and participation rates of different transportation services are shown in Table 4.6 and Table 4.7. First, we notice that, for most of the transportation services, the awareness rates were slightly higher in the 2016 survey than those in the 2018 survey. This was probably due to the accompanying awareness campaign of AccessMIT before the 2016 survey.

Second, as can be seen in the figures, "Subsidized MBTA Pass" (the "pass"), "MIT Parking and Transportation Office website" (the "website"), and "MIT Shuttles/Daytime weekday shuttle services (The Tech Shuttle, Daytime Boston Shuttle, etc.)" were the top 3 in the services that individuals had awareness of. This result was likely because these services are among the most popular ones that employees may consider using. Yet regarding the participation, the "pass", the "website", and

“AccessMIT Commuting Benefits” are the top 3 in the list. This might be because, on one hand, public transit is the most popular primary commuting mode reported by the employees in the surveys; on the other hand, the incentive had contributed to the participation rates.

It is also interesting to note the fact that, for a significant majority of the services, a considerable proportion of employees were not aware of them, making it difficult for the employees to take full advantage of these services. For example, 55% of the respondents of the awareness question were not aware of the AccessMyCommute Dashboard, which was designed for monitoring individual commuting behavior and offering useful commuting related information. The lack of awareness of these services might be due to the small proportion of employees who choose those modes or the lack of awareness marketing efforts.

Table 4.6 Awareness and participation rates of MIT's transportation services in the 2016 and 2018 survey

(SOV & public transit)

	2016				2018			
	Sample size*	Aware of service, USE IT	Aware of service, DO NOT USE IT	Not aware of service	Sample size*	Aware of service, USE IT	Aware of service, DO NOT USE IT	Not aware of service
MIT Parking and Transportation Office website	5399	58%	34%	8%	5596	51%	37%	12%
Subsidized daily pay-per-day parking at all MIT owned lots and garages	-	-	-	-	5381	27%	45%	28%
Subsidized Zipcar (car sharing)	5369	12%	68%	20%	5534	9%	54%	38%
Electric Vehicle Charging Stations	5343	1%	64%	35%	5550	1%	59%	40%
Emergency Ride Home Program	5360	5%	60%	35%	5546	5%	59%	37%
AccessMIT Commuting Benefits	5061	49%	31%	19%	5377	42%	31%	27%
AccessMyCommute Dashboard	5041	12%	37%	52%	5331	13%	32%	55%
Subsidized MBTA Pass	5082	73%	25%	2%	5392	77%	20%	3%
Parking subsidy at MBTA stations and lots	-	-	-	-	5373	11%	51%	39%
Private Transit Subsidy	5335	4%	34%	62%	5527	3%	28%	69%
* The response rates vary for different transportation services.								

Table 4.7 Awareness and participation rates of MIT's transportation services in the 2016 and 2018 survey

(Bicycle, shuttle, carpooling, & job flexibility)

	2016				2018			
	Sample size*	Aware of service, USE IT	Aware of service, DO NOT USE IT	Not aware of service	Sample size*	Aware of service, USE IT	Aware of service, DO NOT USE IT	Not aware of service
Subsidized Blue Bikes/Hubway (bike sharing)	5352	11%	80%	10%	5544	10%	65%	25%
Secure bicycle storage and/or repair facilities	5349	10%	64%	26%	5531	9%	62%	29%
Locker and/or shower facilities for runners and bicyclists, other than in DAPER facilities (e.g., Zcenter)	5354	7%	44%	49%	5555	7%	46%	48%
Qualified Bicycle Commuter Benefit	5350	5%	52%	43%	5541	4%	47%	48%
MIT Shuttles/Daytime weekday shuttle services (The Tech Shuttle, Daytime Boston Shuttle, etc.)	5368	32%	60%	8%	5555	27%	57%	15%
Evening SafeRide shuttle services	-	-	-	-	5554	4%	70%	26%
Specialty shuttles (Airport Shuttle, The Grocery and Weekend Shuttles, etc.)	-	-	-	-	5555	4%	59%	37%
MIT Mobile Shuttle Tracking	5358	24%	46%	31%	5550	20%	39%	41%
Carpools/Vanpool Parking Programs	5335	3%	66%	32%	5523	3%	60%	37%
Flexible hours to accommodate schedules	5344	41%	27%	31%	5523	38%	27%	35%

* The response rates vary for different transportation services.

Then, in order to compare the performance of different services in terms of awareness and participation rates, we create a group of bar charts. Each one of them denotes a specific transportation service, indicating how each service is perceived and used by employees. We use transportation services related to SOV and transit as examples here to investigate the service performance since they occupied a major proportion of the employees mode choices.

It is interesting to note that, regarding the participation rates, the “website” and “Subsidized daily pay-per-day parking at all MIT owned lots and garages” gained a dominant position in SOV related services, which meant these two services are more used than other ones. Similar trends can be seen in the public transit related category, where the “pass” and “AccessMIT Commuting Benefits” were more utilized than other services.

Other than these dominant services in each service category, other transportation services were much less used, yet the situations of SOV related services and transit related services were different. While most of the SOV-related services denoted in Figure 4.7 other than the dominant two were at least known by the employees, most of the transit services were not, including the AccessMyCommute dashboard.

Despite the fact that the different awareness and participation rates of various transportation services are understandable and expected since they have different target groups and involve different incentives, the lack of awareness for a great proportion of these services cannot be ignored. Therefore, awareness campaigns and promotional messages about specific groups of transportation services are included as policy options recommended in Chapter 6.

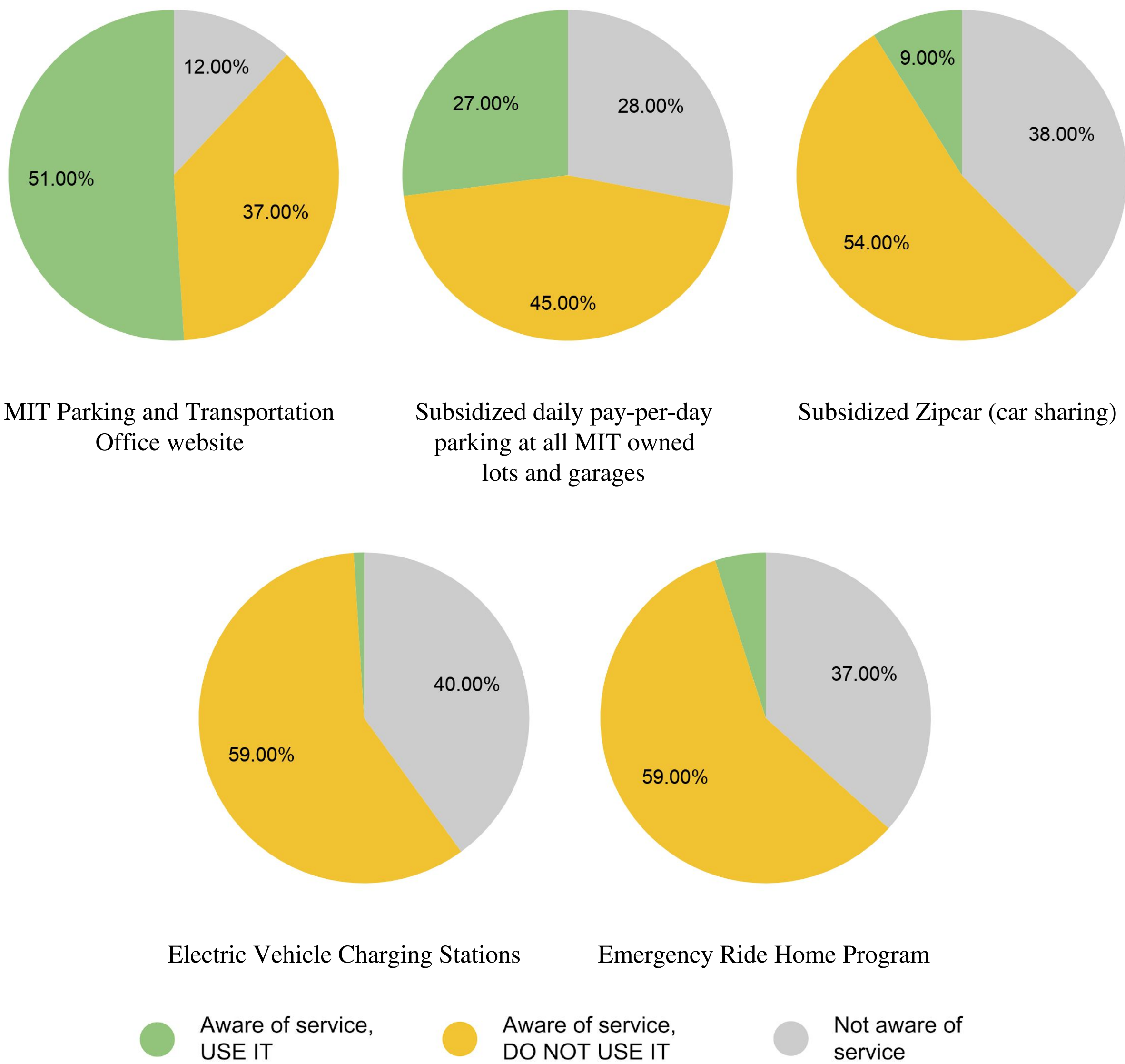

Figure 4.7 Awareness and participation rates of SOV related transportation services

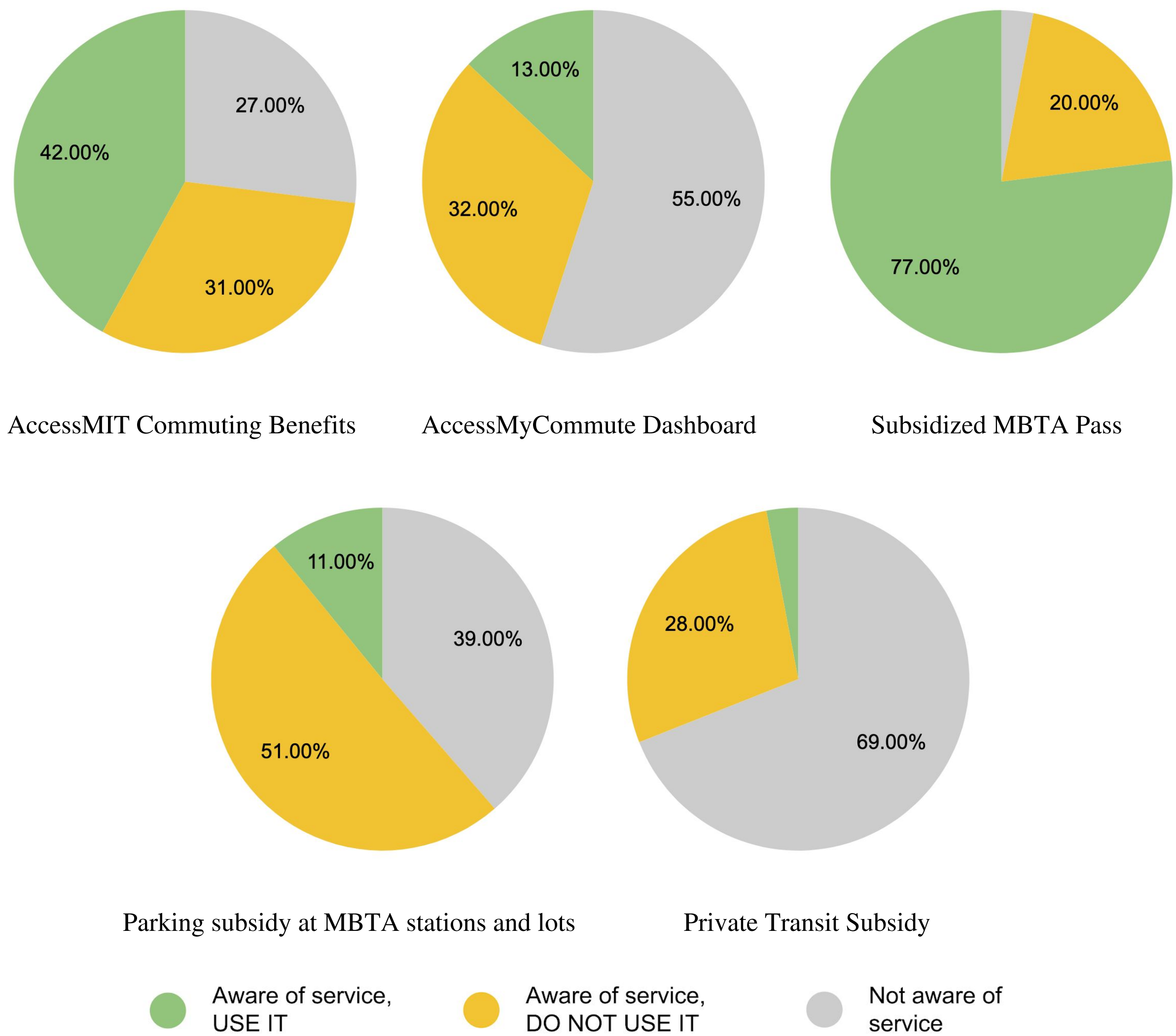

Figure 4.8 Awareness and participation rates of transit related transportation services

4.6 Expected Mode Shifts

Other than the stated mode shifts from the previous year to the present year, employees were also asked in the survey to describe whether they expected to change to another commuting mode in the coming year. Here we use the 2018 survey as an example to investigate the expected mode shifts reported by the respondents, which is suggested by the Sankey diagram in Figure 4.10.

Two interesting results can be seen in this diagram. First, there was a clear trend of reduced SOV mode choices expected by the respondents, and about half of the respondents who chose to shift from SOV expected they would use public transit, indicating their shifting potentials towards public transit. Another noticeable point is the respondents' enthusiasm towards carpooling.

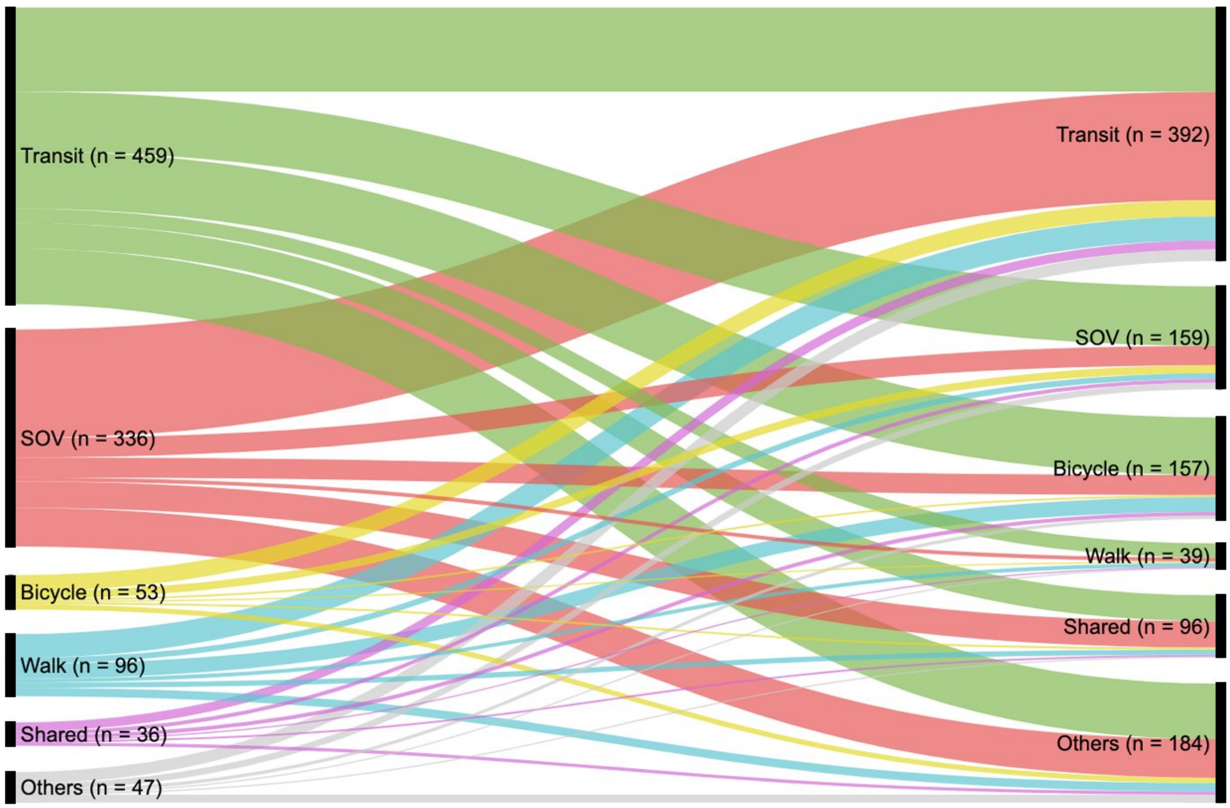

Figure 4.9 Expected mode shifts from 2018 (left) to 2019 (right) among respondents. The continuity of the same mode implies the choice of a new secondary mode.

4.7 Carpooling

Moreover, carpooling programs have been expected to be another engine for the ongoing shift to more sustainable commuting behavior and greener environmental impacts at MIT. To investigate employees' attitudes towards new carpooling related programs, employees were requested to describe their likelihood of considering carpooling on an occasional basis in the 2018 survey, the results of which are suggested by Figure 4.11 and Table 4.8. Although over half of the repondants of this question (N = 1962) indicated they would not consider carpooling, around 34 percent of the respondents reported they might consider it, which is relatively positive compared with the share of carpooling in employees' commuting mode choices.

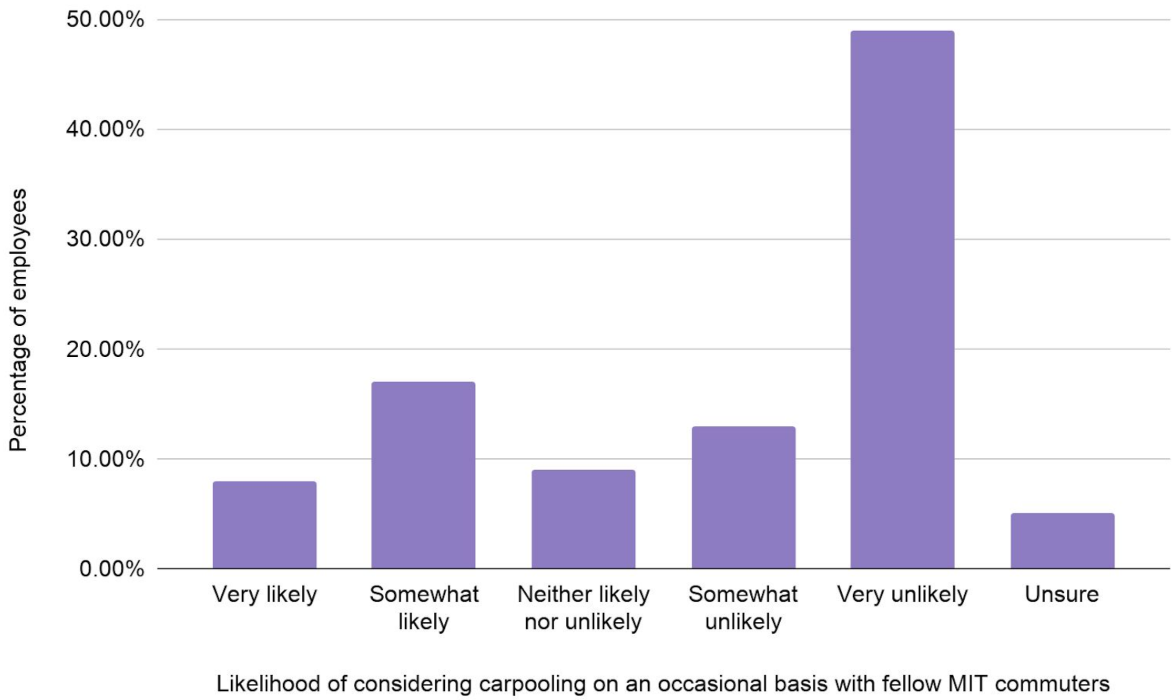

Figure 4.10 Likelihood of considering carpooling on an occasional basis with fellow MIT commuters

Table 4.8 Stated Attitudes towards the possible carpooling program

	N	Very likely	Somewhat likely	Neither likely nor unlikely	Somewhat unlikely	Very unlikely	Unsure
Employee types							
Faculty	214	2.80%	11.21%	6.54%	11.68%	64.49%	3.27%
Research staff	476	8.61%	15.76%	9.87%	13.87%	47.90%	3.99%
Administration, service, and medical staff	999	8.21%	18.22%	9.41%	13.31%	45.15%	5.71%
Support staff	274	6.93%	18.25%	7.30%	8.76%	50.36%	8.03%
Primary commuting modes							
SOV	1408	6.32%	15.77%	8.24%	12.50%	51.92%	5.26%
Public transit	417	10.07%	19.42%	9.59%	15.83%	38.61%	6.47%
Bicycle	44	6.82%	27.27%	9.09%	2.27%	54.55%	0.00%
Walk	25	16.00%	8.00%	20.00%	0.00%	56.00%	0.00%
Carpool/Vanpool/Private Shuttle	42	23.81%	23.81%	16.67%	7.14%	23.81%	4.76%
Others	23	0.00%	17.39%	13.04%	8.70%	56.52%	4.35%

In order to explore the potential associations between the stated likelihood of using carpooling and socio-demographic, commuting related, and attitudinal, attributes, we employ an ordinal logistic regression model. The hypothetical dataset has a six level dependent variable: likelihood, which includes levels “very unlikely”, “somewhat unlikely”, “unsure”, “neither likely nor unlikely”, “somewhat likely”, and “very likely”. The levels are coded 1, 2, 3, 4, 5, and 6, respectively. Based the results illustrated in Table 4.7, we can see that, with 90% confidence, the age dummy (*isOver60*), two employee type dummies (*isFaculty, isAdmin*), one primary mode dummy (*isCarpool*), and mode shift dummies (*changeLastYear, changeNextYear*) are statistically significant. The estimated ordinal logistic regression model is shown as Eq. (4), where $logit(\widehat{P}(Y \leq k))$ denotes the log odds, and *k* equals 1, 2, 3, 4, 5, and 6.

$$logit(\widehat{P}(Y \le k)) = Intercept - (-0.679) * isOver60 - (-0.360) * isFaculty - 0.332 * isAdmin \\ - 1.488 * isCarpool - 0.636 * changeLastYear - 1.042 * changeNextYear \tag{4}$$

As can be seen from the results denoted in Table 4.9, for employees who are over 60 years old, they are less likely to consider the possible new carpooling program on an occasional basis, holding constant all other variables. Similarly, faculty are less likely to consider carpooling as well. On the contrary, administration, service, and medical staff are more likely to consider carpooling on an occasional basis. It is interesting to notice that, employees who reported carpooling as their primary commuting mode in the 2018 survey are more likely to consider the possible new carpooling program, with the highest odds ratio. This means that, holding all other variables constant, this group of employees are 4.428 times more likely to consider the possible new program. In addition, both of the mode shift dummy variables show positive associations with the likelihood.

This ordinal logistic regression model reveals four key takeaways. First, aging employees are less likely to consider a possible new carpooling program. Second, the likelihood of considering the program varies across different employee types, where administration, service, and medical staff tend to be more likely while faculty are more unlikely. Third, both a stated mode shift from the previous year and an expected mode shift towards the coming year indicate higher likelihood. Finally, job flexibility, satisfaction, and car ownership are not shown significantly associated with the likelihood of considering the possible carpooling program.

Table 4.9 Ordinal logistic regression analysis of carpooling likelihood

	coefficients	odds ratio	Std. Error	t value
isFemale	0.111	1.118	0.093	1.198
isOver60	**-0.679**	**0.507**	**0.123**	**-5.535**
isFaculty	**-0.360**	**0.697**	**0.204**	**-1.768**
isSupport	0.251	1.285	0.159	1.574
isAdmin	**0.332**	**1.393**	**0.137**	**2.413**
isRecentHire	0.200	1.222	0.126	1.593
isSOV	0.201	1.222	0.430	0.467
isTransit	0.581	1.789	0.436	1.335
isCarpool	**1.488**	**4.428**	**0.515**	**2.888**
isActiveMode	0.484	1.622	0.494	0.980
changeLastYear	**0.636**	**1.888**	**0.136**	**4.679**
changeNextYear	**1.042**	**2.835**	**0.132**	**7.906**
isFlexible	0.056	1.058	0.100	0.557
isSatisfied	-0.061	0.941	0.105	-0.583
ownCar	0.016	1.016	0.630	0.025

	Intercepts	Std. Error	t value
Very unlikely|Somewhat unlikely	0.739	0.789	0.937
Somewhat unlikely|Unsure	1.308	0.789	1.657
Unsure|Neither likely nor unlikely	1.553	0.789	1.967
Neither likely nor unlikely|Somewhat likely	2.015	0.790	2.551
Somewhat likely|Very likely	3.469	0.794	4.369

4.8 Job Flexibility and Remote Working

In order to better accommodate the diverse working patterns and preferences of employees, MIT Human Resources has released guidelines for job flexibility (https://hr.mit.edu/jobflex). The term "job flexibility" involves two different types of flexibility at MIT: *occasional flexibility* and *ongoing flexibility*. Occasional flexibility is usually informal and involving unwritten agreement between employees and supervisors. More formally, ongoing flexibility generally involves written agreements and includes compressed workweek and telecommuting.

The job flexibility policies are valuable at MIT, because on one hand, they fulfill the needs of employees with diverse working patterns and preferences, and on the other hand, they help the university to become more "green" by reducing greenhouse gas emission associated with commuting. In addition, job flexibility policies, especially telecommuting, can alleviate the stress on employees of long commuting times, since around one half of the respondents reported they chose to work remotely due to transportation related issues (Figure 4.11).

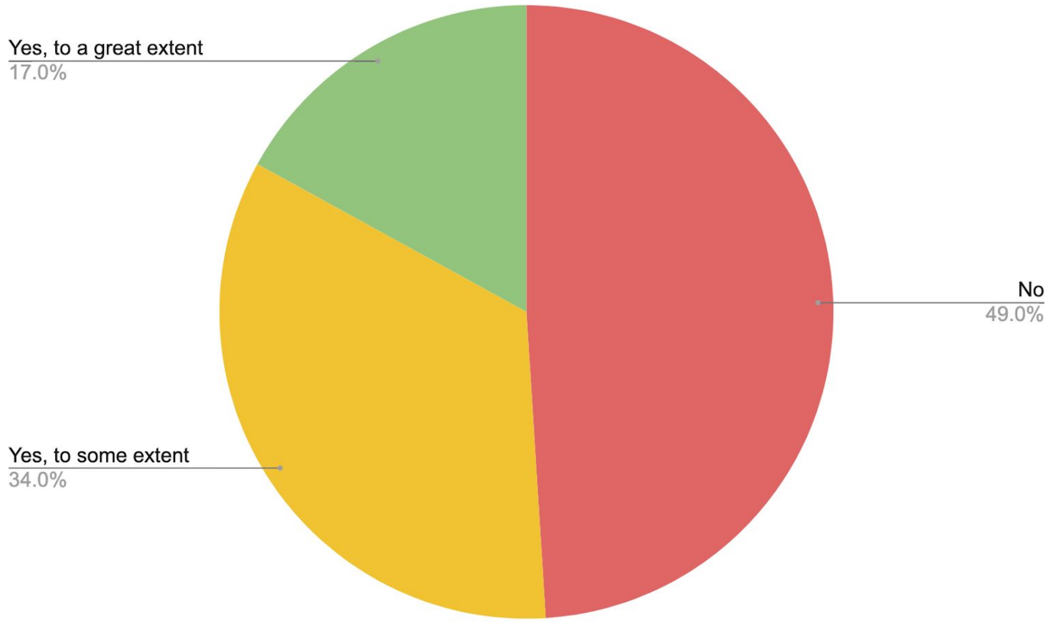

Figure 4.11 Aggregated answers towards the question “Do transportation related issues play a role in your decision to work remotely?”

Moreover, putting job flexibility at a higher priority has become more essential due to the pandemic of COVID-19, which significantly transformed the working patterns and changed the way both employees and employers perceive job flexibility, especially telecommuting. As of MIT, most of the teaching, research, and administration activities have been moved online to reduce physical interactions, and the university has put huge efforts towards making this transition as smooth as possible. It is necessary to review how the situation of job flexibility is reported in the 2014, 2016, and 2018 survey, and take this opportunity to plan for the post-pandemic future.

Table 4.10 indicates the flexibility of scheduling work hours and the frequency of remote working reported by the respondents of the 2014, 2016, and 2018 survey. We can see that, among all the respondents, more than 70% of them reported having the flexibility to schedule their work hours and this percentage has been slightly increasing in these three surveys. Since some employees types such as support staff require a fixed working schedule, the percentage reported in the surveys were reasonable.

Furthermore, the increase of the frequency of remote working is more interesting. A clear drop of the proportion of the employees who never worked remotely occurred from 2014 (50%), to 2016 (47%), and finally in 2018 declined further (43%). At the same time, we can notice the proportion who work remotely 1-8 times a month has increased significantly, while the proportion who work remotely more frequently stayed steady. This trend was likely because the benefits of telecommuting have been more and more recognized by both employers and employees, and this working manner has been more and more accepted. Also, a more open and enthusiastic attitude towards telecommuting and flexible work schedules can be expected after the recovery from the pandemic.

Table 4.10 Job flexibility and frequency of remote working

		2014 Survey	**2016 Survey**	**2018 Survey**
N		6,368.00	5,633.00	5,837.00
Flexibility	Flexibility in scheduling work hours	72.00%	74.00%	74.00%
How many times a month, on average, do you work from a remote location instead of on campus?	Never	50.00%	47.00%	43.00%
	1 to 4 times per month	35.00%	38.00%	41.00%
	5-8 times per month	8.00%	9.00%	10.00%
	9-12 times per month	3.00%	3.00%	3.00%
	More than 12 times a month	4.00%	3.00%	3.00%

Table 4.11 Job flexibility and percentage of SOV mode across employee types

	N	Flexible to schedule work hours	Percentage of SOV
Faculty	496	90.12%	29.04%
Research staff	2019	88.91%	15.90%
Administration, service, and medical staff	2298	67.06%	33.63%
Support staff	1024	51.86%	18,83%

4.9 Lessons for AccessMIT 2.0 and Commuting Survey Design

Examining the answers from successive MIT Commuting Surveys in 2014, 2016, and 2018, we can report the sustained impact of the AccessMIT program in motivating employees to choose more sustainable commuting modes and improving their commuting experience. However, the transportation services are still facing many challenges such as the lack of awareness. The following research explores how finer-grained transportation modeling can assist the design and implementation of next-stage TDM at MIT, by identifying distinct employee groups regarding commuting patterns and recommending actionable policy options. Informed by the results in this Chapter, the policy options are selected from the following categories:

- **Public transit benefits**
- **Carpooling programs**
- **Job flexibility and remote working**
- **Awareness campaign and promotional messages**

Also, in the analysis of survey results, we find that some improvements to the survey design may help the university better understand how the needs of employees and students are met. First, since the difference of satisfaction rates between employees and students has been identified by this research, we may recommend the Institutional Research to add a few questions to learn about the preferences of students, to be specific, whether similar benefits would be welcomed by the students. This can offer new insights valuable for next-stage TDM at MIT. In addition, several questions, especially the questions on awareness, usage, and satisfaction, mentioned a huge list of transportation services for the employees to evaluate, but did not provide explanations for each service. This, though, can be used as an opportunity of awareness campaign by attaching some basic information and a web link to each service. Several more suggestions for the survey design are offered in Chapter 5 since they are informed by the results that Chapter.

Chapter 5

Discrepancy between Self-Reported and Actual Commuting Behavior

As a common approach to investigate travel behaviors, survey-based travel diaries have been widely used in commuting behavior analysis. They have the advantage of simplicity and a wide coverage of different commuting modes, yet the accuracy of them are influenced by many underlying factors including self-images and misreporting. The discrepancy between self-reported commuting diaries and actual commuting behavior derived from passive mobility data was briefly mentioned by Rosenfield (2019) as a background of his RCT experiment on commuting mode shifts at MIT. This research takes advantage of both active and passive mobility data available to assess the discrepancy between self-reported and actual commuting behavior.

5.1 Sample Pool and Representation

The primary research sample pool we established for this research question is illustrated in Figure 5.1. Among ten-thousand MIT employees, 57% of them responded to the 2018 survey, which provides us the information about their self-reported commuting behavior. Then, 3753 of the survey respondents have actual commuting activities recorded during our research time period: September 16, 2018 to October 27, 2018, which were the six weeks before the launch of the 2018 survey, and also the first six weeks of Parking Year 2019 at MIT.

One important fact to notice here is that based on the responses to the 2018 survey, only 66% of the responding employees parked at MIT parking facilities. According to the traceability, we select a subset (Figure 5.2) of the research sample pool, the employees who reported they primarily parked at MIT parking facilities, to study the discrepancy between self-reported and actual parking activities.

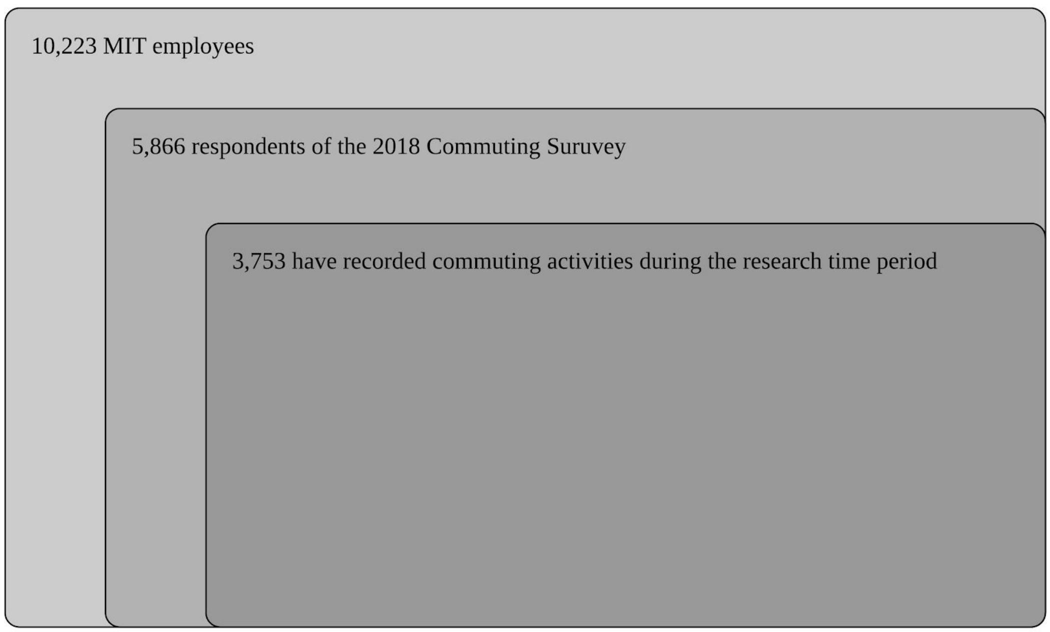

Figure 5.1 Composition of the primary research sample pool

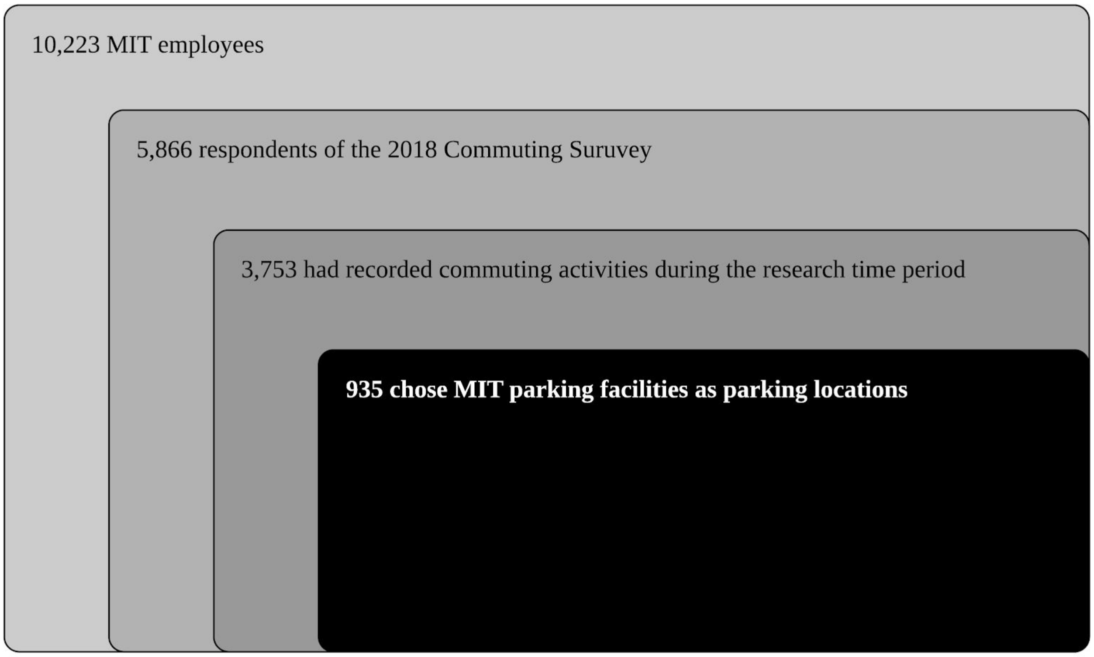

Figure 5.2 Composition of the designated sample pool for analyzing parking discrepancy

Similar to the last Chapter, the sample representation of the primary research sample pool is summarized and compared with the characteristics of all the MIT employees, which is indicated in Table 5.1.

Table 5.1: Sample Representation

		All MIT Employee	Sample
N		10223	3753
Female		44.80%	53.50%
Age	< 40	45.40%	56.40%
	40-59	36.70%	31.70%
	60+	17.90%	11.90%
employees type	Faculty	10.30%	8.10%
	Research	39.60%	37.90%
	Admin, service, and Medical	35.70%	34.60%
	Support	14.40%	19.40%

First of all, considering gender, age, and employee types, the primary sample has a roughly similar representation compared to all the MIT employees, yet, we can notice some difference between these two. As can be seen from Table 5.1, the primary sample has a higher female proportion, which is likely due to the higher survey response rates from females than males. Also, distinct response rates of different employee types explain the disparities of the proportions of them in the primary sample and all employees.

5.2 Parking and Transit Discrepancy Indices

As outlined in Chapter 3, the self-reported and actual commuting behavior are reconstructed utilizing different transportation datasets we collected for this research. The self-reported commuting behavior is represented by the commuting diaries extracted from the 2018 Commuting Survey, while the actual commuting behavior was captured by passive mobility data sets including gated parking records and transit tap-ins. Details about how the data is processed and how the indices are calculated are covered in this Section.

5.2.1 Self-Reported Commuting Behavior

Other than investigating the overall trends of commuting mode choices, the survey results also affords us to understand finer-grained commuting behavior via the self-reported commuting diary. Several questions were asked in the 2018 survey with the purpose to understand the patterns of weekday and weekend commuting activities, which includes:

- “Please indicate how you commuted to campus each day last week.”

- "On any day last week, did you travel back to your home from MIT using a different mode?"
- "How many days last week did you use a different method to get home?"

Since we are more concerned about the commuting behavior at a longitudinal time period, rather than the daily commuting variances, we aggregate the answers to the first listed question above into weekday and weekend, which are indicated in Table 5.2.

We can see that the shares of different commuting mode categories on weekdays aligned with the primary mode choices noted in the Chapter 4. For example, SOV was used by 22% of the respondents on an average weekday, while the proportion of the employees who chose SOV as their primary commuting mode categories was reported to 24.5%. However, the reported uses of other modes (e.g. "worked at home or other remote location" and "dropped off at work") were notably higher than those in the primary mode choices. This phenomenon was probably because these modes were regarded by a large group of employees as their secondary commuting modes. In addition, the occasional conditions might have contributed to this difference as well. Then, on the weekend, more than 70% of the respondents were off work , while another 30% employees still commuted to the campus via different modes.

Table 5.2 Proportions of different commuting mode categories reported for “last week” in the 2018 surveys

Commuting mode categories	Commute method	Weekday average	Weekend average
SOV	Drove alone the entire way	22.00%	5.50%
Public Transit	Drove alone, then took public transportation	43.00%	6.50%
	Walked, then took public transportation		
	Shared ride/dropped off, then took public transportation		
	Bicycled and took public transportation		
Carpool/Vanpool/Private Shuttle	Rode in a private car with 1-4 commuters	3.60%	0.00%
	Rode in a vanpool (5+ commuters) or private shuttle (e.g. TechShuttle, SafeRide)		
Bicycle	Bicycled	8.00%	2.00%
Walk	Walked	8.40%	3.00%
Others	Worked at home or other remote location	13.40%	11.00%
	Dropped off at work		
	Out of office (e.g., sick, vacation, jury duty, business trip)		
	Took a taxi or ride service (e.g., Uber, Lyft)		
	Other		
Scheduled Day off	Scheduled day off (e.g., weekend)	1.60%	71.50%

After analyzing the characteristics of the commuting diaries, we aggregate the data in a different way. We extract driving days and uses of public transit from the one-week long travel diaries and construct a self-reported weekly driving days and a self-reported weekly transit days for each respondent of this question. The distributions of this pair of self-reported commuting days are illustrated in Figure 5.3 and Figure 5.4.

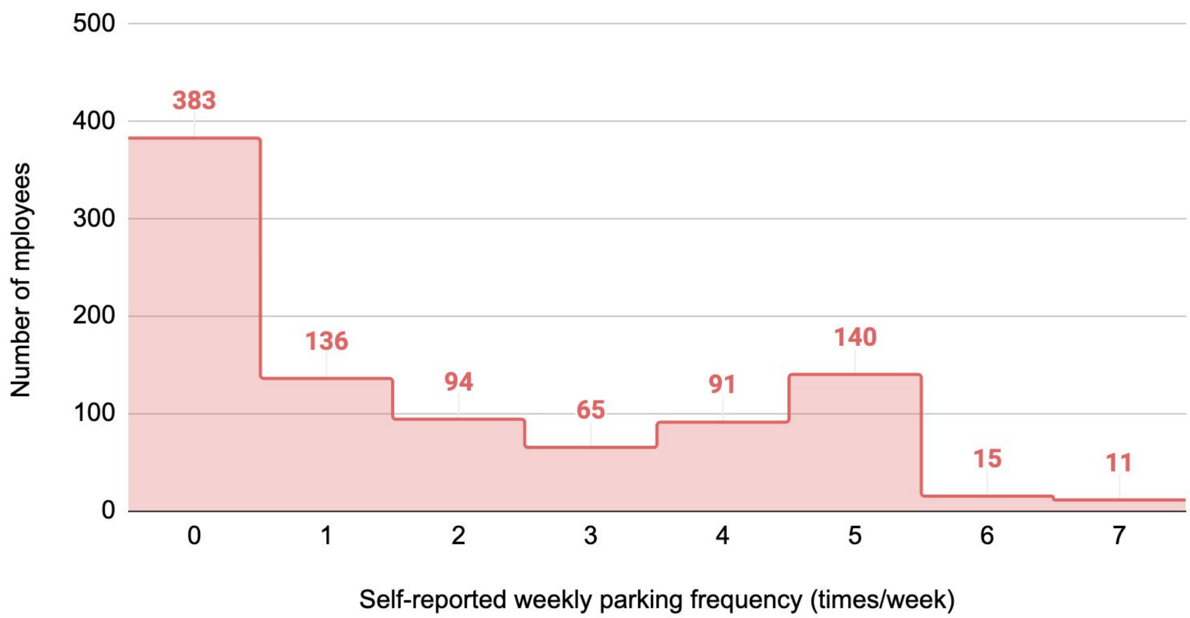

Figure 5.3 The distribution of self-reported weekly parking days

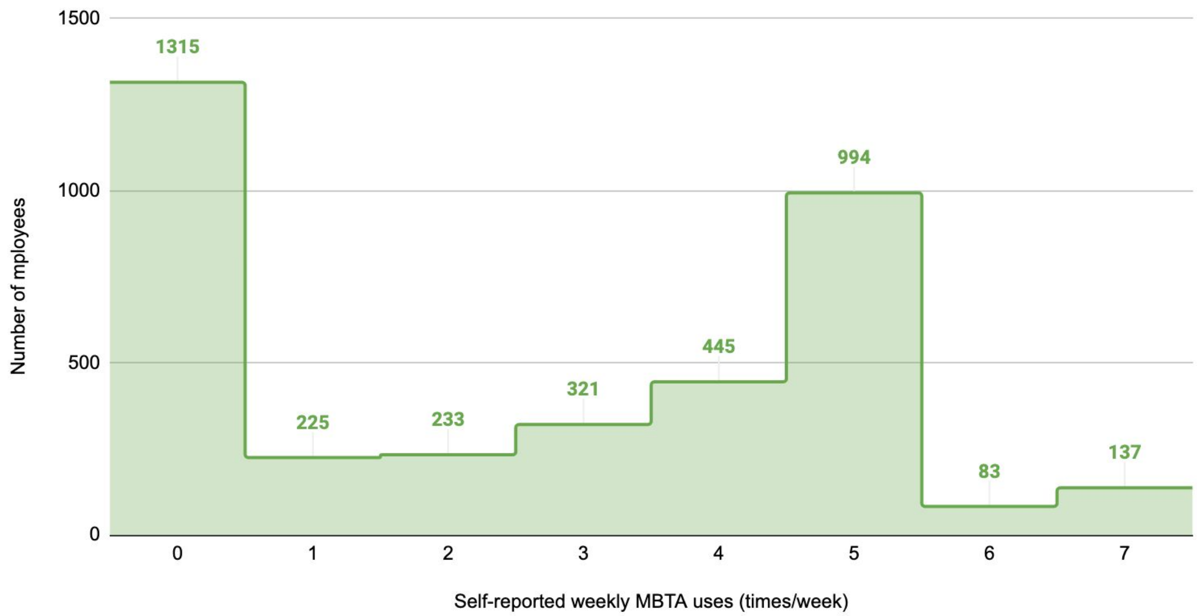

Figure 5.4 The distribution of self-reported weekly transit days

5.2.2 Actual Commuting Behavior

In this research, actual commuting behavior is measured using multiple passive mobility data sources, namely gated parking records (records of MIT gated parking) and transit tap-ins (smart card tap-ins at public transit stations and stops). To represent actual commuting behavior, we utilize the median of multi-week, namely 6-week, parking and transit frequencies rather than the data of the exact "last week" to alleviate the influence of the accidental error. To be specific, when being asked about behavior of the most recent week, employees were likely to report their travel activities of a normal week. Another factor contributing to our selection of this representation methodology is the various answering time of different employees, which made it infeasible to identify which week was the explicit "last week". Similar to the self-reported commuting frequencies, the distributions of represented actual self-reported commuting frequencies are illustrated in Figure 5.5 and Figure 5.6.

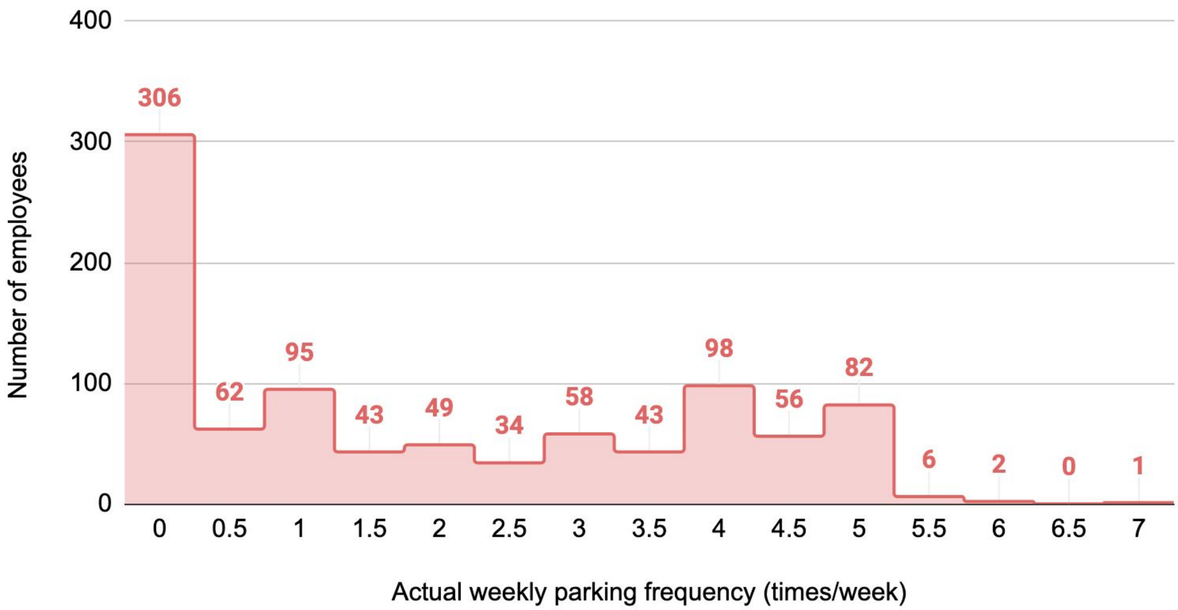

Figure 5.5 The distribution of actual weekly parking days

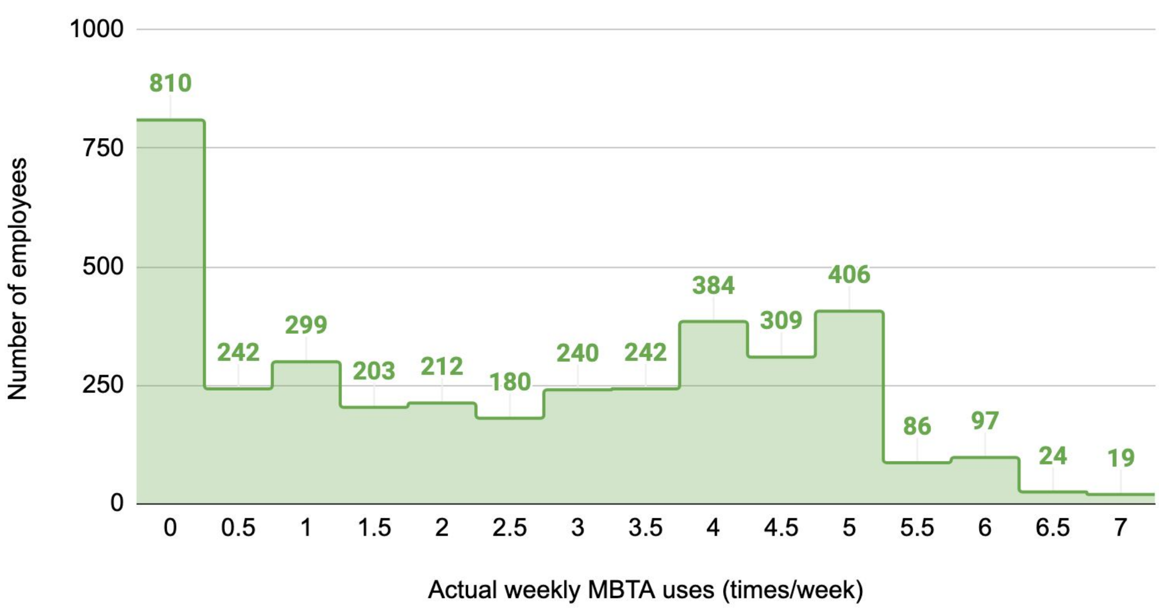

Figure 5.6 The distribution of actual weekly transit days

5.2.3 Parking and Transit Discrepancy Indices

By comparing the distributions of self-reported and actual parking/transit days, we can notice the similar patterns they have, yet smaller disparities around specific values. In order to quantify the discrepancies between these two sets of commuting data, we propose a methodology to measure these discrepancies at the individual level using a pair of discrepancy indices, which was introduced in Chapter 3.

Before diving into empirical analysis utilizing these indices, we visualize several anonymous examples of self-reported and actual commuting behavior by joining the two sets of data based on the unique user ID. Figure 5.7, Figure 5.8, and Figure 5.9 exemplifies three employees whose actual weekly parking days are notably lower, notably higher, and align with his/her self-reported weekly parking days. Similarly, three examples of the comparison of self-reported and actual transit days are visualized in Figure 5.10, Figure 5.11, and Figure 5.12 following the same manner.

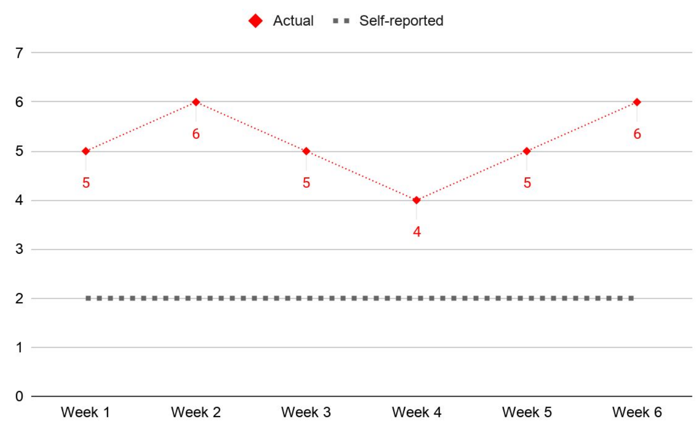

Figure 5.7 Self-reported and actual parking frequencies of example user 1

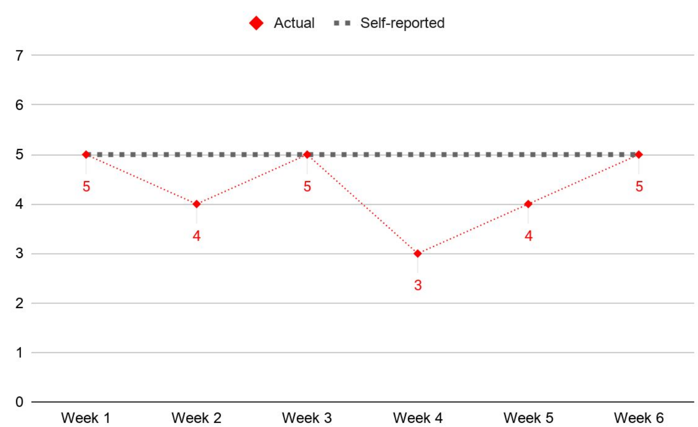

Figure 5.8 Self-reported and actual parking frequencies of example user 2

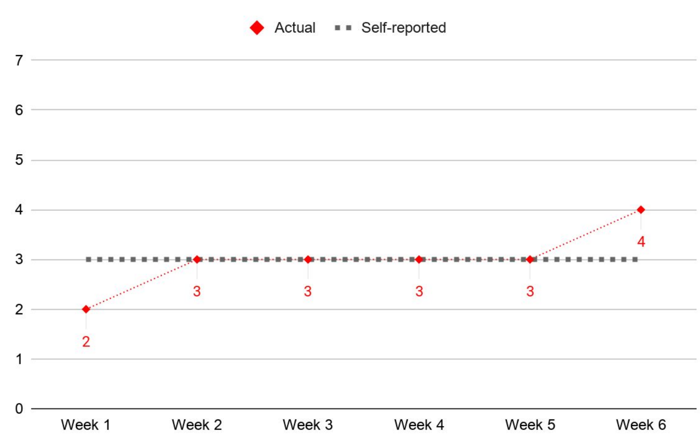

Figure 5.9 Self-reported and actual parking frequencies of example user 3

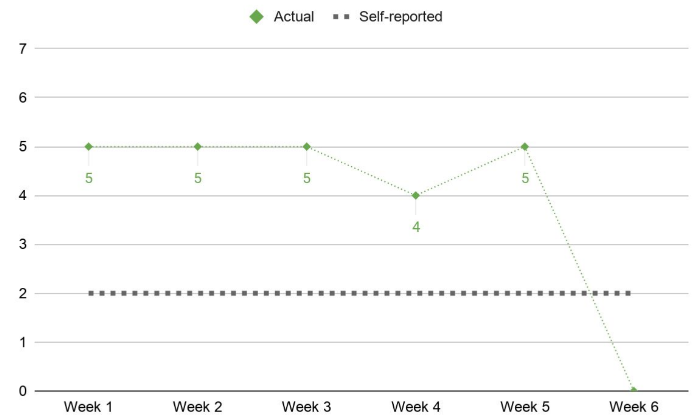

Figure 5.10 Self-reported and actual transit frequencies of example user 1

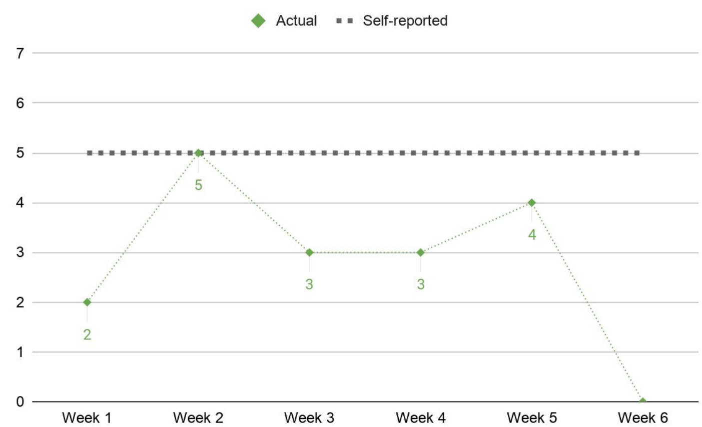

Figure 5.11 Self-reported and actual transit frequencies of example user 2

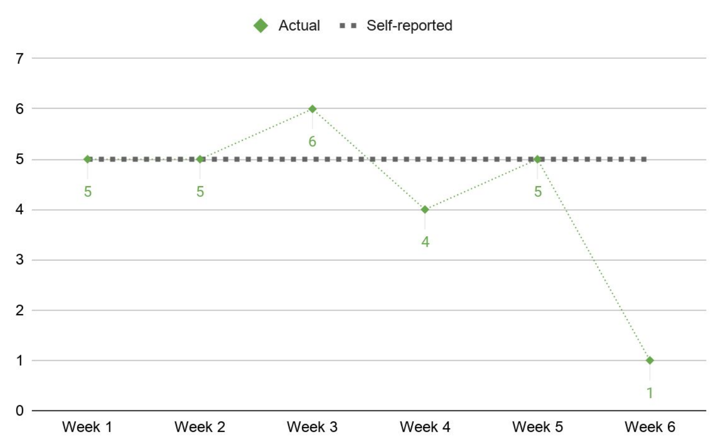

Figure 5.12 Self-reported and actual transit frequencies of example user 3

In order to quantify the discrepancy between self-reported and actual parking days and that between self-reported and actual transit days, we propose a pair of indices denoted in equation (1) and (2) in Chapter 3, which are revisited below.

$$\Delta p, m \ = \ Ap, m \ - Sp, m \tag{1}$$

$$\Delta t, m \ = \ At, m \ - St, m \tag{2}$$

The distributions of PDI and TDI are illustrated in Figure 5.13 and Figure 5.14, from which we can observe several interesting facts. Firist, 31.7% employees in the parking sample pool and 40.7% employees in the transit sample pool (primary sample pool) have, respectively, zero TDI and PDI value, which means that they reported exactly the same as their actual commuting behavior defined by our methodology. Second, the distributions of these two indices roughly align with normal distributions, and they are more concentrated in the center where the value is relatively small. Therefore, these facts means a majority of our sampled employees are not reporting very disparately from their actual commuting behavior. As a result, the self-reported commuting behavior extracted from the Commuting Surveys is good for understanding the overall trend of commuting activities of employees. However, more than a half values that differ from 0 can be seen in the PDI and TDI distributions, which requires more detailed investigations.

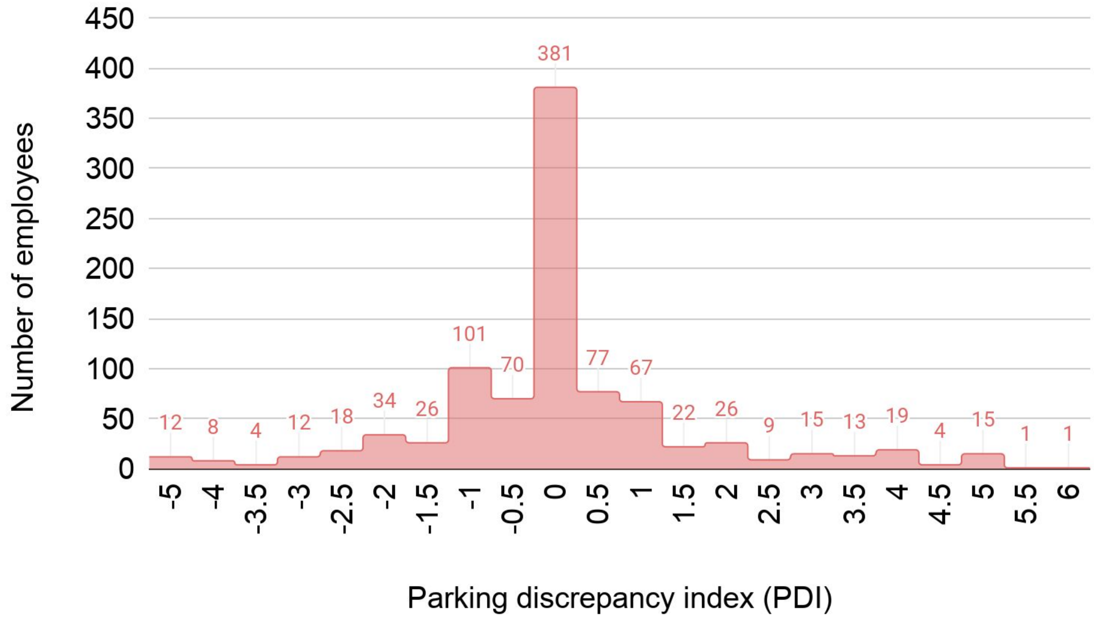

Figure 5.13 The distribution of parking discrepancy index (PDI)

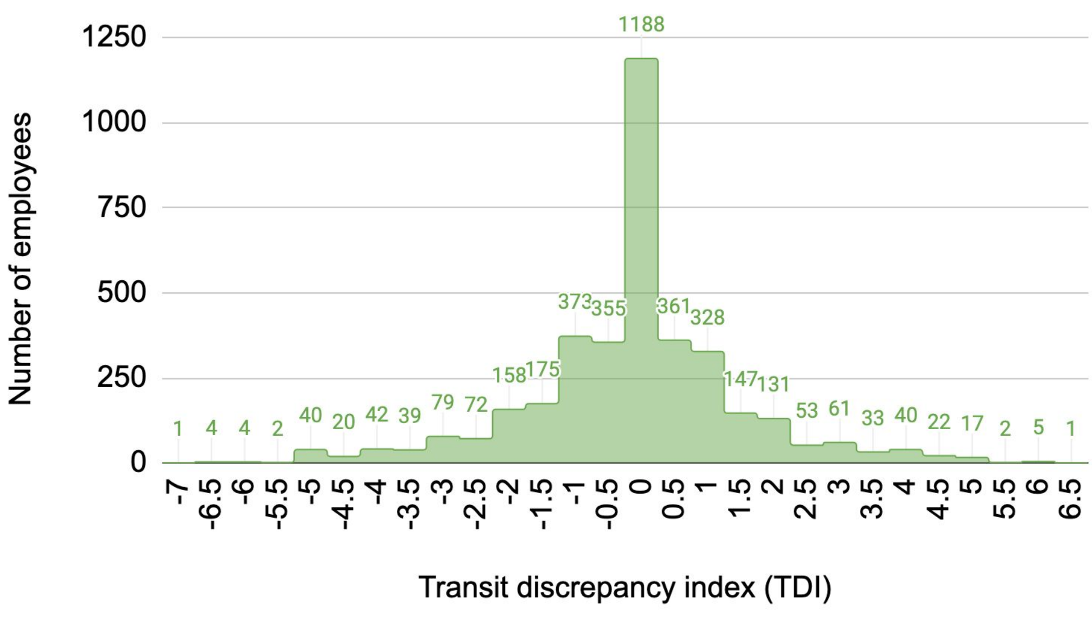

Figure 5.4 The distribution of transit discrepancy index (TDI)

5.3 Multivariate Linear Regressions (MLR) for Discrepancy Indices

Despite the fact that PDI and TDI of the majority of the sampled employees are among the [-2, 2] range, we still do not who reported higher, while who underestimated their commuting activity frequencies. However, this information is essential to determine either self-reported commuting behavior or actual commuting behavior is more suitable for the research scenario. In order to identify what are the factors correlated with the discrepancies, we employ a series of multivariate linear regressions (MLR) in this Section.

Focusing on the individual characteristics rather than occasional factors, four broad dimensions of attributes have been proposed as likely correlates of parking and transit discrepancy index (PDI & TDI):

- socio-demographic attributes such as gender, age, employee types, and hiring time
- commuting mode related attributes such as primary mode choices, and stated mode shifts
- attitudinal characteristics including expected mode shift for next year, satisfaction, and working flexibility
- ground truth of actual weekly parking and transit frequency

5.3.1 Results of PDI Regressions

The results from the MLRs of PDI are indicated by Table 5.3. From these regressions, first we can see that primary modes are the main factors correlated with PDI, since they show significant correlations in all of the regressions. It is interesting to notice that the choice of SOV has a negative coefficient across the three models, which is probably because the employees who chose SOV as the primary mode had a better sense of how frequently they drive. Then, employee types, specifically whether faculty or not, is correlated with PDI under the circumstance that no covariates are introduced. In this model, faculty tended to park more than their reported parking frequency, compared to other employees types. Other socio-demographic attributes such as gender and age are not suggested to be significantly correlated with PDI.

Among the attitudinal characteristics including intention to change to another commuting mode next year, job flexibility, and overall satisfaction, job flexibility dummy shows significance in the mode with mode-related and attitudinal covariates and the model with all covariates. The employees who had flexibility in scheduling their work hours tended to park more than their reported frequency. In addition, the actual weekly parking frequency (medain_parking) is positively associated with PDI.

Table 5.3 Regression analysis of PDI (N = 913)

	PDI	PDI with mode-related covariates	PDI with mode-related and attitudinal covariates	PDI with all covariates
(Intercept)	0.168	1.764***	1.818***	-0.063
isFemale	0.032	0.004	0.009	0.060
isOver60	0.011	-0.014	-0.007	0.146
isFaculty	**0.444***	0.327.	0.194	0.131
isSupport	0.024	0.020	-0.102	-0.089
isAdmin	-0.079	-0.027	-0.092	-0.074
isRecentHire	-0.205	-0.228.	-0.217	-0.115
isSOV		**-2.166*****	**-2.184*****	**-2.873*****
isTransit		**-1.565*****	**-1.563*****	**-0.543*****
isActiveMode		**-1.461*****	**-1.460*****	**-0.358***
changeLastYear		-0.030	-0.026	0.128
changeNextYear		0.246.	0.230	**0.230***
isFlexible			**0.285***	**0.275****
isSatisfied			-0.215	0.038
median_parking				**0.653*****
R-squared	0.020	0.190	0.200	0.510
Adj R-squared	0.010	0.180	0.190	0.500
For the hiring time dummy, "isRecentHire" means the the hiring time is shorter than 10 years				
*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.10				

5.3.2 Results of TDI Regressions

Similarly, Table 5.4 indicates how TDI is associated with these four categories of exploratory factors. Primary commuting modes were shown to have high level of statistical significance associated with TDI. Among the three mode category dummies, the SOV dummy and the public transit dummy are negatively correlated with TDI in the model with mode-related covariates and the model with mode-related and attitudinal covariates. This indicates employees who chose these two modes as their primary commuting modes tended to use public transit less than they reported, compared to the reference case: “other” modes. In addition, the mode shift dummy (changeLastYear) is also found to be negatively associated with PDI in these two models.

Compared to PDI, more socio-demographic attributes were found associated with TDI. Employee types were shown to be significantly correlated with TDI under the circumstance that the actual transit days are not included as a covariate. Notably here, age and gender are also identified to be associated with TDI in the complete model; to be specific, female and elder employees tended to use public transit more than they reported. Similar patterns were not found in the models of PDI.

Among attitudinal variables, only the satisfaction dummy was found negatively correlated with TDI in the complete model, indicating these variables were less correlated with the transit discrepancy. In addition, the actual weekly transit days are shown to have statistical significance associated with TDI, with a positive coefficient.

Table 5.4 Regression analysis of TDI (N = 3624)

	TDI	TDI with mode-related covariates	TDI with mode-related and attitudinal covariates	TDI with all covariates
(Intercept)	-0.121	0.722***	0.819***	-0.132
isFemale	-0.050	-0.001	-0.003	**0.111 ***
isOver60	0.095	0.145.	0.147.	**0.246*****
isFaculty	0.016	**-0.302*****	**-0.302****	0.180.
isSupport	-0.035	**-0.225****	**-0.2259****	-0.036
isAdmin	-0.109	**-0.197****	**-0.196****	0.051
isRecentHire	0.117	0.090	0.092	0.018
isSOV		**-0.552*****	**-0.557*****	-0.003
isTransit		**-1.132*****	**-1.124*****	**-2.431*****
isActiveMode		0.123	0.128	**0.192***
changeLastYear		**-0.213****	**-0.212****	-0.051
changeNextYear		-0.106	-0.111	-0.028
isFlexible			-0.011	0.080
isSatisfied			-0.109	**-0.266*****
median_MBTA				**0.579*****
R-squared	< 0.01	0.120	0.120	0.390
Adj R-squared	< 0.01	0.120	0.120	0.380
For the hiring time dummy, "isRecentHire" means the the hiring time is shorter than 10 years				
*** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.10				

5.4 Discrepancy Indices of Different Employees Groups

Informed by the regression results introduced in the last Section, PDI and TDI are shown to be significantly associated with various mode-related, socio-demographic, and attitudinal attributes. In this Section, we separate the primary research sample and the parking research sample into multiple groups following employees' primary mode choices and employees types, which were found to have statistical significance correlated with the commuting discrepancies.

Table 5.5 shows how PDI varies across different employees types and primary mode choices. As can be seen from the table, PDI of different groups is largely different. For example, faculty as a group have the highest average PDI among all four employees types, while administration, service, and medical staff have the lowest. This result also aligns with the insight offered by the regression results of PDI. Regarding the results of different primary commuting modes, it is interesting to notice the very high average PDI ($PDI_{Carpooling} = 2.2$) of the employees who chose carpooling as their primary commuting mode, especially considering the distribution of PDI.

As discussed in earlier Chapters, some of this difference among groups may be due to mis-reporting or self-image bias, but this may not explain the reason why the average PDI of carpoolers is 2.7 higher than that of SOV drivers. After reviewing the questions asked in the Commuting Surveys, we think this phenomenon is very likely that the commuting dairy related questions are not very clear for carpoolers, which made them confused or misreporting the numbers. Also, TDI of different employees groups is indicated in Table 5.6.

Therefore, we can see that the discrepancies between self-reported and actual commuting behavior is not substantial when looking at all MIT employees , but it vary largely among different groups of employees . While the self-reported commuting behavior can be useful for understanding the overall trends of employees commuting activities, actual commuting behavior derived from passive mobility data is more suitable to design targeted TDM programs based on an accurate observation of individual commuting activities.

Table 5.5 PDI of different employees groups

N = 935*		
Employee type	Number of employees	PDI
Faculty	155	**0.500**
Research	245	0.039
Admin, Service, and Medical	411	-0.068
Support	117	0.043
Total	928	0.058
Primary commuting mode categories	Number of employees	PDI
Drive alone the entire way	361	-0.525
Take public transportation (4 items)	366	0.075
Carpool (2 items)	94	**2.202**
Bicycle	50	0.090
Walk	38	0.382
Other (4 items)	25	-0.300
Total	934	0.058
* 7 of 935 have no employee types recorded, and 1 of 935 has no primary commuting mode reported.		

Table 5.6 TDI of different employees groups

N = 3753*		
Employee type	Number of employees	PDI
Faculty	298	-0.012
Research	1394	-0.057
Admin, Service, and Medical	1271	-0.144
Support	714	-0.048
Total	3677	-0.105
Primary commuting mode categories	Number of employees	PDI
Drive alone the entire way	440	0.019
Take public transportation (4 items)	2174	-0.555
Carpool (2 items)	134	0.354
Bicycle	403	0.433
Walk	454	0.926
Other (4 items)	108	0.875
Total	3713	-0.105
* 76 of 3753 have no employee types recorded, and 40 of 935 has no primary commuting mode reported.		

5.5 Lessons for AccessMIT 2.0 and Commuting Survey Design

5.5.1 Comparison Between Two Sets of Commuting Data

According to the distribution of the discrepancy indices, a major proportion of the employees at MIT reported approximately similar to their actual commuting behavior, which is true for both gated parking and public transit. Thus, the survey-elicited commuting diaries are reliable for understanding the overall trends and conditions, and they are particularly useful for investigating some specific modes such as walk and bicycle, which are not currently captured by passive mobility data. However, for finer-grained transportation modeling, especially for target TDM program design and policy recommendations, the bias of self-reported commuting behavior is not negelectable, regarding the large difference between employee groups.

Other than the group difference, which makes it hard to overcome the self-reported bias, another important advantage of actual commuting behavior motivates us to use it in segmenting commuting behavior clusters among MIT employees. It can quantify and represent the longitudinal commuting behavior patterns including changes of commuting frequencies and mode shifts, while self-reported commuting behavior only afford the static situation. This application of actual commuting behavior is elaborated in Chapter 6.

In addition, since the passive mobility data used to reconstruct actual commuting behavior is “naturally” created and recorded by the transportation systems, it is easy and not expensive to collect and can be collected at any time while the survey data can only be collected annually or even longer.

5.5.2 Suggestions for Commuting Survey Design

The discrepancies between self-reported and actual commuting behavior also inform us to improve the design of the MIT Commuting Survey. First, the differences inspire us to rethink the question on commuting diary. For example, either a reminder of actual commuting frequencies or the information about recent commuting behavior can be helpful for the employees to report more accurately. Also, a more targeted question for carpoolers may be helpful for alleviating the issue described in Section 5.4.

Chapter 6

Commuting Behavior Segmentation

As outlined in Chapter 3, we propose a methodology based on previous research to represent the longitudinal commuting behavior of individual employees and then employ *k-means* clustering analysis via PCA to segment commuting behavior clusters among diverse employees. Informed by the results from the last Chapter on the discrepancy between the self-reported and actual commuting behavior, we choose the actual commuting behavior as our primary data sources to investigate individual commuting activities and longitudinal patterns. In addition, based on the clusters we identify, actionable policy options are offered to inform next-stage TDM at MIT.

6.1 Sample Pool and Representation

As introduced in Chapter 3, the primary dataset available for this research is the gated parking records and transit tap-ins collected between September 16th 2016 and September 7th 2018 (MIT Parking Year 2017 and 2018). Figure 6.1 illustrates the primary research sample pool established for this empirical analysis. Among 10223 employees of MIT, 9230 of them have commuting activities recorded by passive mobility data in our dataset, either gated parking activities or public transit uses or both. Since the purpose of this research is more focused on changing SOV drivers' car uses towards more sustainable commuting modes including public transit, carpooling and active modes, we select the primary sample to only include employees who have at least one parking record in our research time period.

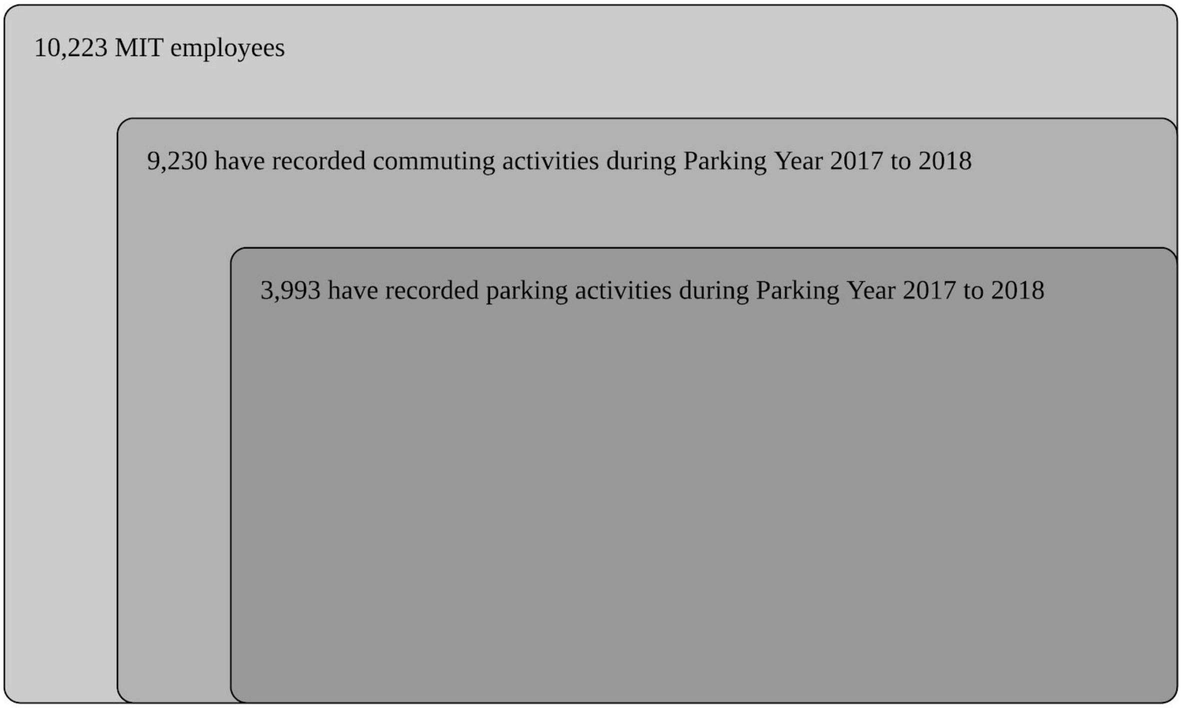

Figure 6.1 Composition of the primary sample pool

Then, similar to Chapter 4 and Chapter 5, this research summarizes the sample representation in Table 6.1, in which we compare the representation of the all MIT employees, that of the primary sample pool (cluster sample, N = 3993), and that of a smaller sample pool (profiling sample, n = 1193) for which socio-demographic and attitudinal attributes are available. As can be seen from Table 6.1, the representations of the clustering sample and the profiling sample are relatively resemblant, while they are slightly different with that of all MIT employees. Two samples we establish have relatively high percentages of female employees and notably high percentages of older employees than the holistic sample. In addition, administration, service, and medical staff take up more in these two samples, while research staff are less.

Table 6.1: Sample Representation

		All MIT Employee	Clustering Sample	Profiling Sample
N		10223	3993	1193
Female		44.80%	49.40%	53.20%
Age	< 40	45.40%	21.30%	12.30%
	40-59	36.70%	51.10%	54.10%
	60+	17.90%	27.60%	33.50%
employees type	Faculty	10.30%	16.70%	13.50%
	Research	39.60%	27.20%	23.80%
	Admin, service, and Medical	35.70%	46.20%	50.60%
	Support	14.40%	9.90%	12.20%

6.2 Consistency of Passive Mobility Datasets

Before applying the methodology to represent the longitudinal commuting behavior of the sampled employees , we first investigate the consistency of the two sets of passive mobility data. As the primary research objective in this Chapter is to identify commuting behavior segments among MIT employees, passive mobility data is aggregated by day and assigned the value 1 or 0. Thus, for any particular day, the following analysis investigates how many employees parked at MIT gated parking facilities and used public transit services.

Figure 6.2 illustrates the daily total amount of gated parking activities in MIT parking facilities recorded by the Department of Facilities at MIT. The horizontal axis denotes dates, whereas the vertical axis indicates daily parking amounts. In order to better observe the temporal patterns, weekends are removed from the graph. As can be seen from the graph, around 2000 to 2500 employees parked at MIT gated parking facilities on a normal school day. Then, parking at MIT had clear seasonal, monthly, and weekly patterns, which corresponds to school periods and holidays. For example, we can notice the clear yet smooth reduction in parking amount during the summer (from June to August), while large drop occurred during the winter break (January).

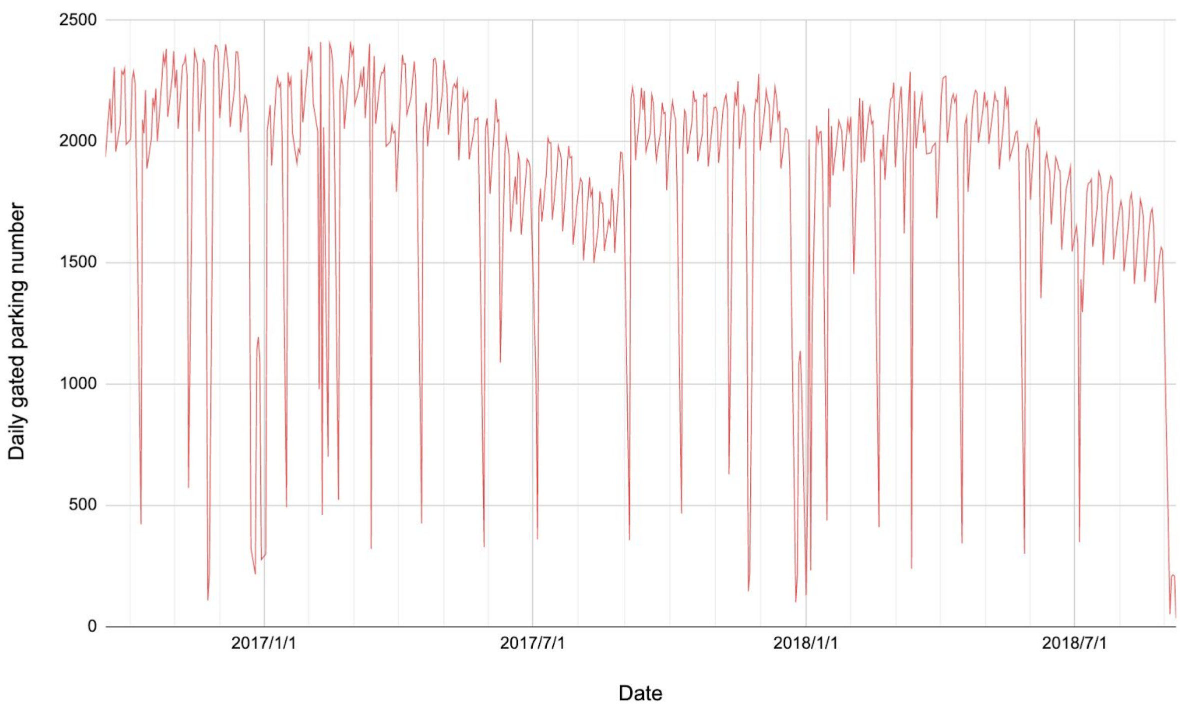

Figure 6.2 Daily gated parking numbers in MIT parking facilities for Parking Year 2017 and 2018

Similarly, the daily total of public transit users of MIT can be seen in Figure 6.3. The horizontal axis denotes dates, whereas the vertical axis indicates daily transit uses. Weekends are removed from the graph to reflect better temporal patterns. We can notice that, compared to parking records, the public transit data was notably less consistent, while seasonal and monthly patterns of class periods were still traceable. Moreover, public uses reflected by this data had some extremely low points, which may be caused by actual less commuting behavior or systematic errors of the public transportation services.

Among these low points, the most significant one is in November 2017, when a multi-day low value occurred. This was likely due to a systematic error or a transit health issue since no similar patterns are detected from the gated parking records.

Despite the fact that the consistency of the public transit data is not perfect, we utilized the complete dataset in the following representation and clustering process with two considerations. First, the detected inconsistency had the same impact on the commuting behavior data of all the sampled employees. Second, we want to explore whether the methodology we apply is able to capture this apparent temporal pattern in the clustering process.

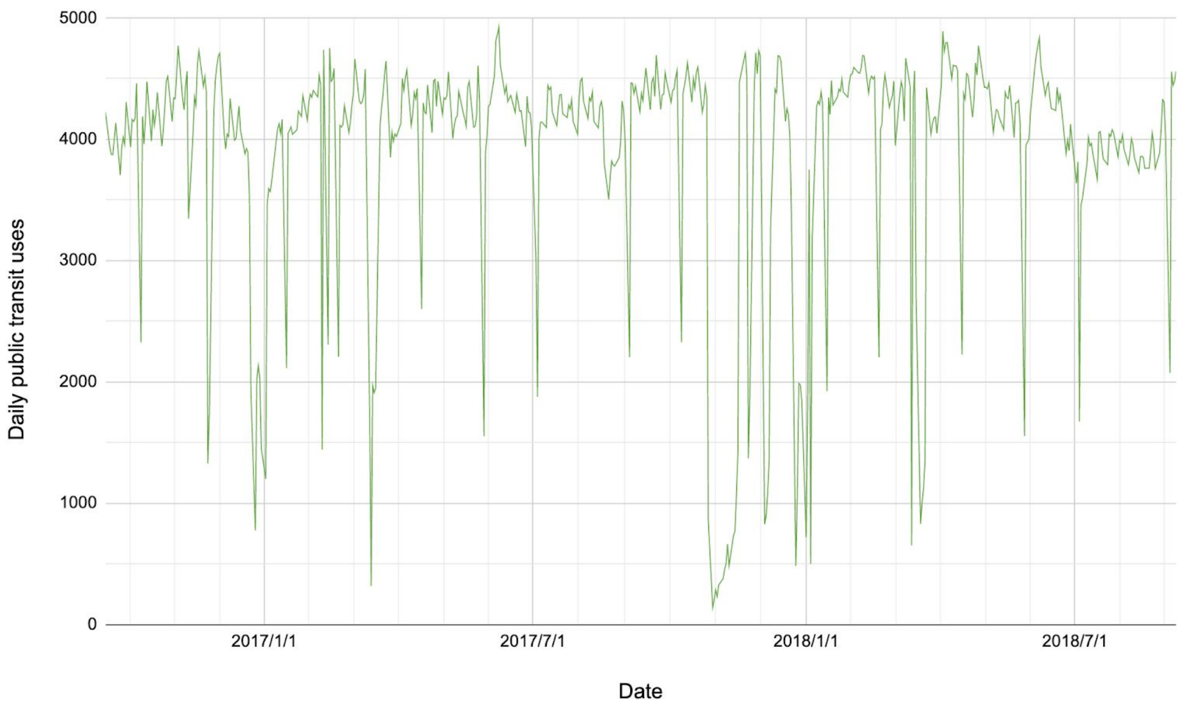

Figure 6.3 Daily public transit uses of MIT employees for Parking Year 2017 and 2018

6.3 Longitudinal Representations of Actual Travel Behavior

In order to identify the underlying heterogeneity among the users of MIT transportation services and cluster these users into meaningful and actionable commuting behavior segments, one of the key steps is to represent their commuting activities. As introduced in Chapter 5, actual commuting behavior derived from passive mobility data is more reliable than survey-explicit commuting diaries when conducting analysis on longitudinal commuting behavior at the individual level.

Thus, this research applies the representation methodology proposed in Chapter 3 to a sample of MIT employees using the passive mobility data we collect. As described before, the primary datasets available are gated parking records and transit tap-ins, which are exemplified in Table 6.2 and Table 6.3.

Table 6.2 Example gated parking record data

User ID	Date	Time	Parking Lot	Allowed
********	2017-09-21	09:50:22	West Gate	Yes
********	2018-02-22	17:20:30	West Gate	No

Table 6.3 Example public transit tap-in data

User ID	Date	Time	Station Code	Tap-in Allowed
********	2017-08-20	08:50:22	3005	Yes
********	2018-01-12	09:20:30	5170	No

We then clean the raw mobility datasets and aggregate individuals' commuting behavior by day, which results in a cleaned dataset shown in Table 6.4. In order to reconstruct individuals' commuting pattern as commuting sequences, a chain of commuting activities, the cleaned commuting behavior data is represented following the rules outlined in Section 3.2.3.

By applying this representation methodology, all commuting activities completed by an employee can be linked and be encoded as a longitudinal commuting sequence, which is a high-dimensional vector with categorical commuting statuses of 722 days. Values of these commuting status are assigned based on the rules and Table 3.3, resulting in the encoded commuting sequence. Figure 6.4 illustrates one-hundred examples of encoded commuting sequences, where the horizontal axis denotes dates; the vertical shows sample IDs. The commuting sequence of each employee is represented by one line of pixels in the graph, in which different colors indicates different commuting statuses: red - gated parking; green - public transit; yellow - both commuting activities; and grey - other modes.

It is interesting to notice the seasonal and monthly patterns of the commuting behavior of these random sampled employees, notably winter break, which is similar to what we describe for the total daily gated parking amount and public transit uses. Moreover, by comparing the commuting sequence across different employees via looking at the colors of different lines, we can see some underlying heterogeneity.

Table 6.4 Cleaned commuting behavior

User ID	Date	Gated Parking Record	Transit Tap-In
********	2017-08-20	1	0
********	2018-01-12	0	1

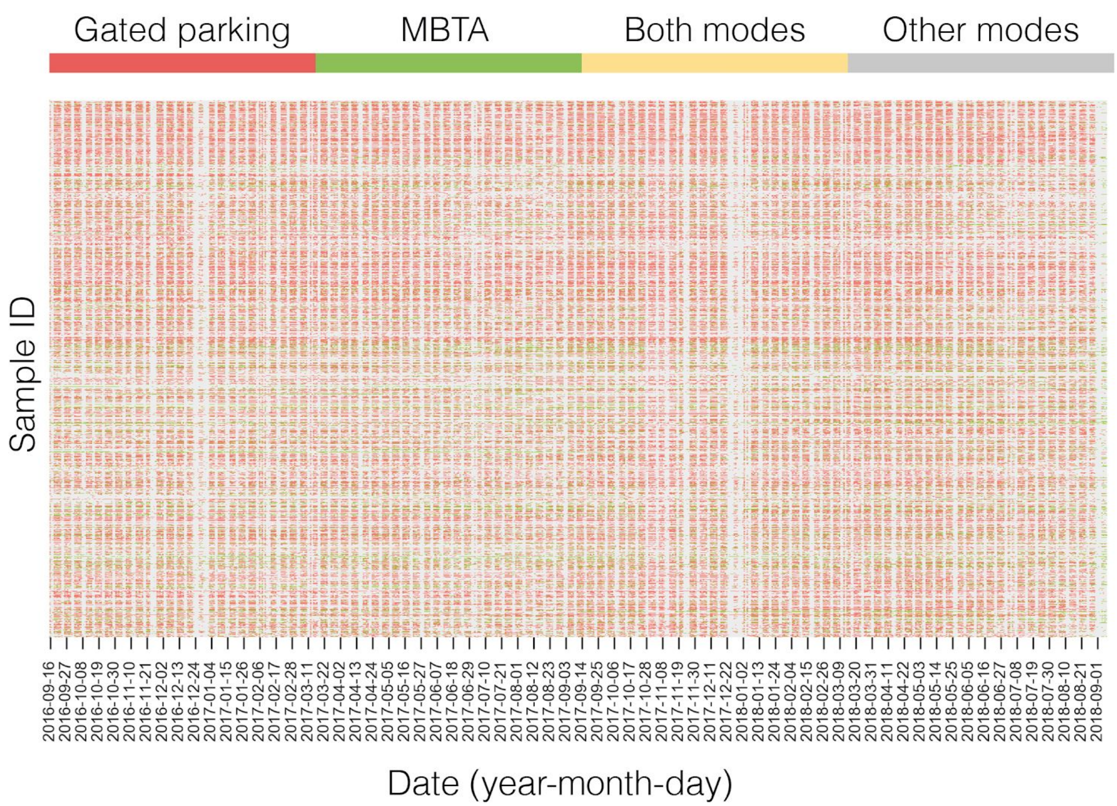

Figure 6.4 Example encoded commuting sequence

6.4 Eigen Sequences

In order to avoid exhaustive computation in employing *k-means* clustering onto high-dimension data, we apply a PCA process to generate the uncorrelated and independent components to reconstruct the encoded longitudinal commuting behavior as introduced in Chapter 3. For each employees in our primary research sample, the categorical vector with 722 elements is transformed into a binary vector with 722 x 4 elements since there are four possible commuting statuses for each day. Then, all vectors of our sample are assembled into a N x 722 x 4 matrix, where N denotes the sample size and is equal to 3993. Before feeding it into a PCA process to indicate the PCs, we standardize this binary matrix by subtracting the column mean from values in each column.

Figure 6.5 illustrates the percentages of explained variance of the first 15 PCs.As can be seen from the graph, the first 7 PCs are able to explain more than 99% of the variances of the original representation. Then, the commuting sequence matrix is reconstructed using these first 7 PCs and used to finish the *k-means* clustering process.

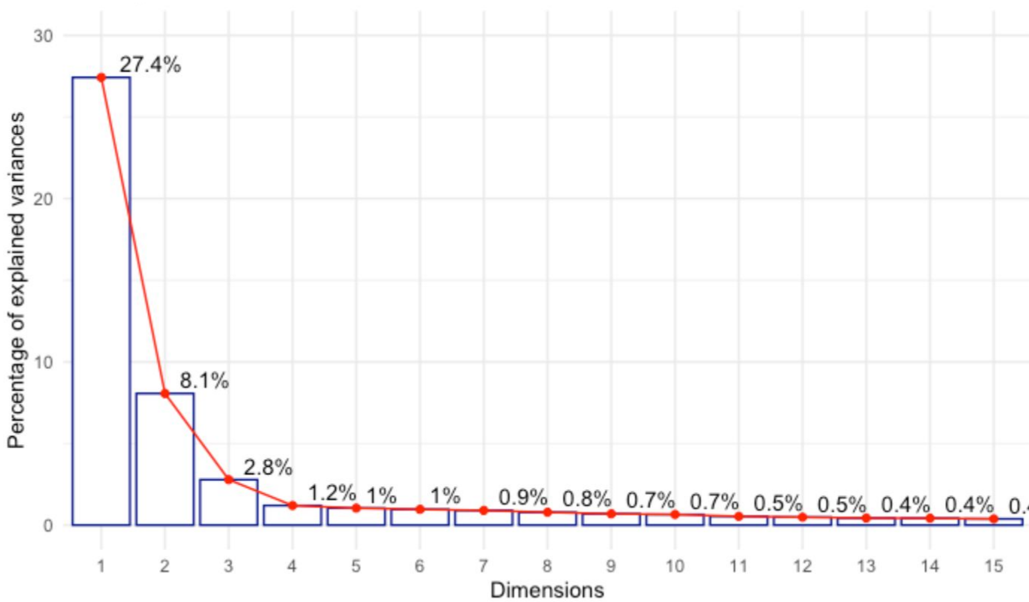

Figure 6.5 Percentages of explained variance of principal components

6.5 K-Means Clustering via PCA

The reconstructed matrix with the first 7 PCs of the commuting sequences of the clustering sample are then clustered utilizing a k-means clustering process. In order to determine the optimal k in the *k-means* clustering process, a *k-means*++ initialization approach is applied and k = 2 to 19 are tested. The performance of different k values are measured by the DB index (Davies and Bouldin, 1979) and the average Silhouette index (Rousseeuw, 1987). Figure 6.6 illustrates the DB index values of different k, for which lower value means better clustering results. In order to identify the diverse patterns of commuting behavior rather than grouping them by their primary commuting mode categories (6 commuting mode categories) or employees types (4 employees types), we choose the best DB index value for *k* larger than 6. As can be seen from the graph, the value of the DB index is at its minimum when *k = 9*.

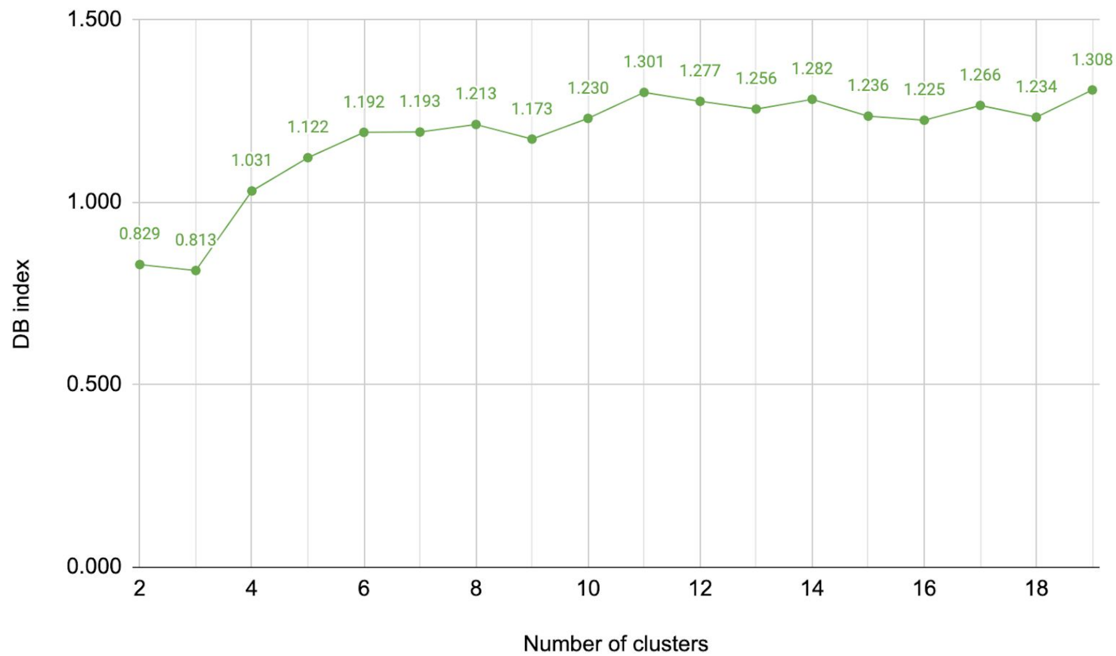

Figure 6.6 DB index for 7 principal components

Similar principle is applied when we evaluate the clustering performance using the Silhouette index illustrated in Figure 6.7, for which a larger value indicates a better clustering result. We can see the value of the Silhouette index reaches its high point when *k = 9*, under the circumstance that *k* is larger than 6. Hence, k = 9 is chosen as the optimal k for the k-means clustering process.

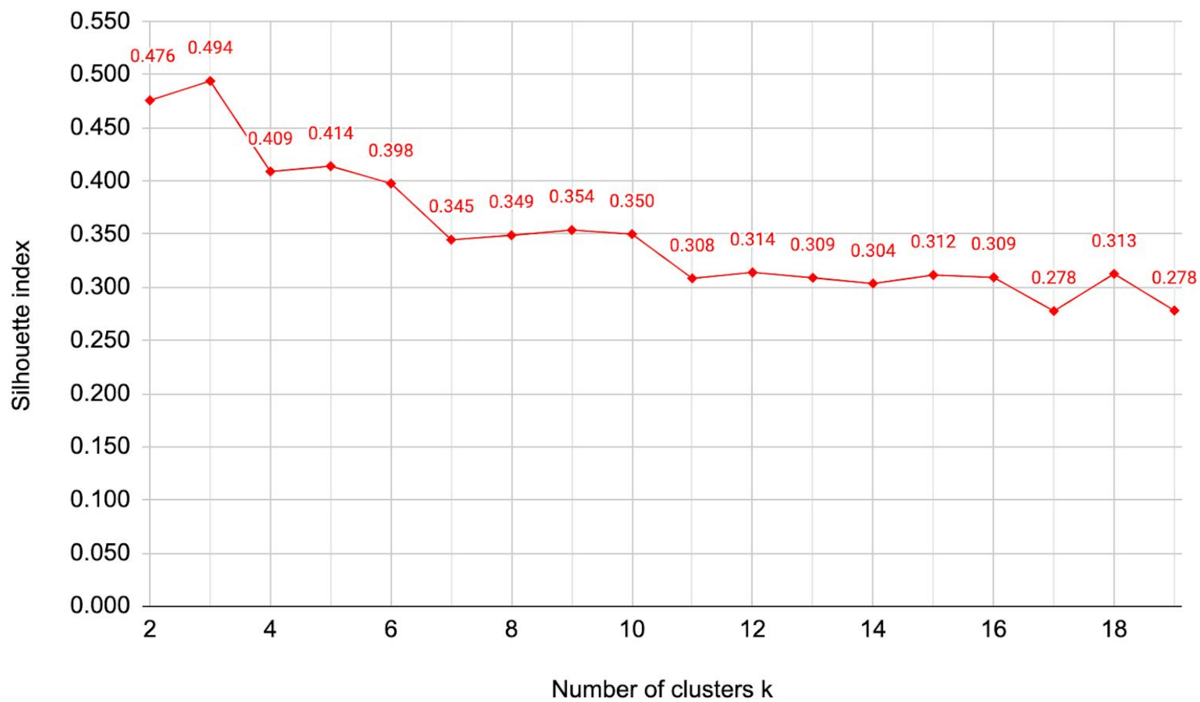

Figure 6.7 Silhouette index for 7 principal components

The 3993 employees are clustered into 9 commuting behavior segments based the underlying structure of their commuting sequences, and each cluster is associated with distinct commuting sequence patterns. The commuting sequence structures are visualized in Figure 6.8 following the color code introduced before. As can be seen from the graph, this methodology has the capacity to identify distinct commuting patterns such as Cluster 3: Determined Riders and Cluster 8: Addicted Drivers. Moreover, it is able to capture temporal evolution of commuting patterns including mode shifts: for example Cluster 1: Drive-less Explorers and Cluster 6: Unsatisfied New Drivers. Based on the structural similarity among these 9 clusters, they are classified into 5 larger sets: steady drivers, driving less, driving more, public transit users, and sparse commuters. The clusters are profiled using socio-demographic, attitudinal and commuting-related attributes in the following Sections.

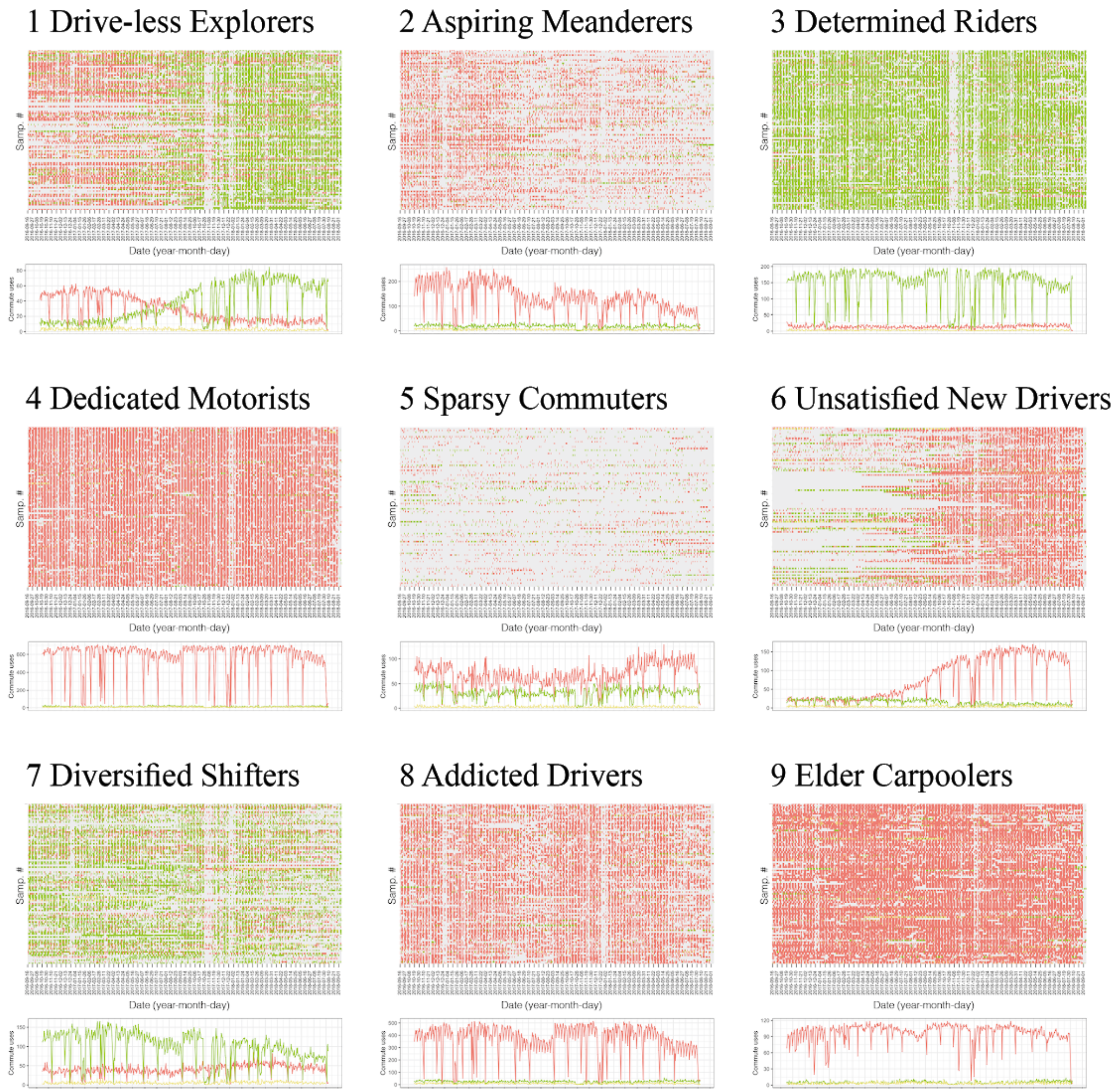

Figure 6.8 Commuting sequence structure and daily commuting patterns associated with each cluster

6.6 Profiling Commuting Behavior Clusters

In order to quantify the socio-demographic, attitudinal, and commuting-related characteristics commuting behavior clusters, we profile each cluster using the comprehensive data we collect for the profiling sample (n = 1193) from different departments at MIT. We introduce each cluster in the five larger commuting behavior sets and their characteristics in this Section.

6.6.1 Steady Drivers

This set includes 3 clusters: Cluster 4, 8, and 9. The employees segmented into these three clusters are basically consistent drivers but have different frequencies and temporal patterns, as well as distinct socio-demographic and attitudinal characteristics.

Cluster 4 (dedicated motorists):

Cluster 4, firstly, is marked by its second highest average weekly parking frequency at 4.23 (after cluster 9) and lowest average weekly public transit uses at 0.005. This indicates a clear dominance of driving activities in their commuting sequences, which can be seen from the commuting sequence structure in Figure 6.9. It is also interesting to notice that apparent seasonal and monthly pattern in their total parking amount every day, similar to what we have introduced in Section 6.2. Second, the aggregated home locations of this cluster indicates a substantial spatial pattern, which is indicated by a significant Moran's we value, suggesting a significant spatial autocorrelation. As we can see from the map, the majority of this cluster lives at a moderate to long distance from the campus. This is probably because either they chose to leave far since they could drive, or they cannot afford living close to the campus and they had to drive.

Third, we can see a relatively high percentages of support staff and administration, service, and medical staff in this cluster compared to those in the complete profiling sample, while faculty take up less seats. Forth, a majority (86.38%) of the employees in this cluster chose SOV as the primary commuting mode in the 2018 survey, the highest among all 9 clusters. This fact aligns with the commuting sequence structure described earlier.

In addition, we can notice the relatively low job flexibility as well as a limited use of remote working opportunities, which is likely due to the high percentage of support staff in this cluster. Finally, regarding the awareness and participation of MIT transportation services, this cluster has high awareness rates in all 5 categories, yet the participation is low to moderate, except for driving-related services. This may indicate that employees in this cluster either had limited flexibility in choosing among different options, or did not want to change.

Cluster 8 (Addicted drivers):

Compared to cluster 4, Cluster 8 has a visually less intense parking frequency pattern, with an average weekly parking frequency at 3.14, which is around 1 time less than “dedicated motorists”. Also, this cluster has largely different socio-demographic attributes, notably the second highest percentage of faculty in the 9 clusters.

Then, this cluster has relatively high job flexibility as well as high uses of remote working opportunities. The percentage of employees who never worked remotely is the lowest, indicating a larger freedom to schedule their own work for the employees . This may due to the higher percentage of faculties in this cluster than the average. It is interesting to note here the relatively high percentage of employees who might consider carpooling, suggesting relatively enthusiastic attitudes toward the potential carpooling programs.

In this cluster, over 49% of employees used flexibility-related services, which is 5% higher than the average value. However, the employees in cluster 8 had relatively low to moderate awareness rate among all five service categories.

In addition, it is interesting to notice the difference between the spatial patterns between cluster 4 and cluster 8. Both of these two clusters have a significant spatial autocorrelation, yet the employees in cluster 8 tended to live more concentrated and relatively closer to the campus. Furthermore, cluster 8 employees had a concentration in the census tracts of and around Lexington, which includes the richest census tracts surrounding the campus based on the 2018 American Community Survey.

Cluster 9 (Elder carpoolers):

Marked by its highest average weekly parking frequency (5.0) among the 9 clusters, cluster 9 is one of the most interesting commuting behavior segments we identify. It has the most disparate socio-demographic, attitudinal and mode-related attributes compared to the average value. Based on the highest faculty proportion (50%) with much lower other types, and the highest percentage of employees over 60, employees in these clusters can be profiled as a group of elder faculty. The spatial distribution of the home locations are visually sparse, yet has a significant spatial autocorrelation. This contrast may be due to the concentration of homes in Arlington and Medford.

More than 33% of the employees in this cluster reported carpooling as their primary commuting mode, which is 25% higher than the average value. Although this fact is not surprising if we take into consideration their concentrated home locations, it is still interesting to acknowledge a group that use carpooling extensively. Another fun fact about this cluster is their extremely low interest in the new carpooling program, which is probably because lots of employees in this cluster was already satisfied by the existing carpooling program. A relatively high participation rate of carpooling-related services may verify this assumption.

However, other than the services related to carpooling, employees in this cluster were less aware of other transportation services--let alone utilized them. Many factors might have contributed to this phenomenon. For example, older employees might check their email and other messages less frequently than young employees . Also, they might be less willing to shift among different modes, and, thus, they were less interested in learning about other services other than the ones they were using. Both of these implications suggest that some extra approaches may be necessary to improve the awareness rates among particular segments of employees , notably cluster 9.

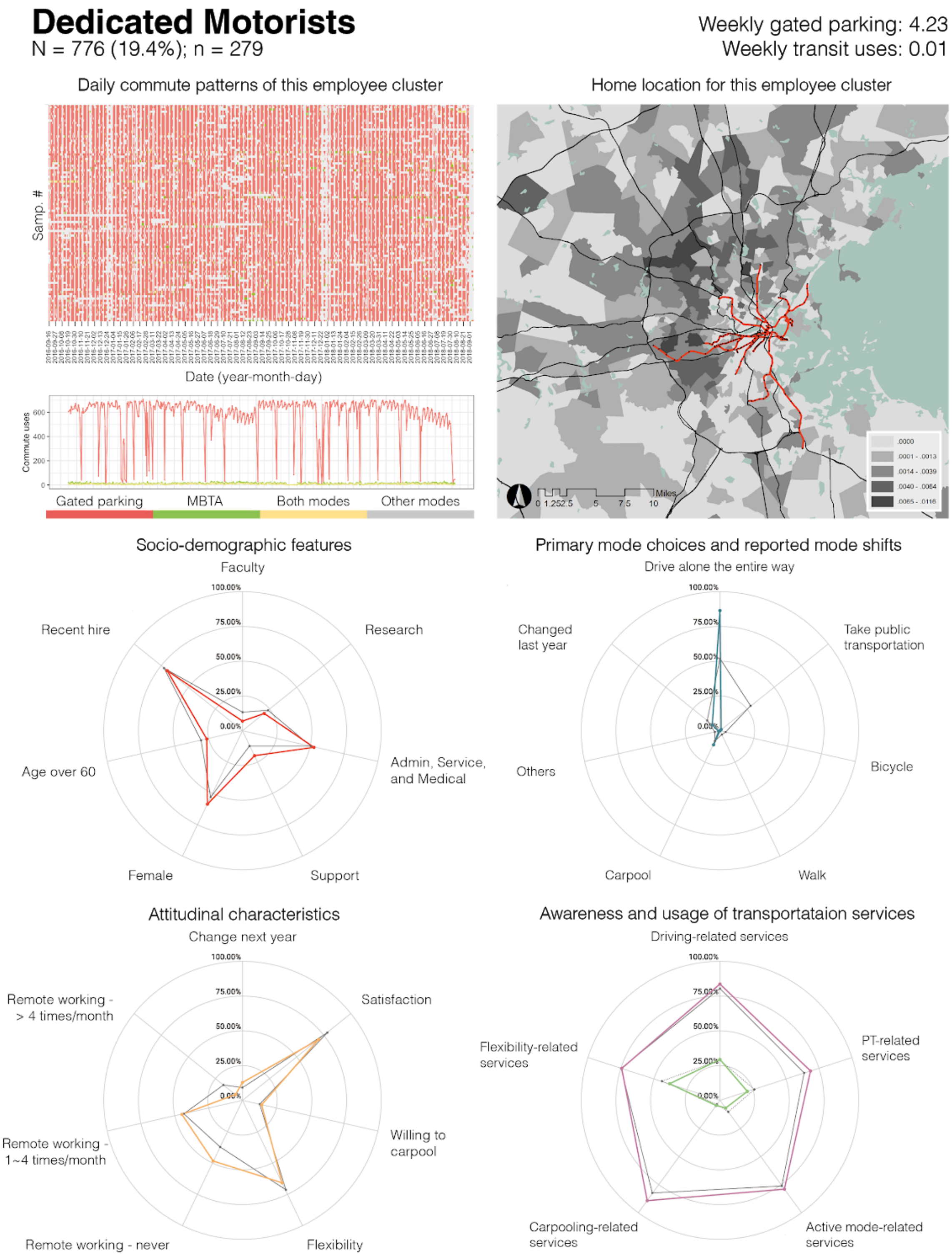

Figure 6.9 Commuting sequence structure and cluster profiling of cluster 4 (dedicated motorists)

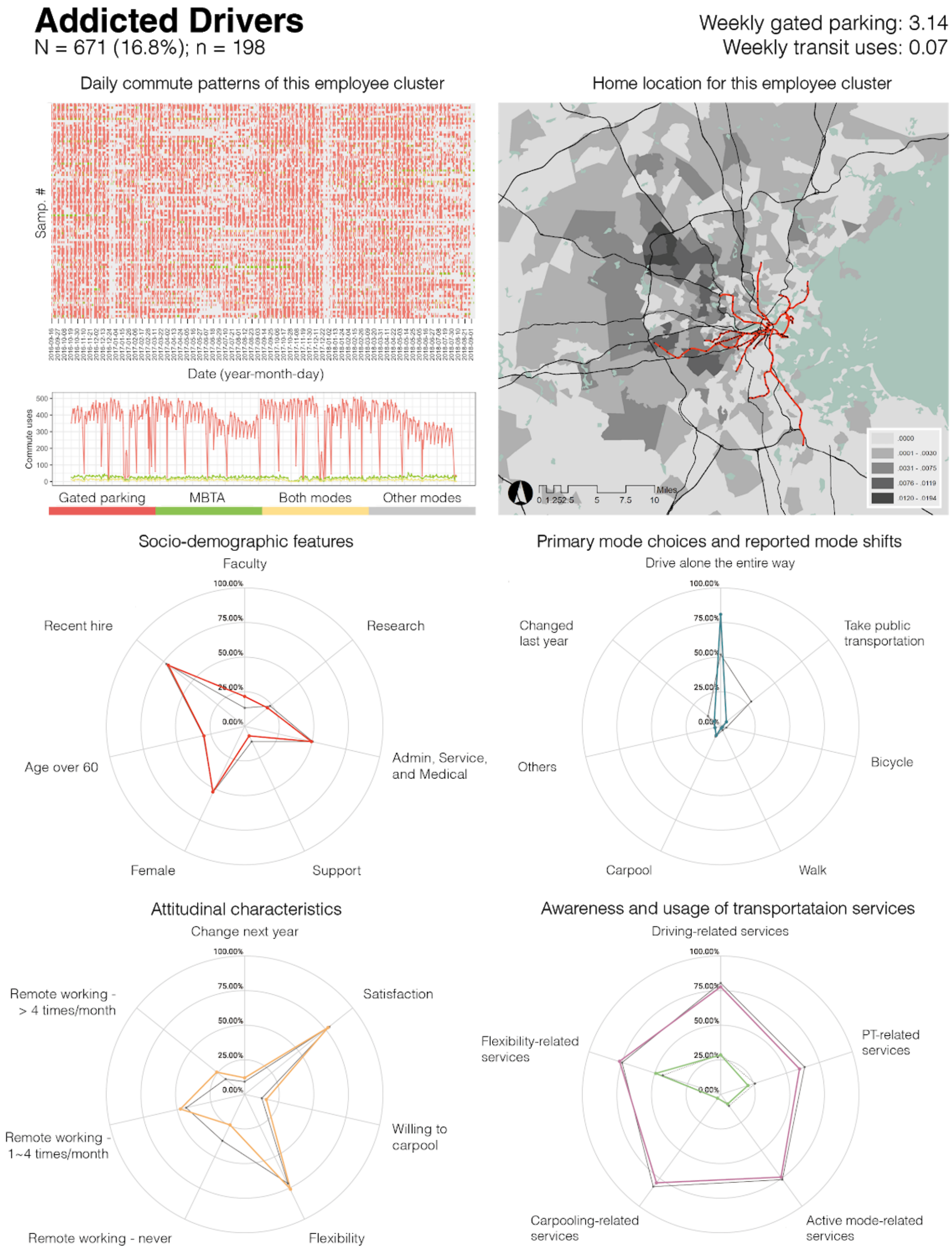

Figure 6.10 Commuting sequence structure and cluster profiling of cluster 8 (addicted drivers)

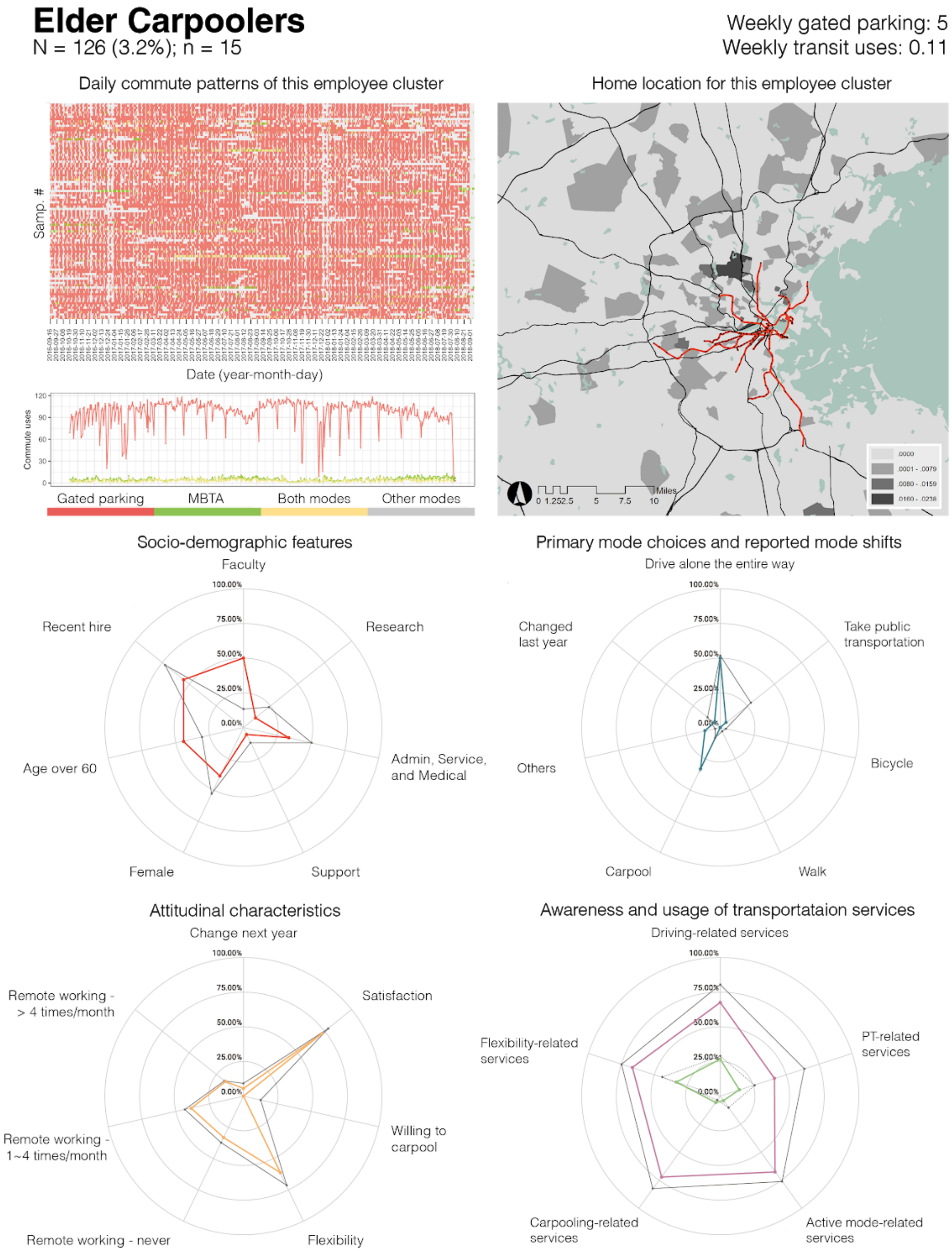

Figure 6.11 Commuting sequence structure and cluster profiling of cluster 9 (elder carpoolers)

6.6.2 Driving Less

This “driving less” set includes 2 clusters: Cluster 1 and 2. As discussed before, our proposed methodology is able to not only identify distinct temporal commuting patterns but also capture the changes of employees ’ commuting behavior.

Cluster 1 (Drive-less explorers):

Cluster 1 is noted by clear mode shifts, indicted by reduced parking amounts and increasing public transit uses. Via looking at the visualized commuting sequence structure and the temporal patterns of daily commuting activity numbers, we can find a majority of the employees in this cluster changed from driving (indicated by gated parking) to public transit, which is also justified by the stated mode shifts. To be specific, this cluster has the highest stated mode shifts and the second highest percentage of employees who chose public transit as primary commuting mode.

It is interesting to notice the relatively low percentages who occasionally or frequently worked remotely although this cluster has a moderate job flexibility rate. Moreover, this cluster has a relatively high awareness rate and participation rate of flexibility-related services. Hence, we can see the flexibility of this cluster involves more flexible working schedules rather than telecommuting. This fact is probably because of the relatively high percentages of support and administration, service, and medical staff in this cluster.

In addition, this is the only cluster that does not have a significant spatial autocorrelation of home locations.This fact is not surprising considering the visually sparse spatial distribution.

Cluster 2 (Aspiring meanderers):

Cluster 2 is also marked by a clear pattern of less driving activities, yet public transit uses stayed consistent. This trend indicates employees ' potential mode shifts to other modes. In addition, another possible scenario is some employees changed from gated parking at MIT parking facilities to outside parking facilities which were not included in our data.

An investigation of the spatial distribution of the home location may also support our hypothesis. As can be seen from the map in Figure 6.13, there are basically two spatially distinct group in this cluster. One of them lived relatively close to the campus and the other one lived substantially far from MIT. Moreover, the polarization of primary commuting modes (i.e., SOV and others) verify our assumption.

Different from cluster 1, this cluster has a relatively higher percentage of faculty and research staff, who might have more commuting mode options and the possibility to try out different commuting modes, as meanderers. With the highest job flexibility rate, employees in this cluster also had the highest percentage of frequently working remotely and a relatively higher of occasionally working remotely, which also indicates their freedom in scheduling their work and related commuting activities. In addition, it is interesting to note the larger enthusiasm towards new carpooling programs compared to the average level, and this characteristic is also used to inform targeted TDM programs for this cluster.

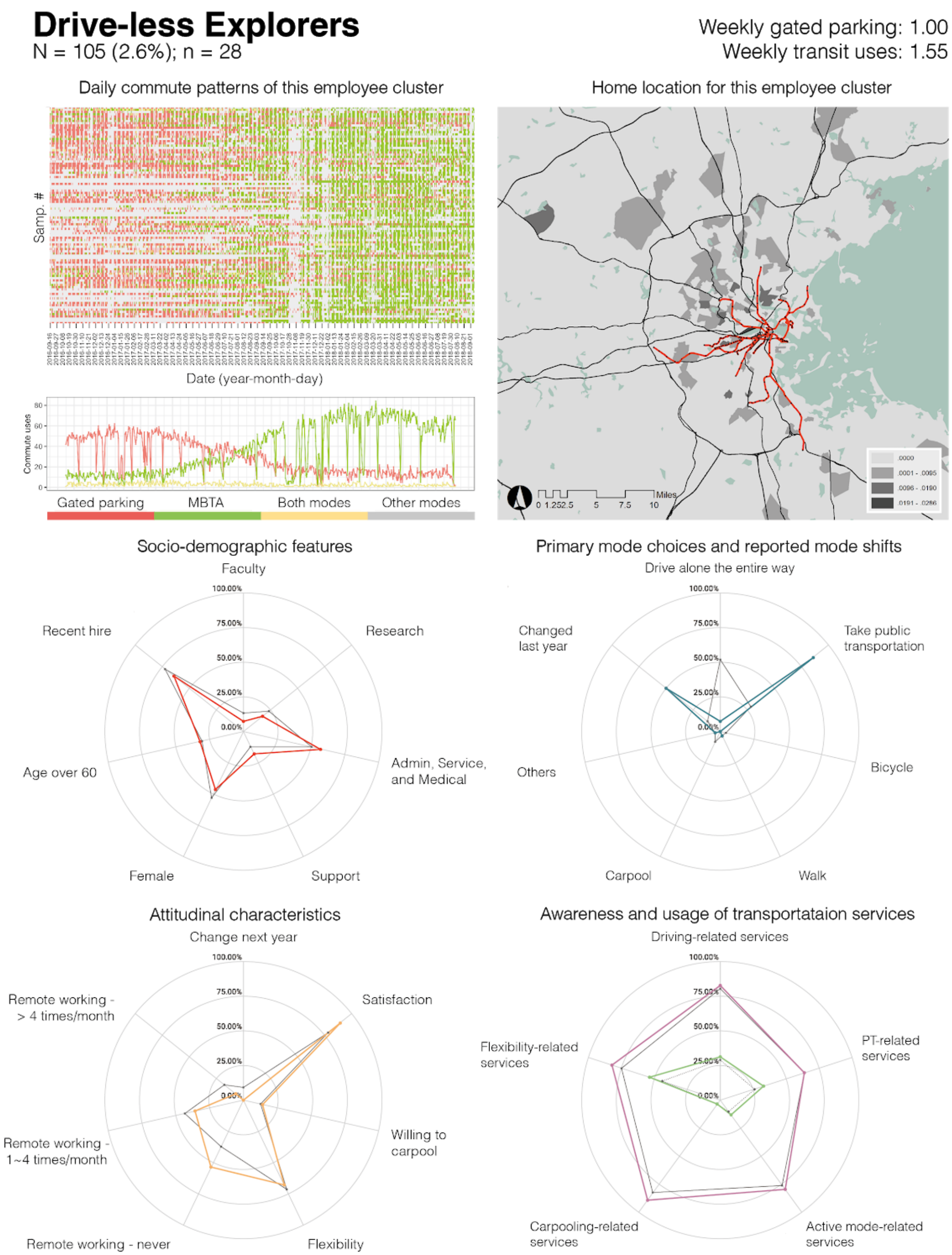

Figure 6.12 Commuting sequence structure and cluster profiling of cluster 1 (drive-less explorers)

Figure 6.13 Commuting sequence structure and cluster profiling of cluster 2 (aspiring meanderers)

6.6.3 Driving More

The “driving more” set only includes one cluster: Cluster 6, which is very interesting and among the clusters with high mode switchability.

Cluster 6 (Unsatisfied new drivers):

Noted by its ascending parking frequency in Figure 6.14, Cluster 6 is the only cluster we identify to have a substantial increase of SOV activities, which also only takes up 5.3 percent of the clustering sample. However, this small proportion does not mean we can ignore their needs and concerns. Rather, it is even more necessary to understand the implications of the reasons behind the changes of their commuting behavior. Moreover, this cluster has the lowest satisfaction rate toward MIT transportation services among all of 9 clusters, indicating that the existing services had not well met their needs.

By observing the socio-demographic attributes, we can see that this cluster has the highest recent hire rate and the lowest percentage of faculty, which suggests a large proportion of new research staff and administration, service, and medical staff in this clusters. Also, employees in this cluster were relatively younger compared to the average level.

It is necessary to notice that this cluster has the lowest satisfaction rate at 66.67%, indicating the commuting-related needs of employees in this cluster were not well served. This fact might be due to different reasons. For example, since they are relatively new to the university and its transportation services, they might be less aware of some services and benefits which had been introduced before they were hired. Yet the moderate to high awareness rates of all five categories indicates their acknowledgement of these services. However, the participation rates are not as positive as the awareness rates. Thus, more “radical” incentives may be necessary to motivate employees of this cluster to try other modes. As can be seen from the attitudinal graph in Figure 6.14, this cluster also has a high interest in the potential new carpooling programs, informing us to offer targeted policy recommendations.

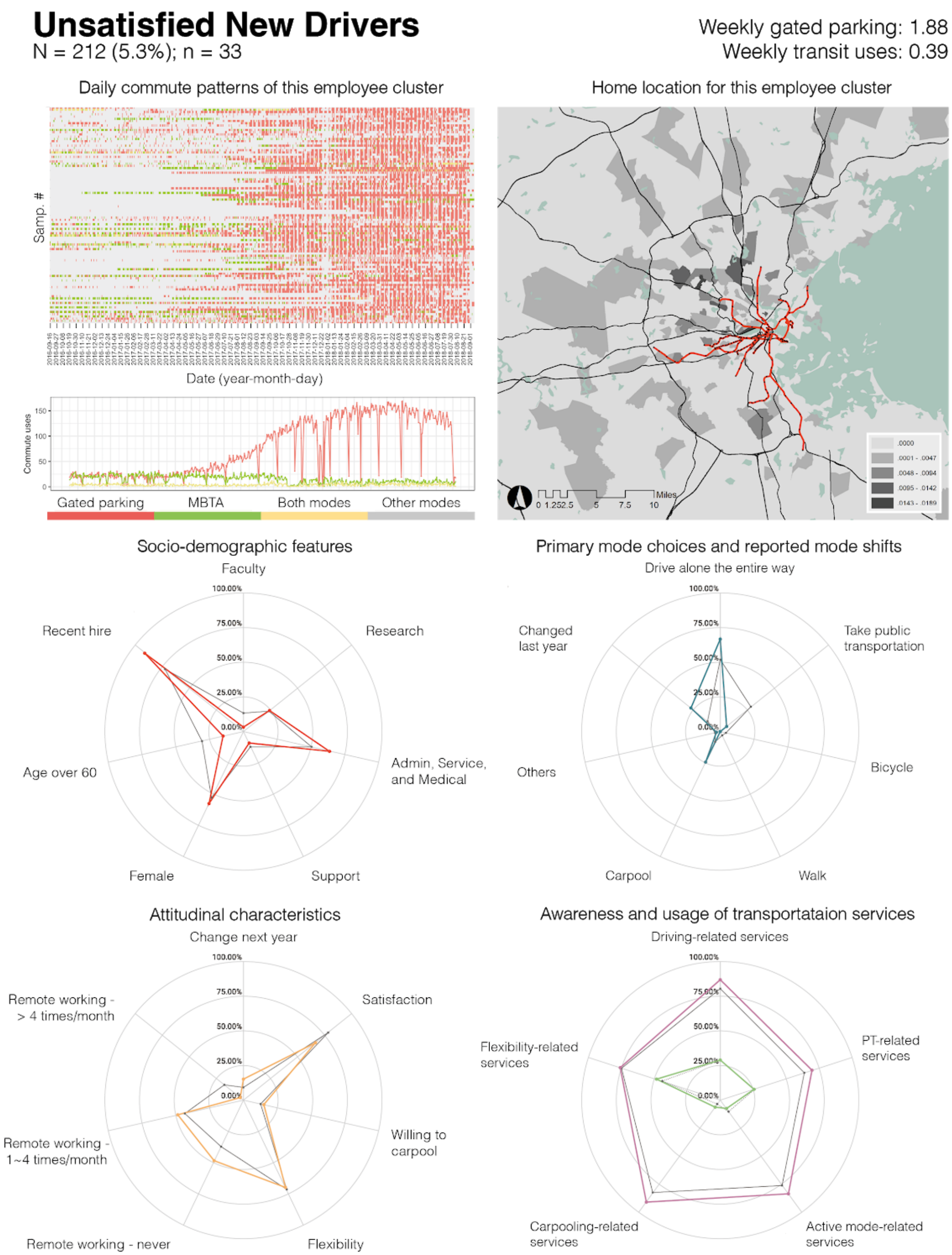

Figure 6.14 Commuting sequence structure and cluster profiling of cluster 6 (unsatisfied new drivers)

6.6.4 Transit Riders

Two clusters--Cluster 3 and 7--are classified into this set, whose main characteristic is a frequent use of public transit. More details about each cluster are available in this Section.

Cluster 3 (Determined riders):

Marked by the most frequent weekly uses of public transit (3.89), cluster 3 is defined as “determined riders" among the 9 clusters. Looking at the commuting sequence structure denoted in Figure 6.15, we can identify a dominant pattern of public transit. It is interesting to notice the apparent missing of data in November 2017 on this individual level while a similar pattern is noticed on an aggregated level in Section 6.2.

The spatial distribution of the home locations of this cluster has a distinct pattern from other clusters, with a significant spatial autocorrelation. The employees of this cluster tended to live along the Red Line, which connects MIT with surrounding areas, or close to the highways that connect with the metro stations of the Red Line. Moreover, we can identify apparent agglomerations around the end stations of the Red Line, notably Alewife and Davis Square. These facts indicate an underlying association between the home location and the uses of public transit.

employees in this group had less job flexibility and less uses of telecommuting, indicating the less freedom they have to schedule their work. A relatively high percentage of administration, service, and medical staff in this cluster may contribute to this trend. However, cluster 3 has the highest satisfaction rate at 91.35%, which is likely because they were taking advantage of the public transit related services and benefits offered by MIT (indicated by the awareness and participation rate).

Cluster 7 (Diversified active commuters):

Different from cluster 3 who shared a higher percentage of administration, service, and medical staff, cluster 7 has a relatively higher percentage of faculty. Another essential characteristic of this cluster is the diverse commuting activities, which can be identified from both the commuting sequence structure and the stated primary mode choices, notably the higher percentages of walk, bicycle, and other modes.

Regarding the spatial patterns of employees' home locations, this cluster has a larger proportion of employees who live closer to the campus, which explains the relatively high percentages of walking and bicycle users. A lower intention of participating in the possible new carpooling program indicates carpooling may not be a good fit for this group. Furthermore, the second highest satisfaction rate of this cluster and a relatively small weekly parking frequency (0.6) suggest that policy interventions may be unnecessary for this cluster in the next-stage TDM program design at MIT.

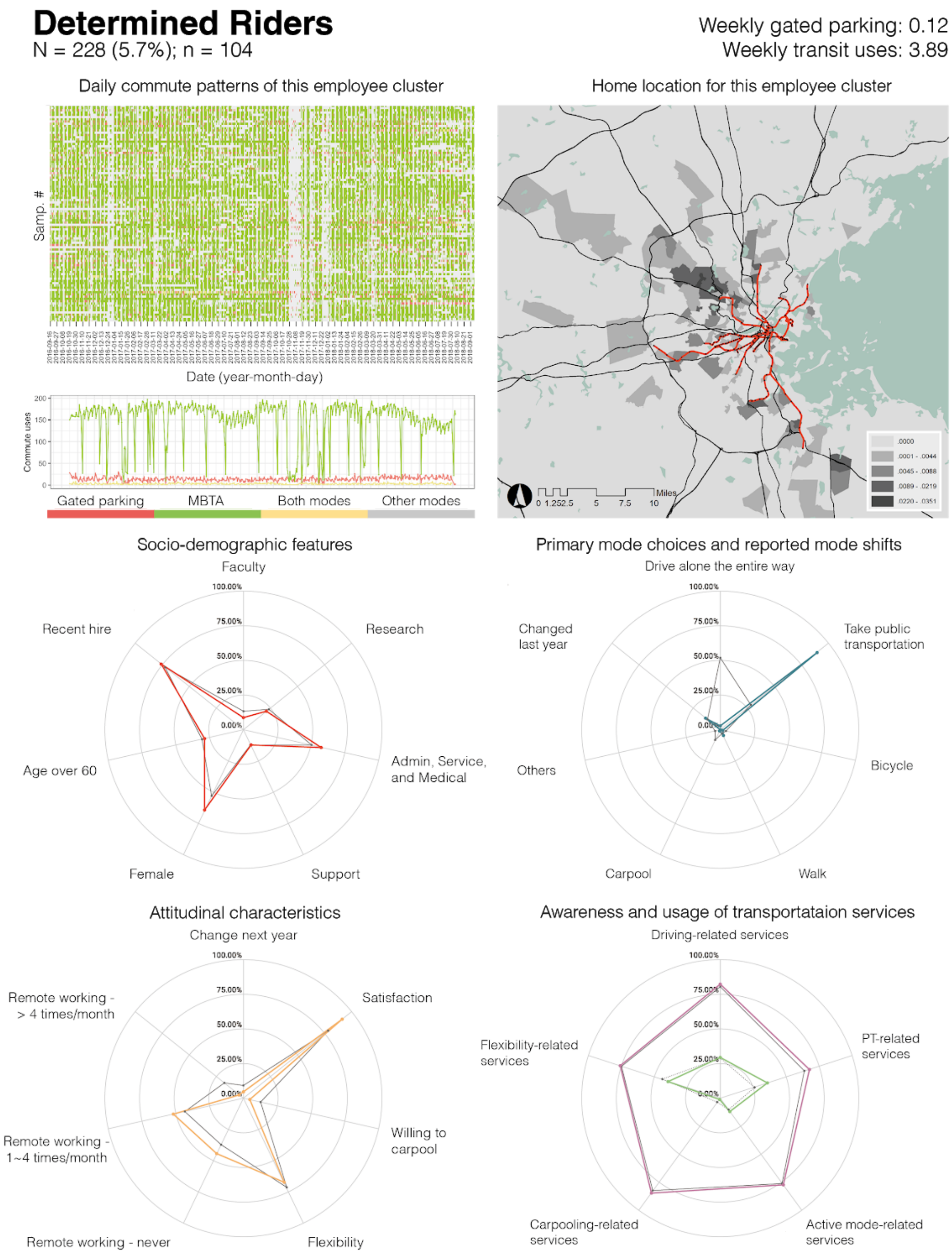

Figure 6.15 Commuting sequence structure and cluster profiling of cluster 3 (determined riders)

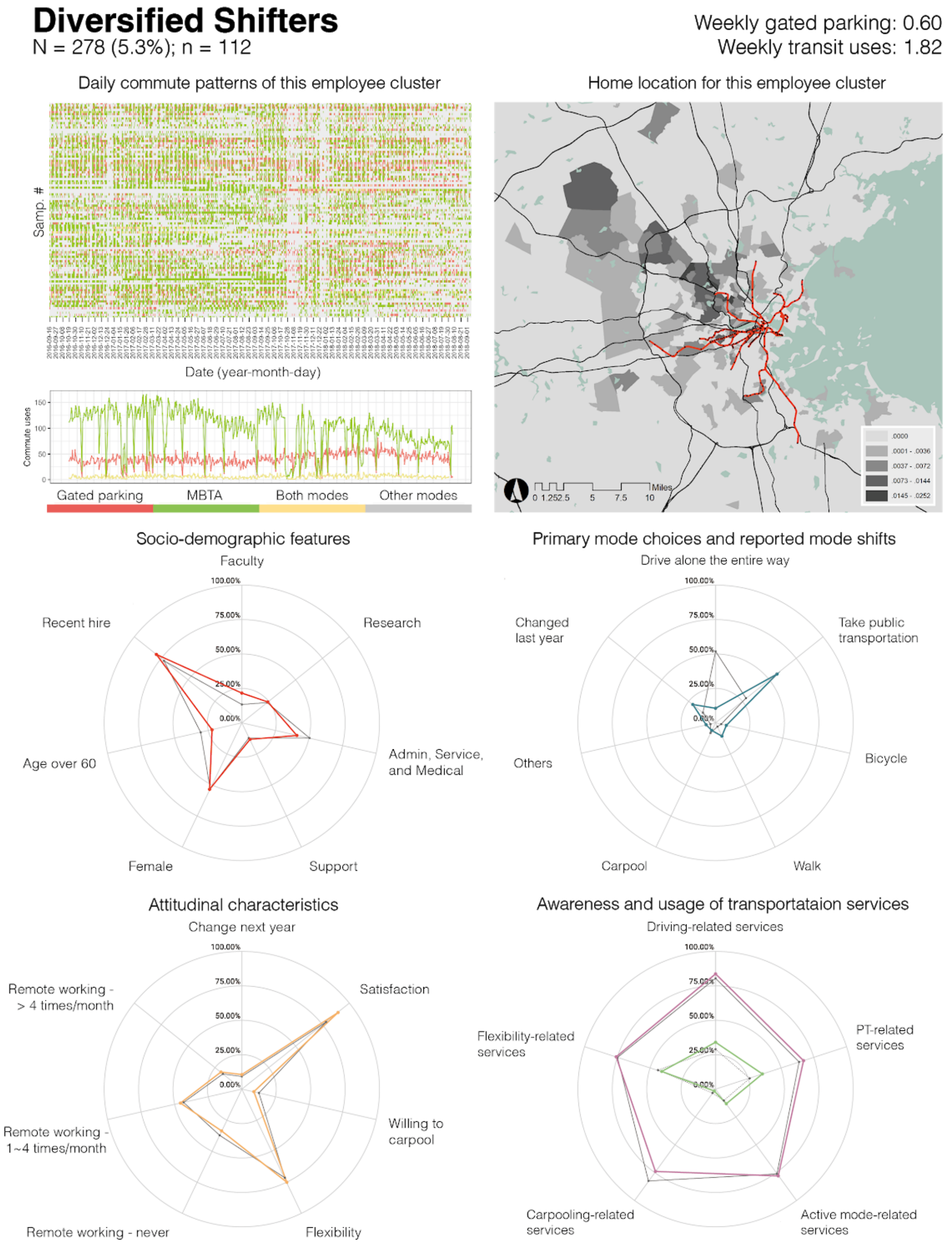

Figure 6.16 Commuting sequence structure and cluster profiling of cluster 7 (diversified shifters)

6.6.5 Sparse Commuters

Cluster 5 (Sparse commuters):

The last cluster we identify via the proposed methodology is cluster 5, which is marked by the visual similarity among the represented commuting sequence structure. Most of the employees in this cluster had few parking activities and public transit uses recorded by the passive mobility data we collect, with an average weekly parking frequency equal to 0.12 and an average weekly transit uses equal to 0.05.

Several possible reasons can contribute to these patterns. For example, employees might drive to the campus yet parked at an ungated parking facility at MIT or and at an outside parking facility, which was not recorded by the parking system of MIT. In addition, some employees might walk or cycle to the campus and these activities were not included in our representation methodology. This hypothesis is justified by the relatively high percentages of employees who choose walk and bicycle as their primary commuting modes. Moreover, a diverse spatial distribution of home locations also indicates the possible heterogeneous commuting behavior inside this cluster.

In order to better capture parking activities of MIT employees , this new control system deployed in 2019 is able to record parking activities as well.

Figure 6.17 Commuting sequence structure and cluster profiling of cluster 5 (sparse commuters)

6.7 Policy Recommendations

As argued by Anable (2005), the purpose of segmenting transportation service users is to better inform policy design and implementation. Despite the fact that this research uses different datasets to conduct the segmentation process, the purpose of policy recommendation aligns the same. Also, as this research is supported by MIT Office of Sustainability, there is a great opportunity that the policy recommendations will inform the design of the next-stage TDM program at MIT (AccessMIT 2.0).

In order to offer actionable policy options, this research builds on the pioneering work by Anable (2015), who segmented users of transportation services based on the attitudinal characteristics collected with a questionnaire. Characteristics such as swichability and constraints of each identified cluster were summarized to help offer policy options, which include promotional messages and hard push approaches.

Even though the attitudinal attributes available for this research is not as comprehensive as what Anable had collected (2015), they are still powerful to inform us of some unique insights. Moreover, our advantage over Anable's research (2005) is a comprehensive understanding of actual commuting behavior and behavior evolution through the time of each cluster, which was not possible for the research by Anable in 2005. Furthermore, we propose to add one more step before offering policy options for the segmented clusters: evaluating the necessity of policy intervention (for each cluster). This step appears to be more essential considering the tighter budget of the university who has been greatly influenced by the pandemic of COVID-19.

Hence, we first determine whether a cluster needs policy interventions by evaluating its average weekly parking frequency and average satisfaction rate. In order to achieve larger impacts utilizing the limited budget, the clusters that have low weekly parking frequencies and high satisfaction rates are not offered policy options. Then, several key characteristics of each cluster including switchability, potentials for using carpooling, and job flexibility are extracted from the profiling process. In addition, the barriers to carpooling are quantified by the percentages of employees who did not own cars. Finally, policy options such as promotions of public transit, carpooling programs, and awareness campaigns are recommended. Table 6.6 summarizes the characteristics of each cluster and offers options for potential policy interventions.

Table 6.6 Potential interventions to influence each cluster's commuting behavior

Cluster num.	Cluster name	Average weekly parking frequency (average: 1.89)	Average satisfaction rate (average: 78.21%)	Necessity of policy interventions	Potential switchability	Potential carpooling uses	Flexibility	Carpooling barrier (percentage of none-vehicle employees)	Policy options
1	Drive-less Explorers	1.00	89.29%	Low	-	Moderate	Low	Low	-
2	Aspiring Meanderers	1.32	77.31%	Moderate	High	High	Very high	Low	1. Promotional messages for carpooling, and active modes 2. Incentives for carpooling
3	Determined Riders	0.12	91.35%	Low	-	Low	Low	Low	-
4	Dedicated Motorists	4.23	70.25%	High	High	Moderate	Low	Low	1. Options for flexible working schedules and possibilities of remote working 2. Promotional messages of flexibility-related services and benefits 3. Promotional messages and incentives for carpooling
5	Sparsy Commuters	0.12	78.48%	Moderate	Very low	Moderate	Moderate	Low	1. Promotional messages for the convenient services of active modes
6	Unsatisfied New Drivers	1.88	66.67%	High	High	High	Moderate	Low	1. Promotional messages about public transit, carpooling and remote working 2. Incentives for carpooling and public transit
7	Diversed Shifters	0.60	89.29%	Low	-	Low	High	Low	-
8	Addicted Drivers	3.14	77.27%	High	High	High	High	Low	1. Promotional messages and incentives for public transit and carpooling 2. Incentives for public transit
9	Elder Carpoolers	5.00	72.22%	High	Low	Very low	Low	Low	1. Awareness campaign about the MIT transportation services

Chapter 7

Conclusion

7.1 Key Findings

Building on previous work and taking advantage of both active and passive data sources, this research reveals these three key findings.

First, the AccessMIT program has had a sustained impact on changing employees' commuting modes and improving their commuting experience. This argument is supported by a lasting increase in public transit mode choice, a drop in SOV mode choice, and an ascending satisfaction rate. However, the impact of AccessMIT varied substantially across different employee groups. For example, the reduction of SOV share in the mode choices happened more quickly in administration, service, and medical staff than in faculty. The disparate satisfaction rate growth among employees groups with different primary mode choices also exemplified this phenomenon.

Second, the discrepancy between self-reported and actual commuting behavior is not substantial when we observe all MIT employees in aggregate. Still, it varies largely among different employee groups (e.g., different employee types and primary mode choices). Therefore, we summarize the scenarios where active and passive mobility data is better for in the case of MIT. Self-reported travel behavior extracted from active mobility datasets is a good source for understanding the overall trend of commuting activities at MIT. Further, these active datasets offer insights for specific modes such as walking and cycling, which have not been captured by passive mobility data. On the other hand, actual travel behavior derived from passive mobility datasets is more suitable for finer-grained transportation modeling, including segmenting commuting behavior clusters and analyzing longitudinal commuting patterns.

Third, by utilizing a longitudinal representation of multi-year passive mobility data and leveraging the up-to-date clustering methodologies on our research sample, we identify 9 significative commuting behavior clusters with distinct commuting sequence structure. This empirical analysis also suggests that the applied methodologies are capable of identifying distinct commuting patterns and of capturing temporal evolution of commuting patterns such as decreased parking frequency and ascending transit uses. Informed by Anable (2005), we profile the resulting clusters using active and passive mobility data, socio-demographic characteristics, and attitudinal attributes to recommend actionable policy options.

7.2 Contributions

The contributions of this research are in three aspects. First, it builds on the work of improving transportation services at MIT by Block-Schachter (2009), Gates (2015), and Rosenfield (2018) and evaluates the sustained mid-term impact of the AccessMIT program using the latest MIT Commuting Survey. This research also explores the disparity of this impact among different employee groups and tests the factors associated with the likelihood of considering new commuting programs, notably carpooling.

Then, inspired by earlier efforts discussing the discrepancy between self-reported and actual travel behavior (e.g., Rosenfield, 2019), this research assesses this difference by proposing a group of indices to measure the disparity between these two sets of travel behavior data. We conduct a series of multivariate linear regressions to analyze the factors correlated with the discrepancies, leveraging the comprehensive socio-demographic and attitudinal data we collect.

Finally, informed by previous research studying the heterogeneity among transportation service users (Anable, 2005; Goulet-Langlois et al., 2016; Jiang et al., 2012; Ortega-Tong, 2013), this research takes advantage of both active and passive data to enhance the clustering results towards better TDM program design. We build on the longitudinal representation of travel behavior introduced by Goulet-Langlois (2016) and extend the studied period to two years, which is later found able to capture commuting mode shifts across multiple years. Furthermore, the comprehensive socio-demographic, attitudinal, and commuting related data available for this research allows us to profile multidimensional characteristics of the resulting clusters and provide policy options for each of them, which has not been done by most of the previous efforts using passive mobility data.

7.3 Future Research

While offering contributions to deepening the understanding of the commuting patterns at MIT and offering actionable policy recommendations with our results, our research also brings several future research directions that are worth more investigation.

First, a careful investigation into the causal relationship between the introduced TDM program (e.g., AccessMIT) and employees' changes in commuting behavior at MIT would be advantageous using both the active and passive mobility data. For example, a *difference in differences* (DID) approach can be helpful in confirming the causality and offers us more information about the associations. Second, future research can expand the scope of analyzing the discrepancy between self-reported and actual commuting behavior by covering more aspects of daily commuting. Finally, as the rapid advances of urban sensing and mobility technology, it is always meaningful to incorporate more and better data sources into the analyses that support the TDM program design. For example, from the 2019 parking year, MIT has started to record the parking activities happening in the ungated parking facilities owned by MIT. Also, the bike-sharing company that collaborates with MIT might be able to offer passive data to help indicate biking activities. These gradually abundant data sources have the potential to optimize the representation of commuting behavior and offer better results and insights.

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Appendix A

Questionnaire of the 2018 MIT Commuting Survey

This appendix includes the questionnaire of the 2018 MIT Commuting Survey, which is analyzed in Chapters 4, 5, and 6. An online version of this questionnaire and questionnaires of the Commuting Surveys of earlier years can be accessed via http://ir.mit.edu/commuting-to-mit.

Introduction

Welcome ${m://FirstName},

The Parking and Transportation Office, the Environment, Health and Safety Office and the Office of the Provost are jointly sponsoring a survey on commuting to the MIT campus. The State of Massachusetts and the City of Cambridge require that MIT collect data related to how you get to MIT every day. This survey has multiple sections and should take about 10 minutes to complete. As an incentive to participate in this survey, we are offering several prizes. **MIT Community members who complete the survey will be entered into a lottery for a grand prize: $500 Visa Gift Card OR TechCASH OR Bicycle from Cambridge Bicycle (your choice).**

Other prizes include:
- 25 TechCASH credits valued at $100
- 50 TechCASH credits valued at $50
- 325 TechCASH credits valued at $25
- 10 $50 Zipcar Gift Certificates
- 10 Hubway annual memberships

The survey is voluntary. You may answer as few or as many questions as you wish.

Please be assured that the data are confidential, and the results of any research or analysis using the data will be presented in a way that individual respondents cannot be identified. For the purposes of analysis, we may combine other data with your responses to this survey.

Occasionally, we receive requests to use administrative datasets--including survey results--for academic research projects. Any researchers using these data for academic research are bound to the same rules of confidentiality and reporting stated above. That is, they may not report results in a way that identifies an individual respondent.

If you have any questions about this survey, please contact commuting-survey@mit.edu.

About You

Is MIT your primary employer/school?

- Yes
- No, I am a student at another institution
- No, MIT is my secondary employer
- No, I am a visitor
- Other, please specify: ____________________

How many hours do you normally work/study on campus each week?

- Less than 17 hours
- 17-30 hours
- 31-40 hours
- More than 40 hours a week

What time do you usually arrive on campus?

What time do you usually depart from campus?

Do you have flexibility in scheduling your work hours? [Excludes undergraduate students]

- Yes
- No

Your Commute

We are interested in learning how long it takes you to get to and from MIT. Using whatever method of transportation you normally use, please indicate your estimated commute time door-to-door under different conditions.

First tell us about your commute TO MIT

Normal Day	▼ 5 minutes or less ... more than 2 hours
Good / Fast Day	▼ 5 minutes or less ... more than 2 hours
Bad / Slow Day	▼ 5 minutes or less ... more than 2 hours

Your commute FROM MIT

Normal Day	▼ 5 minutes or less ... more than 2 hours
Good / Fast Day	▼ 5 minutes or less ... more than 2 hours
Bad / Slow Day	▼ 5 minutes or less ... more than 2 hours

What are your CURRENT commuting method(s) to MIT?
Select your primary method, and if applicable, a secondary method (e.g. during nice weather, flexible hours, etc.).

	Primary (e.g. typical day)	Secondary (only if applicable)
Drive alone the entire way	○	○
Drive alone, then take public transportation	○	○
Walk, then take public transportation	○	○
Share ride/dropped off, then take public transportation	○	○
Bicycle and take public transportation	○	○
Ride in a private car with 1-4 commuters	○	○
Ride in a vanpool (5 or more commuters) or private shuttle (e.g. TechShuttle, SafeRide)	○	○
Dropped off at work	○	○
Take a taxi or ride service (e.g., Uber, Lyft)	○	○
Bicycle	○	○

Walk	○	○
Work at home or other remote location	○	○
Other	○	○
N/A	○	○

Display if: What are your CURRENT commuting method(s) to MIT? Other

Q80 You selected 'Other' as your commuting method, please describe: ____________________

____

Display if: What are your CURRENT commuting method(s) to MIT? Primary = Drive alone the entire way Or Secondary = Drive alone the entire way

Would you consider carpooling on an occasional basis with fellow MIT commuters if:
1. MIT provided a better way to match you up with other commuters near where you live on a daily, real-time basis (perhaps through a phone app); and
2. MIT provided parking incentives, such as discounted rates or preferred parking spots.

- ○ Very likely
- ○ Somewhat likely
- ○ Not very likely
- ○ I would not consider carpooling

In general, my primary commuting method to/from campus...

- ○ Has no financial impact on me
- ○ Has a minimal financial impact on me
- ○ Has a moderate financial impact on me
- ○ Has a considerable financial impact on me

Did you use different commuting method(s) to MIT in the PREVIOUS academic year (2017-2018)?

- Yes
- No
- Was not at MIT during the previous academic year.

Display if: Did you use different commuting method(s) to MIT in the PREVIOUS academic year (2017-2018)? = No Or Was not at MIT during the previous academic year.

Are you considering changing the way you commute to MIT over the next year?

- Yes
- No

Display if: Are you considering changing the way you commute to MIT over the next year? = Yes

Please elaborate. ____

____

Display if: Are you considering changing the way you commute to MIT over the next year? = Yes

Please tell us what commuting method(s) you are considering. Check all that apply.

- Drive alone the entire way
- Drive alone, then take public transportation
- Walk, then take public transportation
- Share ride/dropped off, then take public transportation
- Bicycle and take public transportation
- Ride in a private car with 1-4 commuters
- Ride in a vanpool (5 or more commuters) or private shuttle (e.g. TechShuttle, SafeRide)
- Dropped off at work
- Take a taxi or ride service (e.g., Uber, Lyft)
- Bicycle
- Walk
- Work at home or other remote location
- Other, please specify ____

Display if: Did you use different commuting method(s) to MIT in the PREVIOUS academic year (2017-2018)? = Yes

What were your commuting method(s) to MIT in the PREVIOUS academic year (2017-2018)? Select your primary method, and if applicable, a secondary method (e.g. during nice weather, flexible hours, etc.).

	Primary (e.g. typical day)	Secondary (only if applicable)
Drive alone the entire way	○	○
Drive alone, then take public transportation	○	○
Walk, then take public transportation	○	○
Share ride/dropped off, then take public transportation	○	○
Bicycle and take public transportation	○	○
Ride in a private car with 1-4 commuters	○	○
Ride in a vanpool (5 or more commuters) or private shuttle (e.g. TechShuttle, SafeRide)	○	○
Dropped off at work	○	○
Take a taxi or ride service (e.g., Uber, Lyft)	○	○
Bicycle	○	○
Walk	○	○
Work at home or other remote location	○	○
Other	○	○
N/A	○	○

Display if: What were your commuting method(s) to MIT in the PREVIOUS academic year (2017-2018)? Other (Count) > 0

You selected 'Other' as your commuting method, please describe: ____________________

____

Display if: Did you use different commuting method(s) to MIT in the PREVIOUS academic year (2017-2018)? = Yes

Why have you changed your commuting methods since the previous academic year? Check all that apply.

- ▢ Moved place of residence
- ▢ Changed jobs and/or hours
- ▢ New MIT commuter benefits, please describe: ________________________________
- ▢ Life event (e.g. family structure)
- ▢ Availability of a vehicle (e.g. purchased a car)
- ▢ Other, please describe: ____

How you got to campus

Please indicate how you commuted TO CAMPUS each day LAST WEEK.

Please make one entry for each day of the week.

Monday	▼ Scheduled day off (e.g., weekend) ... Other
Tuesday	▼ Scheduled day off (e.g., weekend) ... Other
Wednesday	▼ Scheduled day off (e.g., weekend) ... Other
Thursday	▼ Scheduled day off (e.g., weekend) ... Other
Friday	▼ Scheduled day off (e.g., weekend) ... Other
Saturday	▼ Scheduled day off (e.g., weekend) ... Other
Sunday	▼ Scheduled day off (e.g., weekend) ... Other

If you indicated 'Other' as your commuting method to get to campus on at least one day last week, please describe that method: ____

____

On any day last week, did you travel BACK TO YOUR HOME from MIT using a different mode than indicated above?

- ○ Yes
- ○ No

Display if: On any day last week, did you travel BACK TO YOUR HOME from MIT using a different mode than indic... = Yes

If YES, how many days last week did you use a different method to get home?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7

How many times a month, on average, do you work from a remote location instead of on campus? [Excludes undergraduate students]

- Never
- 1 to 4 times per month
- 5-8 times per month
- 9-12 times per month
- More than 12 times a month

Display if: How many times a month, on average, do you work from a remote location instead of on campus? 1 to 4 times per month Or 5-8 times per month Or 9-12 times per month Or More than 12 times a month

Do transportation related issues play a role in your decision to work remotely?

- No
- Yes, to some extent
- Yes, to a great extent

Display if: [FCCP Proposal] Do transportation related issues play a role in your decision to work remotely? = Yes, to some extent Or Yes, to a great extent

Please elaborate. ____

____

Use of Transportation Services

The following questions relate to MIT's transportation benefit program called AccessMIT, which includes free unlimited MBTA local bus and subway, as well as increased commuter rail subsidy, MBTA parking subsidy, daily parking pricing at MIT lots and garages, and incentive programs.

[Limited to staff with MIT benefits] **For each of the following AccessMIT benefits, how important is the benefit towards influencing your commuting methods, even on an occasional basis?**

	Not Important Very Important Unaware
	0 1 2 3 4 5 6 7 8 9 10
Free unlimited MBTA local bus and subway	
Daily parking pricing	
Commuter rail subsidy	
MBTA Parking Subsidy	
AccessMyCommute dashboard & incentives	

Display if: For each of the following AccessMIT benefits ... Free unlimited MBTA local bus and subway > 8

Free unlimited MBTA local bus and subway: Please elaborate on your rating. ____

Display if: For each of the following AccessMIT benefits ... Daily parking pricing > 8

Daily parking pricing: Please elaborate on your rating. ____

Display if: For each of the following AccessMIT benefits ... Commuter rail subsidy > 8

Commuter rail subsidy: Please elaborate on your rating. ____

Display if: For each of the following AccessMIT benefits … MBTA Parking Subsidy > 8

MBTA Parking Subsidy: Please elaborate on your rating. ______________________________

____

Display if: For each of the following AccessMIT benefits … AccessMyCommute dashboard & incentives > 8

AccessMyCommute dashboard & incentives: Please elaborate on your rating. __________

____

MIT offers a number of transportation services and would like to know how many community members are aware of and use the services.

Please indicate if you have used or are aware of the following services.

	Aware of service, USE IT	Aware of service, DO NOT USE IT	Not aware of service
MIT Parking and Transportation Office website	○	○	○
BenefitsEligible = Yes AccessMIT Commuting Benefits	○	○	○
BenefitsEligible = Yes AccessMyCommute Dashboard	○	○	○
BenefitsEligible = Yes Subsidized MBTA Pass	○	○	○
BenefitsEligible = Yes Parking subsidy at MBTA stations and lots	○	○	○
BenefitsEligible = Yes Subsidized daily pay-per-day parking at all MIT owned lots and garages	○	○	○
Subsidized Zipcar (car sharing)	○	○	○
Electric Vehicle Charging Stations	○	○	○
Role = Employee Flexible hours to accommodate schedules	○	○	○
Role = Employee Emergency Ride Home Program	○	○	○

Role = Employee Private Transit Subsidy	○	○	○
Carpools/Vanpool Parking Programs	○	○	○
Subsidized Blue Bikes/Hubway (bike sharing)	○	○	○
Secure bicycle storage and/or repair facilities	○	○	○
Locker and/or shower facilities for runners and bicyclists, other than in DAPER facilities (e.g., Z-center)	○	○	○
Role = Employee Qualified Bicycle Commuter Benefit	○	○	○
Daytime weekday shuttle services (The Tech Shuttle, Daytime Boston Shuttle, EZRide)	○	○	○
Evening SafeRide shuttle services			
Specialty shuttles (Airport Shuttle, The Grocery and Weekend Shuttles, The Lincoln Lab Shuttle, The Wellesley College Shuttle, M2 Shuttle)	○	○	○
MIT Mobile Shuttle Tracking	○	○	○

Display if: Aware of service, Count > 0

Carry Forward Selected Choices from "MIT offers a number of transportation services and would like to know how many community members are aware of and use the services. Please indicate if you have used or are aware of the following services."

Please indicate your level of satisfaction with the services you use.

	Very satisfied	Generally satisfied	Generally dissatisfied	Very dissatisfied	N/A
MIT Parking and Transportation Office website	○	○	○	○	○
BenefitsEligible = Yes AccessMIT Commuting Benefits	○	○	○	○	○
BenefitsEligible = Yes AccessMyCommute Dashboard	○	○	○	○	○
BenefitsEligible = Yes Subsidized MBTA Pass	○	○	○	○	○
BenefitsEligible = Yes Parking subsidy at MBTA stations and lots	○	○	○	○	○

BenefitsEligible = Yes
Subsidized daily pay-per-day parking at all MIT owned lots and garages
Subsidized Zipcar (car sharing)
Electric Vehicle Charging Stations
Role = Employee
Flexible hours to accommodate schedules
Role = Employee
Emergency Ride Home Program
Role = Employee
Private Transit Subsidy
Carpools/Vanpool Parking Programs
Subsidized Blue Bikes/Hubway (bike sharing)
Secure bicycle storage and/or repair facilities
Locker and/or shower facilities for runners and bicyclists, other than in DAPER facilities (e.g., Z-center)
Role = Employee
Qualified Bicycle Commuter Benefit
Daytime weekday shuttle services (The Tech Shuttle, Daytime Boston Shuttle, EZRide)
Evening SafeRide shuttle services
Specialty shuttles (Airport Shuttle, The Grocery and Weekend Shuttles, The Lincoln Lab Shuttle, The Wellesley College Shuttle, M2 Shuttle)
MIT Mobile Shuttle Tracking

In general, how satisfied are you with MIT's transportation services?

- Very satisfied
- Somewhat satisfied
- Neither satisfied nor dissatisfied
- Somewhat dissatisfied
- Very dissatisfied

Display if: In general, how satisfied are you with MIT's transportation services? = Very dissatisfied Or Somewhat dissatisfied

Please suggest how MIT's transportation services can be improved. ____________________

____

Do you use any smartphone apps to plan your commute?

- Yes
- No

Display if: Do you use any smartphone apps to plan your commute? = Yes

Which apps do you use to plan/manage your commute? Select all that apply.

- MIT Mobile App
- Google Maps
- NextBus
- MBTA Transit
- CityMapper
- Waze
- Blue Bikes/Hubway
- Other (please specify) ____

In the past month, please estimate the number of days that you have used a ride-hailing service (Uber, Lyft, etc.) to commute from home to the MIT campus or from the campus to your home.
(dropdown box 0 – 31)

In the past month, please estimate the number of days that you have used a ride-hailing service (Uber, Lyft, etc.) to travel locally other than between MIT and home.
(dropdown box 0 – 31)

Driving, Car Ownership, and Bicycling

How many total licensed drivers reside in your current household?

- 0
- 1
- 2
- 3
- 4
- 5+

How many total motor vehicles are CURRENTLY registered to members of your household?

- 0
- 1
- 2
- 3
- 4
- 5+
- Not applicable

In the last year, have you driven to campus for work or study?

- Yes
- No

Display if: [NEW GATEWAY QUESTION] In the last year, have you driven to campus for work or study? = Yes

What type of vehicle do you typically use to drive to campus?

- Gas/diesel vehicle
- Plug-in electric vehicle (including plug-in hybrid)
- Hybrid vehicle
- Motorcycle
- Other ____

Display if: [NEW GATEWAY QUESTION] In the last year, have you driven to campus for work or study? = Yes

Where is your motor vehicle usually parked?

- ○ MIT Parking Facility
- ○ Other paid parking lot or garage
- ○ On-street parking (meter, unrestricted)
- ○ On-street resident permit parking
- ○ Other (please specify) ____

Display if: Where is your motor vehicle usually parked? = MIT Parking Facility Or Other paid parking lot or garage Or On-street parking (meter, unrestricted)

Once you have parked your vehicle on or near campus, how long does it usually take you to get to your office or primary work area?

- ○ Less than 5 minutes
- ○ 6-10 minutes
- ○ 11-15 minutes
- ○ 16 minutes or more

Display if: Where is your motor vehicle usually parked? = MIT Parking Facility Or Other paid parking lot or garage Or On-street parking (meter, unrestricted)

In general, how would you describe your parking spot in relation to your office or primary work area?

- ○ Very close
- ○ Somewhat close
- ○ Somewhat far
- ○ Very far

In September 2018, the Office of Transportation and Parking revamped its parking system, eliminating physical parking permits and utilizing license plate recognition software.
Thinking about the last time you obtained or renewed your MIT parking permit, how would you rate the process?

- Very easy
- Somewhat easy
- Neither easy nor difficult
- Somewhat difficult
- Very difficult

Display if: Somewhat difficult or Very difficult.

Please elaborate on your rating. ____

____

Would any of the following make you more inclined to bike to campus (whether you currently bike to campus or not)?

- Safer bike routes to campus
- More bike routes to campus
- Better bike parking facilities
- Locker and/or shower facilities in or near your building
- Better weather
- Shorter commute distance
- Nothing would make me more inclined to cycle to campus
- Not an option (e.g., health reasons, safety concerns, not near a bike path)
- Other (please specify) ____

Last Section

What is the most important thing MIT could do to improve commuting? ________________

____

____

May we follow up with you if we have questions about your commuting patterns for additional MIT research? (By answering Yes, your survey response will include your email address when shared with researchers.)

- ○ Yes
- ○ No

If you are selected as a grand prize winner, please tell us which prize you would prefer:

- ○ $500 MIT TechCash
- ○ $500 Visa Gift Card
- ○ Bicycle from Cambridge Bicycle
- ○ I do not wish to be entered in the drawing.

Appendix B

Primary and Secondary Commuting Mode Choices

This appendix includes a comprehensive analysis of the choices of the primary and secondary commuting modes collected by 2014, 2016, and 2018 MIT Commuting Surveys.

Table B-1 Primary commuting mode choices (2014 MIT Commuting Survey)

		2014
N		6,335
SOV	Drive along the entire way	28.00%
Public Transit	Bicycle and take pubic transportation	3.00%
	Drive alone, then take public transportation	6.00%
	Share ride/dropped off, then take public transportation	3.00%
	Walk, then take public transportation	30.00%
	Public transportation without explicit information	-
Bicycle	Bicycle	9.00%
Walk	Walk	9.00%
Carpool/Vanpool/Private Shuttle	Ride in a private car with another person	5.00%
	Ride in a private car with 2-4 commuters	1.00%
	Ride in a vanpool (5 or more commuters) or private shuttle (e.g., TechShuttle, SafeRide)	0.50%
	Carpool without explicit information	-
Others	Work at home (or other remote location)	0.20%
	Dropped off at work	0.30%
	Take a taxi or ride service (e.g., Uber, Lyft)	0.20%
	Other	5.00%
No secondary mode		-

Table B-2 Primary and secondary commuting mode choices (2016 MIT Commuting Survey)

		2016	
N		5,563	
		As primary modes	As secondary modes
SOV	Drive along the entire way	24.00%	11.00%
Public Transit	Bicycle and take pubic transportation	2.00%	2.00%
	Drive alone, then take public transportation	8.00%	3.00%
	Share ride/dropped off, then take public transportation	4.00%	2.00%
	Walk, then take public transportation	33.00%	14.00%
	Public transportation without explicit information	-	-
Bicycle	Bicycle	11.00%	6.00%
Walk	Walk	10.00%	9.00%
Carpool/Vanpool/Private Shuttle	Ride in a private car with another person	4.00%	2.00%
	Ride in a private car with 2-4 commuters	1.00%	0.30%
	Ride in a vanpool (5 or more commuters) or private shuttle (e.g., TechShuttle, SafeRide)	1.00%	1.00%
	Carpool without explicit information	-	-
Others	Work at home (or other remote location)	0.30%	6.00%
	Dropped off at work	1.00%	1.00%
	Take a taxi or ride service (e.g., Uber, Lyft)	0.40%	5.00%
	Other	1.00%	1.00%
No secondary mode		-	38.00%

Table B-3 Primary and secondary commuting mode choices (2018 MIT Commuting Survey)

		2018	
N		5,766	
		As primary modes	As secondary modes
SOV	Drive along the entire way	24.50%	9.90%
Public Transit	Bicycle and take pubic transportation	2.40%	1.70%
	Drive alone, then take public transportation	9.60%	3.40%
	Share ride/dropped off, then take public transportation	3,8%	2.30%
	Walk, then take public transportation	33.20%	2.50%
	Public transportation without explicit information	-	14.40%
Bicycle	Bicycle	9.80%	7.60%
Walk	Walk	9.30%	0.80%
Carpool/Vanpool/Private Shuttle	Ride in a private car with another person	3.70%	1.50%
	Ride in a private car with 2-4 commuters		
	Ride in a vanpool (5 or more commuters) or private shuttle (e.g., TechShuttle, SafeRide)	0.60%	5.40%
	Carpool without explicit information	-	0.50%
Others	Work at home (or other remote location)	0.50%	1.30%
	Dropped off at work	0.70%	5.20%
	Take a taxi or ride service (e.g., Uber, Lyft)	0.60%	7.80%
	Other	1.30%	0.00%
No secondary mode		-	35.70%