ACTIVITY SPACE AND ACCESSIBILITY: CHARACTERIZING COMPLEX URBAN ACTIVITY-TRAVEL AND OPTIMIZING SERVICE PROVISION PLANNING

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DEDICATION

To my dear mother
For her love and devotion
Joy in heaven
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ABSTRACT

Research on urban travel represents an important area in geography, transportation planning and urban studies. Compared to the traditional trip based approach, the activity based approach offers a better understanding of the motivations underlying travel, that is, activity participation. Urban activity-travel is complex as it takes place both in space and time. Building upon the time geography framework, this study provides new ways to characterize urban activity-travel and examine the association with accessibility. A new optimization model incorporating complex urban travel is also proposed for service provision planning.

Activity space represents an important concept for understanding human activity-travel. The geometry based approaches widely used for delineating activity spaces are limited in fully characterizing real-world travel behavior. To address the issue, Chapter 2 proposes a new time geography based approach to more accurately portray urban activity spaces. The proposed approach takes into account the full complexity of real-world travel and underlying urban structures. Results of an empirical study are presented based on the 2008 Add-on National Household Travel Survey conducted in Tucson, Arizona. Activity spaces of 1,164 sample travelers are delineated and analyzed. Results show the effectiveness of the new approach in more realistically depicting urban activity-travel.

Understanding the impact of the built environment on travel is important for formulating effective travel reduction policies. In Chapter 3, a study is presented to examine the relationship between accessibility to urban opportunities and urban travel. Activity spaces are drawn to characterize the spatial extent of activity-travel, and a new accessibility measure is introduced to account for the complexity of urban travel. An empirical study based on a travel survey dataset in
Tucson, Arizona shows that improved accessibility is generally associated with reduced travel, but such an effect varies across different activity types. In addition, employment status and trip-chaining behavior can be used to explain the varying influences on the accessibility-travel relationship.

In Chapter 4, a new multi-objective location model is developed with the goal of accessibility maximization. The model extends the classic p-median problem (PMP) to account for accessibility in a more realistic manner. Trip chaining and activity space are incorporated into the location model. In addition to fixed home locations, stops along chained trips are allowed for potential service site visits. The model is applied to locate service facilities in Tucson, AZ. Alternative versions of the objective function are solved exactly with the resulting sets of optimal facility locations displayed and analyzed. Decision makers are given flexibility to determine the relative importance for each of three sub-objective, based on the type of services being located, their preferences and practical needs.
CHAPTER 1
INTRODUCTION

In urban areas, people travel and make an endless variety of daily trips for multiple purposes, starting and stopping at many locations. Demand for a range of activities, such as dining, shopping and entertainment, has resulted in tremendous volumes of travel. Over the past few decades, with improved mobility and personal affluence, people now travel more frequently and over longer distances, resulting in more resources being consumed (energy, time, money, etc.). Ever more demands are being placed on existing infrastructures to accommodate the growth in travel: wider and more roads are built in hopes of speeding traffic and providing more opportunities to visit widely dispersed locations across sprawling metropolitan areas.

Research on urban travel has been a common interest in the fields of geography, transportation and urban studies (Buliung, 2005; Curtis and Perkins, 2006; Pendyala and Bhat, 2004; Handy and Krizek, 2012). Having a clear understanding of individuals’ travel in urban areas is critical for policy makers and practitioners for optimizing land uses, improving mobility, reducing traffic and protecting the environment (Mahmassani and Kitamura, 2000; Badoe and Miller, 2000). In general, two streams of approaches have been used to study urban travel. The first widely used suite of approaches falls into the category of the trip-based approach, where urban travel is assessed via discrete trips. Despite its success in addressing transportation related problems, the trip-based approach, such as by the four-step model (FSM), lacks the ability of explaining the underlying driving demand for urban travel (Buliung, 2005; McNally and Rindt, 2008). In simple words, why people are especially keen to make trips from place to place in urban areas cannot be properly answered using the trip-based approach. The activity-based approach (ABA), on the other
hand, examines travel from an alternative perspective, that is, activity participation. Instead of treating urban travel as a set of independent trips, the activity-based approach considers travel to be driven by the needs of participants to access various activities (Buliung, 2005). Therefore, in the activity-based approach, activity participation and the related decision making processes are integrated into the understanding of urban travel.

A thorough understanding of activity-travel comprises two facets: a temporal component (when) and a spatial component (where), which are equally important (Schönfelder, 2006). The time geography framework, introduced by Hägerstrand (1970), provides a theoretical framework to integrate the two important aspects into studying urban activity-travel. Based on the time geography framework, activity and travel take place in space and time. The spatial and temporal properties of an activity are intrinsically linked to each other (Schönfelder, 2006). As a result, individual’s travel can be represented as a sequence of activities determined by a set of space-time constraints (capability constraints, coupling constraints and authority constraints) (Hägerstrand, 1970). An individual’s maximal travel potential (flexibility) can be visualized as a 3-dimensional space-time prism, where all possible paths of movement are determined by the specific personal space-time budget and mobility (see Figure 1.1). Projecting a space-time prism to the geographical space results in a 2-dimensional potential path area (PPA), indicating the maximal travel extent of the individual, as Figure 1.1 shows. The space-time notion offered by the time geography paradigm is powerful for examining individual activity travel patterns in space and over time. The 2-dimensional time geography measures, such as the PPA, provide a spatial perspective that goes beyond traditional 1-dimensional approaches, such as travel distances (Patterson and Farber, 2015).
Despite its advantages in characterizing activity-travel in time and space, a major issue of the PPA lies in its inability to portray actual (observed) travel, which is an essential component when studying activity-travel. In particular, a PPA mostly focuses on the maximal spatial extent where an individual can participate in activities given the space-time constraints and other personal constraints (e.g., preferences), but actual (observed) travel is not fully addressed.

A closely related concept that accounts for actual (observed) travel is activity space. An activity space refers to a realized spatial extent of movement as a result of an individual’s day-to-day activities (Schönfelder, 2006; Ren, 2016). Therefore, activity space encompasses activity locations that an individual has visited over a specific period of time. Due to its unique ability in characterizing observed activity travel, activity space is employed as a major research approach in this dissertation.

There are a variety of activity space approaches that have been developed over the past few decades. See Patterson and Farber (2015) and Ren (2016) for detailed reviews. Among others, the time geography based activity space approach has been used to describe individuals’ extent of travel in space and time. This method was initiated by Newsome et al. (1998). In their study, the time geography framework was extended to draw the realized (perhaps the minimal) extent of movement of a traveler. Figure 1.2 presents an illustration of an activity space developed by Newsome et al. (1998). A distance threshold is determined by the farthest activity (eat a meal, in

Figure 1.1 Diagram of time geography (Long and Nelson, 2012)
this case) performed on the commutes between home and workplace, which are known as anchor points (Golledge and Stimson, 1997). All locations that maintain the same combined distance to the two anchor points form an elliptical activity space. By situting activity space in the time geography framework, we are given an unprecedented opportunity to examine people’s spatial extent of movement in the context of space and time, where details of the underlying travel program can be understood. The same goal, however, could not be easily achieved by other geometric activity space approaches, such as the Standard Deviational Ellipse (SDE) or Maximal Convex Polygon (MCP), where only the spatial dispersion of locations can be accounted for. In this dissertation the time geography based approach will be used, with a major focus on the activity spaces of individuals.

![Figure 1.2 An illustration of the Newsome et al. (1998) concept of activity space](image)

Although the existing time geography based activity space approach has significant advantages in characterizing urban activity travel, the approach has its limitations. First, similar to other simple geometric approximations of activity spaces, the elliptical activity space in Figure 1.2 may overestimate the actual extent of travel by overlooking the underlying urban structure (Wong and Shaw, 2011; Rai et al., 2007; Sherman et al., 2005; Patterson and Farber, 2015). Second, the ellipse-shaped activity space structure solely based on commutes may not represent very well the reality of complex urban travel patterns as revealed in empirical studies. Therefore, the Newsome
et al. (1998) activity space model needs to be extended to account for the greater diversity of activity-travel patterns now found in metropolitan areas.

One aspect of the complexity of urban travel relates to trip chaining behavior. Such behavior generally refers to combining more than one stop along a single trip, as opposed to only making one stop on the trip (Primerano et al., 2007). Trip chaining behavior has been increasing in recent years. Nowadays, the multi-stop (and possibly multi-purpose) trip chains account for 30% to 70% of all trips made in the U.S. (Mcguckin et al., 2005; Primerano et al., 2007; Santos et al., 2011). Trip chaining can take place on trips both originating and ending at the home location, on commuting trips between home and workplace or workplace and home, or on trips leaving from and returning to the workplace (Mcguckin and Murakami, 1995). The Newsome et al. (1998) activity space approach lacks the ability to account for other types of non-commuting trip chains (home-based and workplace-based), in addition to the commute-based chains. Furthermore, simple, non-commuting trips with no trip chaining involved should be considered as well when building activity spaces for urban travelers.

Another important concept that relates to urban activity-travel is accessibility. According to Hansen (1959), accessibility is an indicator of potential spatial interaction between demand points and the locations of opportunities. Accessibility is a very useful concept in examining urban activity-travel, where travel serves as derived demand for activity participation. Opportunities with higher levels of accessibility are more likely to be visited than those with lower levels of accessibility, everything else being equal (Levinson, 1998). Given this, one question arises as to how travel for various opportunities is influenced by the associated accessibility, considering resources and time budgets for travel are normally limited for most travelers. In the literature examining the accessibility-travel relationship, it has been found that both the distance and frequency of travel generally decreases with increased accessibility. However, whether such an effect functions the same across different activity types is unclear. In addition, effects of other
factors, such as employment status and trip chaining behavior, on the accessibly-travel relationship need to be examined. Activity space, as a two-dimensional indicator to characterize activity-travel, is believed to be more suitable than the one-dimensional distance metrics for investigating the relationship (Nemet and Bailey, 2000; Sherman et al., 2005; Patterson and Farber, 2015). To date, the existing literature on the relationship between activity space and accessibility is very limited.

With a good knowledge of activity space, accessibility, trip chaining and their relationships, it is worthwhile to further explore the relevant applications. An important area for planning practice is location modeling, which aims at identifying the best locations for service facilities. Location modeling has been applied to facilitate placement of various types of service facilities for both the public and private sectors. Applications studied to date include the siting of police and fire stations, health-related services, retail stores, schools, and communication towers. As Murray (2010) noted, major advances of location modeling stem from the mathematical models that have been developed to assist the locational decision making process. In general, a location model consists of three components: one or multiple objective(s), decision variables and a set of constraints (Tong and Murray, 2012). The objective(s) can vary from maximizing the efficiency (accessibility) for service or goods provision, to minimizing service establishment costs. Decision variables relate to what kinds of decision(s) are to be made, such as whether a potential facility is selected. Constraints impose conditions to be satisfied in solving a problem; these are often associated with available resources or budget and system capacities (Tong and Murray, 2012).

In location modeling, one common objective is to maximize the overall system efficiency, often reflected by spatial accessibility. In the classic location models, such as the $p$-median problem (PMP), accessibility is approximated using the shortest travel distance/time from fixed locations (usually home) to the potential service facilities. This home-based accessibility measure may contradict reality, where trip chaining plays an important role in determining choices for visits to various services. As mentioned earlier, trip chaining accounts for a considerable proportion of
people’s daily travel, and it is becoming increasingly common. When a chained multi-stop trip is involved, in addition to the home location, accessibility can be evaluated from the various stops on the trip. In the location modeling literature, efforts have been made to incorporate commute-based trip chaining into location models (Hodgson, 1981; Tong et al., 2012). However, as discussed earlier, other forms of non-commute trip chains could also be as influential on individuals’ daily travel. These, therefore, need to be considered in building location models as well.

Activity spaces can also be incorporated into location modeling. In fact, activity space has been long used as an indicator of accessibility (Gesler and Meade, 1988; Sherman et al., 2005; Wong and Shaw, 2011; Farber et al., 2012; Martinez et al., 2014; Patterson and Farber, 2015). Empirical studies have shown that people may use their daily activity spaces, rather than actual distances, to measure the accessibility to potential urban opportunities (Nemet and Bailey, 2000; Sherman et al., 2005). Opportunities falling inside one’s activity space may be considered more “accessible” than those outside the activity space. As a result, it would be feasible to evaluate accessibility by enumerating the presence of opportunities within one’s activity space (Patterson and Farber, 2015). In a location model, the aforementioned activity space based accessibility measure can be used as a new objective to be maximized. Although similar ideas have been discussed in the literature (Shannon and Spurlock 1976; Cromely and Shannon 1986), very little effort has been made to incorporate them into mathematical formulations.

Given the gaps and issues identified in the existing literature, contributions in this dissertation lie in the following points. First, in order to more accurately portray the extent of travel in space and time, the conventional time geography based activity space approach is improved to account for more complex urban travel and the underlying urban structure. Next, based on activity space, an empirical study is conducted to investigate the relationship between accessibility to urban opportunities and urban travel across various activity types. The roles of trip chaining and employment status in affecting the relationship are assessed as well. Lastly, to locate new facilities
in an urban area, a new multi-objective location model incorporating accessibility and activity space is formulated. Compared to the traditional PMP, the new model handles accessibility maximization in a more realistic manner.

The reminder of the dissertation is organized as follows:

In the second chapter, a new activity space approach based on the time geography framework is introduced. In addition to commute-based trips, other trip instances such as home-based and workplace-based trips are also accounted for in the model. Additionally, the urban structure, as represented by land uses and road networks, is incorporated into the generation of human activity spaces. A GIS-based activity space generation algorithm is elaborated in detail. An empirical study based on the National Household Travel Survey (NHTS) data in Tucson, AZ is presented to illustrate the new approach. Results show that the new time geography based approach exhibits significant advantages in more accurately portraying individuals’ activity spaces in space and time.

Based on the same travel dataset, the third chapter presents an empirical study investigating the relationship between accessibility to six opportunity types and urban travel. The activity space model proposed in the previous chapter is used to characterize extent of urban travel for each individual traveler. A new accessibility measure accounting for the complexity of urban travel is introduced. The relationship between areas of activity spaces and accessibility scores are examined using a mathematical model. Results show that although improved accessibility is generally associated with reduced travel, such an effect varies among different activity types. In addition, the roles of employment and trip chaining behavior in affecting the accessibility-travel relationship are evaluated. Insights obtained in the results are expected to help formulate more effective travel reduction policies.
In the fourth chapter, a new multi-objective location model is developed with the goal of accessibility maximization. The model extends the classic PMP to account for accessibility in a more realistic manner. Trip chaining and activity space are incorporated into the development of the location model. In addition to fixed home locations, stops along a chained trip are used to measure spatial accessibility to potential service sites. An activity space based accessibility measure is also introduced to evaluate accessibility. The model is applied to locate facilities in Tucson, AZ. Various alternative versions of the objection function are solved exactly, with the resulting optimal facility location patterns displayed and analyzed. Different weighting of sub-objectives would be appropriate for different types of service facilities, and decision makers are given flexibility to determine the relative importance for each sub-objective, based on their preferences and practical needs for the planning task.

The last chapter summarizes the results and main contributions of the studies. The dissertation concludes with remarks on some future research directions.
2.1 Introduction

Understanding individuals’ travel behavior is important for various urban and transportation planning applications. Among others, constructing activity spaces provides an important way to describe where and how individuals’ travel takes place (Schönfelder and Axhausen, 2004; Buliung and Kanaroglou, 2006a; Järv et al., 2014). Different from concepts that focus on travel potential or accessibility (e.g., space-time prisms, action spaces, perceptual spaces, mental maps), activity spaces are constructed based on locations that individuals have personally visited (Schönfelder, 2006), thereby providing important insights into individuals’ movement dynamics in space-time. Over the past few decades, research on activity spaces has drawn interest from a range of disciplines, including transportation, urban studies, geography, sociology, and public health (Dijst, 1999; Järv et al., 2014; Harding et al., 2013; Parthasarathi et al., 2014; Buliung and Kanaroglou, 2006a, b; Wong and Shaw, 2011; Jones and Pebley, 2014; Hieronimo et al., 2014; Sherman et al., 2005).

A number of approaches have been developed to portray activity spaces with varied emphases. One commonly used approach has been focused on development of certain geometric shapes (e.g. the standard deviational ellipse (SDE) or minimum convex polygon (MCP)) to describe the spatial dispersion of activity locations. Studies have also incorporated the time geography framework into the activity space delineation design (Newsome et al., 1998; Dijst, 1999; Saxena and Mokhtarian, 2010). Time geography based approaches have a unique capability to delineate
activity spaces by also integrating individuals’ travel behavior in space and time. However, all these measures are limited in accurately representing individuals’ activity-travel (Wong and Shaw, 2011; Rai et al., 2007; Sherman et al., 2005; Patterson and Farber, 2015). For example, those approaches may overestimate the actual extent of travel due to the overlooking of the underlying urban structure. Another issue lies in the inability to account for complex urban travel. For example, most geometry based approaches such as SDE or MCP measures pay more attention to the spatial distribution of activity locations but ignore other important aspects of activity-travel. Current time geography based approaches are also limited with a main focus on commuting trip between home and workplace. However, empirical studies (Lockwood and Demesky, 1994; Mcguckin and Murakami, 1995; Strathman and Dueker, 1995; Jou and Hahmassani, 1997; Mcguckin et al., 2001; Primerano et al., 2007) have shown that urban travel is more complex that goes beyond commuting trips.

To the best of our knowledge, little effort has been made to address the aforementioned issues associated with the current activity space measures. Motived by these research needs, in this study we develop a more realistic time geography based approach to account for complex urban activity-travel as well as underlying urban structures. In particular, building on the work by Newsome et al. (1998), we propose a new activity space model to allow for more complex trip cases, such as non-commuting trips (either home-based or workplace-based) and simple trips with no additional stops made. To address the problem of delineating these more realistic network-based activity spaces, we introduce a GIS-based delineation algorithm.

This paper is organized as follows. The next session provides a review of the literature on activity space and urban travel behavior. This is followed by a methodology section describing our new activity space measure. Then the empirical study is presented. Discussion and conclusions are given in the final two sections.
2.2 Literature Review

A number of approaches have been proposed to describe people’s movements. In general, these approaches have focused on either travel potential or observed/realized travel.

The time geography approach (Hägerstrand, 1970; Lenntorp, 1977) has been recognized as the pioneer work in studying travel potential. Under this framework, an Individual’s movement can be captured within a 3-dimentional (3-D) space-time prism (Lenntorp, 1977), which contains all locations that the individual can visit given his/her time constraints. In the past two decades, geographic information systems (GIS) have been highly integrated in constructing space-time prisms and analyzing travel potential (Miller, 1991; Kwan 1998, 1999; Wang and Cheng 2001; Kwan et al., 2003; Frihida et al., 2004). In particular, by projecting the potential path space in the 3-D space-time prism to a 2-D geographical space, Kwan (1998) and Kim and Kwan (2003) demonstrated that the projected geographical area delimits the spatial extent that an individual can reach, also known as the Potential Path Area (PPA). Schönfelder and Axhausen (2004) provided a summary of other approaches used to describe individuals’ travel potential, including cognitive or mental map (Lynch, 1960), perceptual space (Dürr, 1979), action space (Horton and Reynolds, 1971) and awareness space (Brown and Moore, 1970). Overall, space-time prism, along with other approaches, mostly focus on individual travel potential and whether actual travel will be realized in the described space is not addressed.

As opposed to the travel potential-oriented approaches, activity spaces are indicators of observed or realized travel. Activity spaces focus on the actual usage of space. They provide a micro-geographic depiction of the observed travel ranges and locational choices of travelers (Rai et al., 2007). The concept of activity spaces was introduced in the 1960s and 1970s (see Golledge and Stimson (1997) for a detailed discussion). Despite minor variations as the concept has been applied in different disciplines (Sherman et al., 2005), a generally accepted definition is that activity space is a 2-D space consisting of all (local) places that are frequented by an individual over a
certain period of time (Rai et al., 2007; Schönfelder, 2006). The concept has also been distinguished from *action space* (Horton and Reynolds, 1971), in which second-hand experiences are considered as well.

Activity spaces have been broadly adopted and studied in a range of fields. In transportation, various factors influencing activity spaces have been examined, including mode of transportation (Harding et al., 2013), street-network structures (Parthasarathi et al., 2014), and travel behavior patterns (Järv et al., 2014). In social science, Jones and Pebley (2014) used activity spaces to compare social characteristic variations in multiple residential neighborhoods. Wong and Shaw (2011) proposed an activity space based exposure approach to evaluate residential segregation. In public health, activity spaces have been used to link the spatial-temporal occurrence of plague in Western Tanzania (Hieronimo et al., 2014) and evaluate utilization of health services (Nemet and Bailey, 2000). In urban studies, the spatial extent of travel described in activity spaces provides substantive insights into how people interact with the built environment, including urban form (Buliung and Kanaroglou, 2006b) and neighborhood effects (Jones and Pebley, 2014). Interested readers are also referred to Patterson and Farber (2015) for a comprehensive review of various applications of activity space.

Using geometric shapes to describe individuals’ activity spaces represents one of the widely used strategies (Ren, 2016). For example, the standard deviational ellipse (SDE) (Yuill, 1971) is drawn to encompass the smallest area that contains a set of activity sites. The minimum convex polygon (MCP) measure has also been used to delineate activity spaces (Hisch et al., 2014; Buliung et al., 2006a, b). Rai et al. (2007) examined a number of more complex geometric shapes used to draw activity spaces, including superellipse, cassini oval and bean curve. A common characteristic of these geometry based approaches is that they focus on the spatial dispersion of activity locations with little or no details of individuals’ activity-travel accounted for.
Another strategy for delineating activity spaces is built on the time geography paradigm (Ahas et al. 2007; Ren, 2016). The activity space approach offered in Newsome et al. (1998) is the first attempt to incorporate the time geography into the construction of activity spaces. (Ahas et al. 2007; Schöpfel, 2006). Unlike the geometry based approaches that primarily examine the spatial distribution of activities, the time geography based activity space delineation strategy focuses on travelers’ activity-travel behavior in space and time. Anchor points of daily life travel, such as home and workplace, are considered as foci of the ellipse. The boundary of the activity space is determined by the regular activity that has the largest total distance to the foci. Compared to the 2-D potential path area (PPA) projected from the 3-D space-time prism (Hägerstrand, 1970) whose size is solely determined by the space-time budget, the measure introduced in Newsome et al. (1998) takes into account the observed travel behavior of an individual. Therefore, it provides a better understanding of an individual’s activity-travel.

Although the approach introduced in Newsome et al. (1998) has been considered as a useful tool for modeling activity spaces, some issues exist in its implementation. Wong and Shaw (2011) noted that it may be difficult to derive ellipses for some less common but realistic cases, such as when locations visited are in a straight line, or sites visited are too few to meet the geometric requirement for defining an ellipse. In addition, a common issue of the existing activity space measures relates to the tendency of overestimating the actual extent of travel, as a rather large and generalized area is included (Sherman et al., 2005; Wong and Shaw, 2011; Patterson and Farber, 2015). Such an area may sometimes cover places where no opportunity exists, such as “no-go” areas (Rai et al., 2007; Schöpfel and Axhausen, 2004). As suggested by Sherman et al. (2005), with the rapid advance of GIS and growing computational capabilities, new approaches are needed to enhance the capabilities of activity space approaches for a more realistic depiction of spatial travel behavior.
A major problem with the approach described in Newsome et al. (1998) is its inability to fully address the complexity of real-world travel behaviors. Their approach is built upon commuting trips (home-to-work and work-to-home trips) and assumes all other activities are chained to these trips. To some extent, the focus on commuting can be justified by the importance of work trips in daily lives (Golledge and Stimson, 1997). However, as noted by Primerano et al. (2007), work trips do not reflect the activities undertaken by many population subgroups (e.g., non-workers, the unemployed, retirees).

Over the years, an increasing number of empirical studies have indicated that other types of trips can be as important as commuting trips. In particular, home-based non-commuting trips (home-to-home tours) have been found to account for a significant portion of all trips made by individuals (or households). For example, based on the 1995 National Personal Transportation Survey Mcguckin and Murakami (1995) found that most trips were completed as home-based trips. After examining the personal travel data in San Francisco, Adiv (1983) reported that the majority of daily activities were independent from commuting trips. Strathman and Dueker (1995) also estimated that commuting-related trips only accounted for 30% of all personal trips, compared to 70% home-based non-commuting trips. A similar finding was noted by Lockwood and Demesky (1994), in which non-commuting trips were estimated to account for 75% of all trips made by households in Northern Virginia.

Another weakness of the approach provided in Newsome et al. (1998) is that it is constructed based on the farthest activity site along a commuting trip. However, empirical studies indicate that only a small fraction of workers make additional stops when traveling between home and work, although such trip chaining has been becoming more common. Mcguckin et al. (2001) showed that only 25% and 27% of week-day workers chained their commuting trips in 1995 and 2001, respectively, buttressing the earlier findings of Jou and Hahmassani (1997) that 75.06% and 64.1% of morning and evening commuting trips had no stops in Dallas.
In this research, we aim to develop a new time geography based approach to better describe individuals’ activity-travel. Our approach explicitly incorporates urban structure (street network and urban land use) and accounts for a wide range of trips. By also incorporating non-commuting trips (both home-based and workplace-based) into the activity-space framework, the new approach provides a more realistic description of individuals’ activity-travel. The incorporation of urban structure also presents a possible solution to the overestimation issue.

### 2.3 Methodology

According to Newsome et al. (1998), the activity space for an individual is constructed using a locus of point locations that maintain a constant distance to the foci, namely, home and workplace (or school) (see Figure 2.1). The resulting shape is an ellipse. We note that the ellipse derived in Newsome et al. (1998) is different from the geometry based ellipse approach (e.g., SDE) where an ellipse is generated to encompass activity sites. The ellipse to be discussed from now on refers to the one by Newsome et al. (1998). Such an ellipse has a number of important properties. First, as shown in Figure 2.1, the constant distance \( D_F \) is determined by the location of the farthest “mandatory” activity chained to the work trip. In the example, this location is the one marked “eat meal.” The individual prefers to dine at the specified “eat meal” location on a daily basis, thus qualifying the activity as a “mandatory” one.

The location of the mandatory activity might be subject to a number of space-time constraints (e.g., time availability, mobility, service hours), as well as personal preferences. In fact, the ellipse approach in Newsome et al. (1998) is rooted in the time geography framework. As noted by Dijst (1999), the projection of a space-time prism defined by travel between a pair of fixed pegs (home and workplace) is in an elliptical shape; if only one peg is involved in the travel, the ellipse will simply be a circle. Note that here the “elliptical shape” and “circle” refer to the potential spaces...
of travel, which is determined by an individual’s space-time budget (Miller, 1991), not by the actual locations being visited.

The resulting ellipse given in Newsome et al. (1998) focuses on the travel extent that contains the areas a person actually visits. In other words, we can consider the ellipse activity space as a subset of the “potential activity space.” As Newsome et al. (1998) stressed, this ellipse-shaped activity space may or may not reflect the maximal range of movement of the traveler. Rather, it indicates the observed area with performed activities. The ellipse also serves as the minimal area where travel and activity occurs, based on the realized activity travel history of an individual.

![Figure 2.1 Using an ellipse to delineate an individual’s activity space (Newsome et al., 1998)](image)

As discussed in Section 2, the ellipse model introduced in Newsome et al. (1998) only accounts for activities chained on commuting trips and ignores other types of trips. In reality, due to the significant portion of non-commuting trips in daily travel, it is common that the associated activities may be performed outside the boundary of the ellipse depicted in Figure 2.1. As a result, the ellipse-shaped activity space may be inaccurate in fully capturing people’s activity spaces. According to Golledge and Stimson (1997), activity spaces can be characterized by three components: home location, locations for regular activities (workplace, school, etc.) and movements between or around the centers of daily life travel (pegs). We believe that all these
essential elements described in Golledge and Stimson (1997) should be accounted for in building activity spaces. In this study, we propose to incorporate other types of trips, for example, the home-based non-commuting trips, into the construction of activity spaces.

The overall structure of the new activity spaces is demonstrated in Figure 2.2. In general, it can be broken down into three components: commuting-based sub-activity space, home-based sub-activity space and workplace-based sub-activity space. We note that the activity space given in Newsome et al. (1998) is a special case of our activity space when an individual only conducts commuting trips. The commuting-based sub-activity space component inherits the fundamental composition of the ellipse proposed by Newsome et al. (1998). As discussed earlier, if no stop is involved on the work commute, or the stops are located on the commuting trip, the activity space is no longer an ellipse. Rather, all the travel involved is the commuting trip between the two pegs. In a hypothetical situation as shown in Figure 2.2, the path between home and workplace is shown as a straight line as suggested by Dijst (1999).

The home-based sub-activity space is used to map the spatial extent of home-based non-commuting trips. This sub-activity space represents a critical component in the overall activity space construction, given that empirical studies have showed that most travels start from, as well as end at, home. Home has been regarded as the most important point of daily travel (Golledge, 1999). In contrast with the dual-peg (home and workplace) configuration of commuting trips, home is the only peg for home-based non-work trips. Theoretically speaking, without considering factors such as road networks or other underlying urban structures, home-based sub-activity space can be conceived as a circle centered at home. Similar to the ellipse construction, the radius of the circle is determined by the farthest mandatory activity, beyond which no activities have been observed. As a result, locations of all other chained activities are contained in the circle. Both simple trips (home-activity-home) and complex (home-activity1-activity2-...-home) trip chains can be incorporated in the circle-shaped structure.
Similarly, workplace-based sub-activity space represents the spatial extent of at-work trips and can be constructed using a circle centered at the workplace. Activities that both originate at and return to the workplace are used to determine the radius of the circle. In fact, studies have found that trips performed while at work account for a significant proportion of activity travel: 4.5% of all chained trips (Lockwood and Demesky, 1994), 8.15% of all work involved chained trips (Yang et al., 2007) and 1.2% of all personal trips (Strathman and Dueker, 1995). Note, however, that due to the limited time budget and other personal constraints (personal preferences, mobility, etc.), the workplace-based sub-activity space may well be smaller than the home-based counterpart, as shown in Figure 2.2.

![Figure 2.2 A new approach for delineating activity spaces](image)

Integrating the time dimension, Figure 2.3 shows a 3-D representation of our activity space model. In addition to the two dimensions of geographical space, time, as the third dimension, is represented by the vertical axis. The red dots represent home and workplace; each black dot denotes the farthest activity locations visited via either home-, workplace- or commuting-based trips. The prism shaped spaces are the actual activity spaces that contain all observed travels that occur in time and space. The vertical dimensions of the spaces are determined by time when activities and travel are performed, and the horizontal extent represents the associated spatial territory. Projecting
the 3-D prism to the 2-D geographical space results in the same structure we illustrated in Figure 2.2.

Figure 2.3 A 3-D representation of the new activity space model

To more accurately delineate the spatial extent of an individual’s movement, urban structure can be integrated in the construction of the new activity space. Urban structure, as suggested by Gesler and Meade (1988), can be a more critical factor affecting individuals’ daily travels than demographic characteristics. In particular, transportation networks (mainly road networks) and land uses are used in this research to illustrate the influence of urban structures on activity spaces.

An illustration of an activity space incorporating urban structures is shown in Figure 2.4. The theoretical regular activity-space geometries (gray dashed lines) are compared with the one
refined with a consideration of the actual urban structure (black solid lines). In the refined activity space, travel is assumed to follow road networks. For each of the three sub-activity spaces, the distance \( D_F \) from the observed farthest mandatory activity location to the pegs (home and/or workplace) is now calculated based on the shortest network distances (black dashed lines) as opposed to the Euclidean distance used in the theoretical model.

**Figure 2.4 An activity space incorporating urban structures**

When travel along networks is considered, GIS software can be used to derive the home-based and workplace-based sub-activity spaces (e.g., Service Area functionality provided by ArcGIS with the Network Analysis Extension enabled). However, for the commuting-trip based sub-activity space, no GIS software exists to derive the network-based “ellipse” boundary.

We designed a GIS-based algorithm to specifically address this issue. A simple example is shown in Figure 2.5 to illustrate the algorithm. Following the definition of an ellipse, the boundary of the network-based “ellipse” contains points with a constant total travel distance, \( D_F \), to the two foci (home and workplace). Therefore, for any given point on the boundary of the network-based “ellipse,” we have the network-based distance, \( D_h + D_w = D_F \). Given \( D_F \), which can be computed based on the observed activities along the commute trip, \( D_w \) (or \( D_h \)) can be derived by fixing the \( D_h \)
(or $D_w$). Also note that both $D_h$ and $D_w$ fall in the range of $[0, D_F]$. By discretizing $D_h$ or $D_w$, we have the procedure to derive the network-based “ellipse” boundary.

Step 1 Compute $D_F$ and initialize n. Set $k=0$ and $NE=\emptyset$

Step 2 $k=k+1$ ($k \leq n$)

1. Set $D_h = k \times D_F / n$ and compute $D_w = D_F - D_h$.
2. Generate the two network-based “service areas,” with one using the travel distance $D_h$ from home and another using the travel distance, $D_w$, from the workplace.
3. Intersect the two “service areas.” If the intersection is not null, add the intersection polygon to $NE$.

Step 3 Merge and dissolve the intersection polygons in $NE$.

Step 4 Evaluate the quality (completeness, connectivity, etc.) of the resulting commuting trip-based activity space. If sufficient details are included, go to step 5; if not, increase $n$ and repeat steps 1 to 4.

Step 5 Stop.
In addition, certain areas are “accessible” through road networks but have no opportunities available, such as vacant spaces or waterbodies, and therefore may be considered as “no-go” areas that might need to be excluded from the final activity space map. The gray-colored “gaps” in Figure 2.4 are used to illustrate such areas.

Finally, all three sub-activity spaces together form a combined activity space for the traveler. These will most likely be unique for each individual. The activity spaces constructed for different individuals may vary substantially in terms of shape, structure and spatial coverage. Such variation is among the topics we will examine in the following section.

2.4 Empirical Study

The City of Tucson, Arizona was selected as the case study site. The study area was sampled intensively as part of the 2008 Add-on National Household Travel Survey (NHTS) data.
in Pima County. The interview based survey was conducted from April 2008 to May 2009 with most data collected in September, October and November of 2008. The dataset provides one day travel information on all individuals in the sampled households. A typical 24-hour travel day was from 4:00 am to 3:59 am of the following day (Federal Highway Administration, 2011).

The dataset contains demographic information, household characteristics, detailed information associated with travel activities during the survey day (including mode of transportation, purpose of travel, travel distance, travel time, locations of origin and destination, and time spent on particular activities). The survey consists of 2,361 households with a total of 4,777 individuals (about 0.5% of the county population). We removed 3,475 individuals that are outside the study area. Since this study is particularly interested in complete travel sequences in a day, 132 individuals that did not start or finish trips at home locations were also excluded. Accordingly, a total number of 745 households with 1,164 travelers were used in this study.

The street network data were obtained from the Pima County GIS portal. Land use and parcel data were also obtained to identify the potential “no-go” areas. In the study, vacant land and water bodies were used to illustrate “in-accessible” land-use types.

Figure 2.6 shows all the activity locations within the study area. The map indicates that most of the activities concentrated in the northern part of the city. This is what we expected, as much of the southern portion of the city consists of large vacant or military areas containing few or no publically accessible facilities.
With respect to employment status, among all the travelers included in the study, workers and non-workers accounted for 43.5% (402 individuals) and 65.5% (762 individuals) respectively. Within the survey time period, 233 out of the 402 (58%) workers reported work commutes. A summary of workers and non-workers is shown in Table 2.1. We note that the percentage of workers (43.5%) is noticeably lower than the national average labor force participation rate 65% (Bureau of Labor Statistics, 2016). One possible explanation is that the survey includes participants who are younger than 16 years old. Such population is excluded when calculating the labor force participation rate. Another reason relates to the possible bias in the interview-based survey. The retired group might be more likely to participate in the survey especially considering that the city receives a significant amount of snowbirds during the survey data collection period (September through November).
Table 2.1 Composition of the sample population

<table>
<thead>
<tr>
<th></th>
<th>Number of travelers</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workers</td>
<td>402</td>
<td>43.5%</td>
</tr>
<tr>
<td>Non-workers</td>
<td>762</td>
<td>65.5%</td>
</tr>
<tr>
<td>Total</td>
<td>1,164</td>
<td>100%</td>
</tr>
</tbody>
</table>

Activities were also classified based upon the three types of trips defined earlier: home-based trips, workplace-based trips and commuting trips. Table 2.2 provides a summary of the three types of trips extracted from the survey. The majority of the sample population (both workers and non-workers) reported home-based trips (1,071 out of 1,164 individuals). Only 51 workers engaged in work-based trips, accounting for 21.9% of the total number of workers who had work commutes during the survey time. In terms of work related trip chaining behaviors, there appears to be an even split between chained work trips and non-chained work trips. About 56% of workers made at least one additional stop on the commute, which is much higher compared with that of 20% reported in the literature (Mcguckin et al., 2001; Jou and Hahmassani, 1997).

Table 2.2 Summary of the commuting trips

<table>
<thead>
<tr>
<th></th>
<th>Number of travelers</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workers who chained at-work travel</td>
<td>131</td>
<td>56.2%</td>
</tr>
<tr>
<td>Workers who did not chain at-work travel</td>
<td>102</td>
<td>43.8%</td>
</tr>
<tr>
<td>Total</td>
<td>233</td>
<td>100%</td>
</tr>
</tbody>
</table>

Using the new approach described in Section 3, we constructed activity spaces for all 1,164 travelers. Both regular-shaped theoretical activity spaces and more realistic, urban structure based activity spaces were computed. For the purpose of comparison, the original ellipse approach described in Newsome et al. (1998) was also used to generate activity spaces for the 131 workers who chained trips on their work journeys. The activity-space algorithm was programmed in Python 2.7 and ArcGIS scripting library Arcpy was used to perform GIS functions. All the results were visualized in ArcGIS 10.2.
2.5 Results

A total of 1,253 sub-activity spaces were generated for the 1,164 sampled individuals. In particular, the numbers of commuting trip-based, home-based and workplace-based activity spaces are 131, 1,071 and 51 respectively, which represent ratios of 2.6: 21: 1. Table 2.3 provides a summary of the sub-activity spaces generated. Over 85.47% of all the sub-activity spaces generated are home-based activity spaces. This finding is as expected, given that the majority of the population (932 out of 1,164) were either non-workers or workers who did not have work commutes.

We also calculated the areas of the urban structure-based activity spaces. As Table 2.3 shows, the average area of home-based sub-activity space is the highest, whereas workplace-based sub-activity space is the smallest. This agrees with previous findings that people tend to have more constrained time budgets at work (Kim and Kwan, 2003).

<table>
<thead>
<tr>
<th>Sub-activity space</th>
<th>Number of sub-activity spaces</th>
<th>Area of sub-activity spaces</th>
<th>Average area of sub-activity spaces (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Number</td>
<td>Percentage (%)</td>
<td>Sum of areas (km²)</td>
</tr>
<tr>
<td>Commuting trip-based</td>
<td>131</td>
<td>10.45%</td>
<td>10019.02</td>
</tr>
<tr>
<td>Home-based</td>
<td>1071</td>
<td>85.47%</td>
<td>109241.07</td>
</tr>
<tr>
<td>Workplace-based</td>
<td>51</td>
<td>4.07%</td>
<td>2586.64</td>
</tr>
<tr>
<td>Total</td>
<td>1253</td>
<td>100.00%</td>
<td>121846.7</td>
</tr>
</tbody>
</table>

We further examined the 233 workers who reported their work trips in the survey. We classified the workers based on seven sub-activity space combinations. They are individuals who have: home-based (HB) sub-activity spaces, only; workplace-based (WB) sub-activity spaces, only; commuting trip-based (CB) sub-activity spaces, only; home- and workplace-based (HB and WB) sub-activity spaces; home- and commuting trip-based (HB and CB) sub-activity spaces; workplace-
and commuting trip-based (WB and CB) sub-activity spaces and the full set of the three sub-activity spaces (CB, HB and WB). Table 2.4 provides a summary of the various types of activity spaces delineated for all workers in the sample.

<table>
<thead>
<tr>
<th>Activity space combination</th>
<th>Number of individuals</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CB only</td>
<td>65</td>
<td>27.90</td>
</tr>
<tr>
<td>HB only</td>
<td>75</td>
<td>32.19</td>
</tr>
<tr>
<td>WB only</td>
<td>14</td>
<td>6.01</td>
</tr>
<tr>
<td>HB and CB</td>
<td>42</td>
<td>18.03</td>
</tr>
<tr>
<td>WB and CB</td>
<td>14</td>
<td>6.01</td>
</tr>
<tr>
<td>HB and WB</td>
<td>14</td>
<td>6.01</td>
</tr>
<tr>
<td>CB, HB and WB</td>
<td>9</td>
<td>3.86</td>
</tr>
<tr>
<td>Total</td>
<td>233</td>
<td>100.00</td>
</tr>
</tbody>
</table>

As Table 2.4 shows, more than 66% of the workers had only one of the three sub-activity spaces (CB only, HB only or WB only). In particular, HB only accounts for the highest percentage (32.19%), followed by the CB only (27.90%), with WB only being the lowest (6.0%). About 30% of the workers had two types of sub-activity spaces combined, and only 3.86 % of working individuals had all three sub-activity spaces. Despite the importance of home discussed earlier, we noticed that not everyone made home-based trips, especially workers. Of workers who reported commuting travel, 93 out of the 233 (40%) had no home-based activities. For these workers, it may be more convenient or realistic to perform activities around the work locations or along commute trips during the workday. Also the survey data only contain one-day travel information, which might not capture all the travel people make for a longer period of time. Among all the 233 workers, 23 individuals performed both work-based and home-based activities.

We compared the three methods used to derive activity spaces: the original ellipse (see Figure 2.1), the Euclidean distance based activity space with three sub-activity spaces (see Figure 2.2) and the network based activity space incorporating urban structures (see Figure 2.4). To keep
things simple, we will call them “The Ellipse,” “Model 1” and “Model 2,” respectively, for the remainder of the article.

We shall use the travel reported by one of the individuals in the survey to illustrate the differences among the three activity space delineation methods. This traveler is a middle-age, working female. According to the dataset, her travel began from home in the morning. On the way to work, she made a stop at a school to drop off children, then went straight to work. During the lunch break, she ate at a Pizza Hut. In the afternoon, she visited a Wendy’s nearby, then went quickly back to work. After work, no trip was chained, as she returned home directly. After that, she left home and performed a series of food related activities and visited Javelina’s (a restaurant), Jerry Bob’s (a restaurant) and Burger King. Then this person returned home, where her daily travel ended. Her trips and the corresponding trip start and end times are provided in Table 2.5 below.

<table>
<thead>
<tr>
<th>Trip Order</th>
<th>Where To</th>
<th>Trip Start Time</th>
<th>Trip End Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>School</td>
<td>07:40 AM</td>
<td>07:50 AM</td>
</tr>
<tr>
<td>2</td>
<td>Work</td>
<td>07:50 AM</td>
<td>08:15 AM</td>
</tr>
<tr>
<td>3</td>
<td>Pizza Hut</td>
<td>11:10 AM</td>
<td>11:20 AM</td>
</tr>
<tr>
<td>4</td>
<td>Work</td>
<td>12:00 PM</td>
<td>12:10 PM</td>
</tr>
<tr>
<td>5</td>
<td>Wendy’s</td>
<td>16:10 PM</td>
<td>16:20 PM</td>
</tr>
<tr>
<td>6</td>
<td>Work</td>
<td>16:25 PM</td>
<td>16:30 PM</td>
</tr>
<tr>
<td>7</td>
<td>Home</td>
<td>18:30 PM</td>
<td>18:50 PM</td>
</tr>
<tr>
<td>8</td>
<td>Javelina’s</td>
<td>19:00 PM</td>
<td>19:05 PM</td>
</tr>
<tr>
<td>9</td>
<td>Jerry Bob’s</td>
<td>19:05 PM</td>
<td>19:10 PM</td>
</tr>
<tr>
<td>10</td>
<td>Burger King</td>
<td>19:50 PM</td>
<td>20:10 PM</td>
</tr>
<tr>
<td>11</td>
<td>Home</td>
<td>20:15 PM</td>
<td>20:35 PM</td>
</tr>
</tbody>
</table>

Figure 2.7 maps the traveler’s activity space derived using Model 1. Compared with the Ellipse Model, which considers only the commuting trip-based sub-activity space, Model 1 captures a more realistic extent of the travel the individual made. The regular shaped activity space contains three sub-activity spaces, covering an area that is significant larger than the commuting-based sub-activity space given by the Ellipse Model. Furthermore, for this individual the area of
the workplace-based sub-activity space is significantly smaller than the home-based counterpart. As discussed earlier, this is because the dining activity at Pizza Hut occurred during the lunch break, when she had a limited amount of time. The post-work dining activities, on the other hand, may be much less time constrained due to a comparatively abundant time allowance after work. Therefore based on home, the person was able to travel to a restaurant (the Burger King) that is somewhat distant from her residence.

Among all the 131 workers who made one or multiple stops during their commutes, 39 individuals reported additional travel around home or workplace and therefore had additional home-based or workplace-based sub-activity spaces. Activity spaces of these 39 individuals derived from the Ellipse Model and Model 1 are compared. Similar to what we observed for the individual traveler discussed earlier, the activity space given by Model 1 is significantly larger, with an overall increase of 336.47%. This suggests that the new activity space delineation approach helps identify a significant amount of spaces (such as home-based and workplace-based activity spaces) that are ignored by the ellipse model.

![Figure 2.7 The activity space of a traveler according to Model 1](image-url)
Activity spaces of Model 2 are distinctly different from those of Model 1, in both area and spatial coverage. Figure 2.8a maps a traveler’s activity space derived using Model 2. It is clear that the regular shaped sub-activity spaces in Figure 2.7 no longer hold here because travel has to follow the road networks. The “no-go” areas, including vacant land and water bodies, were also excluded from the activity space. This resulted in several holes in the activity space. Activity spaces of Model 1 and Model 2 are overlaid in Figure 2.8b to show the differences in spatial coverage. In terms of size, the activity space given by Model 2 is significantly smaller (approximately 49% less) than its counterpart. There is also a notable inconsistency in spatial coverage identified at the boundary area due to the different distance metrics used to compute \( D_f \) (network distance for Model 2 versus straight-line distance for Model 1). To quantify the difference of spatial coverage, we calculated the non-overlapping ratio (non-overlapped area / area of the activity space by Model 1). The non-overlapping ratio for this traveler is 52%, indicating that activity spaces derived using the two models differ significantly in space.

For all the 131 workers, the average area of the activity spaces given by Model 2 decreased by 41.71% when compared with those generated by Model 1. The average non-overlapping ratio for the 131 travelers is 49.3%, suggesting that nearly half the activity spaces constructed using Model 1 are different from those given by Model 2. These differences are due to the fact that with road networks and urban land uses being considered, activity spaces delineated using Model 2 tend to be more spatially confined. In other words, although Model 1 considers a full spectrum of travel, the regular shaped activity spaces based on ellipses or circles may be unrealistic, especially considering that urban travel mostly occurs along roads and in accessible areas (Weber and Kwan, 2003).
Figure 2.8a The activity space of a traveler according to Model 2

Figure 2.8b Comparison of activity spaces constructed using Model 1 and Model 2
More examples of activity spaces given by Model 1 and Model 2 are presented in Figure 2.9a and 3.9b. Figure 2.9a shows the activity space of an individual who did not chain any activity with commuting. The person’s activities were performed around workplace and home, which thereby defined two sets of activity spaces of varied sizes. To be more specific, her home-based activity space is notably larger than the workplace-based activity space, which is consistent for both models. The traveler in Figure 2.9b had a different activity-travel pattern. The individual has a significantly larger sub-activity space around workplace. Again, results of Model 2 appeared more realistic compared to those of Model 1. The examples demonstrate that travel behavior in urban areas are complex and may vary substantially among people.

Figure 2.9a Activity spaces comparison for an individual with no commuting trip-based activity space
2.6 Discussion

Activity spaces derived based on the case study show that home is the most important “peg” in people’s daily travel, even for workers who have opportunities to engage in trip chaining on work commutes or around workplaces. In fact, the dominance of home-based sub-activity spaces in number and area is consistent with the previous research findings that non-work home-based trips account for a larger proportion of all trips made (Lockwood and Demesky, 1994; Mcguckin and Murakami, 1995; Strathman and Dueker, 1995). Therefore, home-based sub-activity space is an essential component in one’s activity space, which should not be ignored in human activity-space research.

Workplace-based travel also plays an important role in expanding workers’ spatial reach, as according to our empirical study more than 20% workers were found to have workplace-based activity spaces. In general, workplace-based activity spaces are relatively smaller, and they were found to be the least common type of sub-activity space. Workers usually lack time or flexibility
to perform activities around their workplaces, and, therefore, fewer workers are able, or may choose, to travel during their work time. If they do perform activities based from the workplace, the extent of this travel tends to be smaller than that for activities traveled to or from home.

Similarly, we found that commuting trip-based activity spaces, compared with home-based activity spaces, are smaller. This reflects that work commutes are also more time constrained than home-based trips. In the future, it would also be interesting to further divide work commutes into to-work trips and from-work trips to examine possible differing characteristics due to varied travel budgets (time).

As stated before, in addition to transportation networks and land uses, a more comprehensive incorporation of urban structures for activity space construction may involve evaluation of the probability of each individual visiting an urban opportunity considering both the urban form and the individual’s travel behavior. Development of such a detailed activity-space model requires a substantial amount of effort. Constructing the individual level opportunity set can be difficult given data availability. Assessing the probability of an individual visiting an urban opportunity presents another challenge. Such an assessment will require a careful evaluation of the individual’s space-time movement and the interaction dynamics with the urban environment.

Figure 2.10 shows a simple example of an individual’s activity space after accounting for detailed land use patterns. In this example, we removed vacant areas and other less commonly visited sites from the individual’s activity space. Tendencies of visits were approximated using a rank-based method considering land uses and the travel/activities performed by the individual. In the figure, darker colors show higher possibilities that the area would be visited.
Time variability is also worthy of attention when building activity spaces. In our case study, activity spaces were constructed based on the travel made in a single day. As noted by Järv et al., (2014), people’s travel behavior may vary between weekdays and weekends. Therefore, activity spaces should be able to respond to these variations. Furthermore, a further study might involve an examination of an individual’s activity space based on different time intervals to gain insights into the temporal dynamics (also see Figure 2). Such an analysis will provide a better understanding of real-world travel behavior in time and space.

As noted by Sherman et al. (2005), constructing activity spaces is very data intensive and data availability presents a big challenge to activity-space research. In fact, empirical studies on human activity spaces have lagged the theoretical development due to the lack of detailed long-term travel behavior data (Schönfelder and Axhausen, 2004).
Conventional data sources, such as surveys and travel diaries, are disadvantaged in several aspects. First, only a small proportion of population can be surveyed. Therefore, it is difficult to draw a statistically valid picture of the general population. Second, durations of observations are likely to be limited, which may not be adequate to gain a more complete horizon of people’s activity-travel behavior over time. In addition, such data are normally costly to collect or acquire. For example, the NHTS add-on dataset used in this study only recorded an individual’s travel for a day. Although it offers us some insights about people’s activity-travel behavior, especially considering that people tend to repeat their daily activities (Marble and Bowlby, 1968; Huff and Hanson, 1982; Buliung et al., 2008), if we could get data with larger samples and for longer observation periods, a more accurate activity space delineation would be achievable.

Recently, some emerging data sources have been receiving growing attention in activity-travel research, including mobile phone call data, smart card data, GPS data and social media data (Hasan et al., 2013; Yuan and Raubal, 2014; Noulas et al., 2013). The new data sources have a number of advantages, such as better resolution, larger sample sizes and relatively less expensive to obtain. This brings an unprecedented opportunity to activity space research, as noted by Patterson and Farber (2015). The activity space approach proposed in this paper has great potential to be applied to these new data sources.

Our contribution to the activity space literature lies in the efforts to provide an enhanced time geography based activity space delineation approach. Compared to the geometry based approaches (e.g. SDE, MCP, etc.) that focus solely on activity locations, our new activity space measure accounts for more complex urban activity-travel as well as urban structures. Our approach can also be applied to areas such as urban planning, market research and transportation planning. Activity spaces help identify the geographic locations where people tend to visit. For example, if one is interested in knowing whether and where additional service facilities are needed, insights can be gained by comparing service facility sites with the activity spaces of potential customers.
Noticeably underserved areas might indicate the need to introduce additional facilitates to fill in the gaps.

2.7 Conclusion

The concept of activity spaces is very useful for understanding human activity-travel behavior. The existing activity-space approaches in the literature, however, lack the ability to fully capture the complexity of urban travel in space and time, as well as failing to embed the underlying urban structure. This study proposed a new time geography based approach to address these shortfalls.

An empirical study based on the 2008 add-on NHTS dataset of Tucson, Arizona demonstrated the effectiveness of the new approach. By incorporating the home-based, workplace-based and commuting trip-based sub-activity spaces, the new approach was able to more realistically account for the true complexity of urban activity-travel. Moreover, consideration of road networks and land uses also improved the accuracy of activity space delineation.

Future research can be developed to further enhance activity space delineation by incorporating more details of the urban environment and temporal dynamics. Some emerging new data sources, such as geo-tagged social media data, can also be integrated into future activity space research.
CHAPTER 3
ACCESSIBILITY AND ACTIVITY SPACES: ACCOUNTING FOR THE EFFECTS
OF URBAN OPPORTUNITY TYPES AND TIRP CHAINING

3.1 Introduction

In the past few decades, urban expansion has become a global trend in both developed and developing countries. Many cities have grown tremendously in physical size as well as urban population. In the U.S., urban sprawl has transformed former agricultural and rural lands into suburbs and exurbs. Smaller cities have been gradually merging into larger metropolitan areas (Anderson et al., 1996; Dieleman et al., 2002; Curtis and Perkins, 2006; Crane, 2012). While urbanization helps increase overall personal mobility and affluence (Buliung and Kanaroglou, 2006b), it has led to a number of issues, including traffic congestion, energy over-consumption and air pollution. Many of these issues are attributable to increased automobile travel within or between urban areas (Ewing and Cervero, 2001). According to the National Household Travel Survey (NHTS), in the U.S. from 1983 to 2009, daily personal miles traveled and the number of trips have increased 44% and 31%, respectively. In 2009, over 88% of travel miles were made by private vehicles and over 81% were for non-work purposes (Santos et al., 2011). To address the issues associated with excessive automobile travel, policies have been made to reduce travel and car use and as well as to improve pedestrian and public transit access (Handy, 1996; Dieleman et al., 2002; Crane, 2012).

Understanding human travel behavior is important for formulating effective travel-reduction policies. Handy and Krizek (2012) argued that policy interventions will be effective only when we have a good understanding of travel and the factors that shape it. Among other approaches,
activity space has been suggested as a useful tool to characterize individuals’ travel patterns (Schönfelder and Axhausen, 2004; Ren, 2016). Activity space delineates a two-dimensional area covered by an individual over time. The advantage of activity space lies in its ability to portray the spatial extent of travel and provide more information than conventional distance based measures such as vehicle miles traveled (VMT) or trip rates.

It is well recognized that demand for transportation is largely derived from the needs for participating in various activities (McNally, 2000; Buliung, 2005). Urban travel is highly influenced by the distribution of urban opportunities in a city. Such opportunities are often available throughout an urban area to accommodate people’s various daily needs (e.g., dining, shopping, recreating, obtaining medical services, etc.). Accessibility, as an indicator of potential travel, has been widely used to measure the ease to access opportunities. The relationship between accessibility to opportunities and actual travel is often more complex than it may appear. For example, in many studies, such as recreation access and food access, accessibility is often measured based on the closest opportunity available or the number of opportunities within a distance threshold (Talen and Anselin, 1998; Church and Marston, 2003; Cao et al., 2007; Bao and Tong, 2016). However, in reality, people often don’t choose actual the nearest opportunities to obtain services (Nemet and Bailey, 2000; Mack and Tong, 2015). It is generally believed that improving accessibility helps reduce travel (Geurs and van Eck, 2001). However, to what extent such a practice remains effective considering the complexity of urban travel and how the effectiveness differs among various activity types remain challenging questions. These questions are critical for formulating effective policies for reducing excessive urban travel.

In this paper, we analyze the relationship between urban travel and accessibility to urban opportunities. With improved mobility and more frequent trip chaining behavior, our research questions include to what extent various levels of accessibility affect people’s travel and whether and how such an effect varies across different types of urban opportunities and among people with
various employment statuses and different types of trip-chaining travel behavior. Using a real-world travel dataset collected in Pima County, Arizona, our study provides empirical evidence to help answer these questions. We make use of a recent activity space model developed in Li and Tong (2016) to characterize urban travel and we introduce a new gravity-based accessibility measure to account for more complex trip instances.

3.2 Literature Review

Research on urban travel has a long tradition in the fields of transportation, geography, and urban studies (Buliung, 2005; Curtis and Perkins, 2006; Pendyala and Bhat, 2004; Handy and Krizek, 2012). In a large body of literature on travel, Handy and Krizek (2012) highlighted two streams of efforts, with one focusing on factors that shape travel behavior and the other related to policy making that aims to “intervene” travel. The former is particularly important as it serves as a basis for achieving the goal of the latter (Handy and Krizek, 2012). A better understanding of travel has been recognized as critical for improving mobility, reducing excessive automobile travel, addressing environmental issues, and predicting future travel demand (Mahmassani and Kitamura, 2000).

In general, factors affecting travel fall into two broad categories: the built environment (urban form, transportation infrastructure, etc.) and individuals’ socio-demographic characteristics (age, race, income, education level, etc.) (Pendyala and Bhat, 2004; Curtis and Perkins, 2006; Handy and Krizek, 2012). Although there have been continuing debates in the literature about what factors are more influential, it is widely recognized that both the built environment and socio-demographic factors have impacts on travel (Curtis and Perkins, 2006; Crane, 2012). With respect to the built environment, variables such as urban land uses and residential location choices are often found to be highly associated with people’s daily trip making (Handy, 1996). It is generally
believed that higher density, mixed use and more accessible neighborhood design tend to lead to lower VMT, trip rates and car use/ownership, and more use of other modes including walking, transit, etc. (Holtzclaw, 1994; Cervero and Kocklman, 1997; Pendyala and Bhat, 2004; Crane, 2012).

A concept that is highly relevant to the built environment and travel is accessibility. Accessibility is defined as “potential of opportunities for interaction” (Hansen, 1959) or “ease (or difficulty) to reach activity opportunities from a given location” (Chen et al., 2011). It is generally believed that shorter travel distance and less travel are associated with increased accessibility (Hanson and Schwab, 1987; Handy, 1992; Levison, 1998). However, as Zhang (2005) noted, time or distances saved from the reduced travel are likely to be invested on other activities, especially on non-work, discretionary activities, resulting in potentially more travel as a whole.

Research findings on the relationship between the urban accessibility and travel are mixed. Hanson and Schwab (1987) showed that higher accessibility levels are associated with more frequent non-motorized travel and mode use, shorter travel distances for discretionary activities, and therefore smaller activity spaces. Based on an analysis in the San Francisco Bay Area, Handy (1992) reported a negative association of regional and local accessibility with average travel distances for shopping activities and an insignificant association with trip frequencies/rates. In another study, however, Koenig (1980) identified a strong positive association between accessibility and trip rates for non-workers in France. Golob (2000) reported that while improved spatial access helps reduce travel time, it promotes non-work discretionary activities. Zhang (2005) suggested that the effects of accessibility on travel may vary among different activity types. By examining six categories of non-work activity types, Zhang (2005) showed that higher accessibility reduces travel time for school, social and personal business, but has no effect on shopping, civic and religious activities.

Recent years have witnessed increasing trip-chaining travel behavior in urban areas (Primerano et al., 2007). Trip-chaining behavior is more complex due to the involvement of
multiple stops (possibly together with activities of multiple purposes) along a single trip. The impact of accessibility on trip chaining has also been investigated in the literature. For example, by dividing trips into simple and complex forms based on travel survey data in Portland Oregon, Golob (2000) showed that simple trips are more associated with improved spatial accessibility. Hanson and Schwab (1987) and Ewing et al. (1994) also reported similar findings that lower levels of accessibility lead to a higher proportion of complex trips. However, a contrary finding is found in Bhat et al. (2007). Their empirical results indicated that the number of stops on a home-based trip was positively associated with accessibility to shopping opportunities when the accessibility level is low. Nevertheless, more research and empirical studies are needed to better understand how trip chaining is interwoven into individuals’ daily travel programs and whether and how trip chaining affects the accessibility-travel relationship across various urban opportunities.

As mentioned earlier, travel distance has been heavily relied upon for studying the relationship between accessibility and travel (Geurs and Ritsema van Eck, 2001). A more sophisticated approach to assess individuals’ spatial travel has been through the construction of their activity spaces. Activity space contains information about the space individuals have visited (Schönfelder and Axhausen, 2004). The activity-space approach goes beyond the travel-distance measure (Patterson and Farber, 2015) and has been used to characterize patterns of travel behavior (Axhausen, 2002, Li and Tong 2016) and mobility (Hansen, 2008; Vallée et al., 2010). Compared with the widely used travel distance, activity space is advantageous in several aspects for describing urban travel. For example, activity space allows one to visually comprehend “personal extensibility,” in other words, the spatial extent of movement given certain space-time budget (Given and Leckie, 2003). In GIS, activity space can be illustrated using a 2-dimensional area or even 3-dimensional construct if time or other properties (such as intensity or frequency) are incorporated. Visualization of activity spaces, along with locations and routes traversed, directly informs how travel is made in space and time. Moreover, activity space can be interpreted as the “experience of space,” which is
more informative than distance, per se, when studying individual travel behavior (Nemet and Bailey, 2000). Sherman et al. (2005) also noted that in the real world individuals might not simply rely on distance to evaluate their interactions with potential opportunities. Rather, opportunity locations falling within an individual’s “perceived” activity space may be considered “near and familiar,” while those located outside the activity space are often considered “far and unfamiliar,” regardless of the actual distances involved.

To our knowledge, the use of activity space to study the relationship between accessibility and urban travel is very limited. Hanson and Schwab (1987) provided one pioneering study. In the study, accessibility to opportunities was measured from both home and workplace: two important nodes of individuals’ daily travel (Hanson and Schwab, 1987). Activity spaces were drawn using the sets of destination points that were visited over a 35-day period. Their results showed that size of activity space is negatively correlated with accessibility.

Research is ongoing on the relationship between the built environment and urban travel (Crane, 2012). Still particularly needed is better understanding of the relationship of accessibility to non-work opportunities. Although general trends about how accessibility affects travel have been extensively studied, few studies have explored how the effect varies across meaningfully disaggregated non-work activities. Moreover, empirical studies are needed to assess the role of employment status and trip chaining in affecting the accessibility-travel relationship. Through the construction of activity spaces and an introduction of a new accessibility measure, our study contributes to the accessibility-travel literature by accounting for a wide spectrum of non-work activity types as well as by examining the roles of employment status and trip-chaining behavior.

3.3 Methodology
In this section, we describe the methodological framework used in this study, including an activity space delineation approach, a new accessibility measure and an activity classification scheme.

### 3.3.1 Activity Space Construction

A variety of activity space approaches have been developed with different emphases. In this study, we use a recent activity space delineation method proposed by Li and Tong (2016). Building upon time geography and extending the approach of Newsome et al. (1998), the new activity method accounts for more complex instances of urban activity-travel. As Figure 3.1a shows, an activity space consists of three components: a home-based sub-activity space, a workplace-based sub-activity space and a commuting trip-based sub-activity space. The size of a sub-activity space is determined by the distance from the farthest observed or realized activity location to the anchor point(s) of travel. For home-based and workplace-based sub-activity spaces, the anchor point is either home or workplace; for commute-based sub-activity space, a combined distance is measured based on home and workplace, the resulting sub-activity space is in the form of an ellipse under the Euclidean distance metric where each point on the ellipse has a constant distance to the two foci (home and workplace). In the real world, because of the vagaries of specific urban settings, as well as requirement that travel occurs over the links of transportation networks, activity spaces may not maintain the regular shape as described in Figure 3.1a. A GIS-based algorithm was introduced in Li and Tong (2016) for delineating such irregularly shaped urban-structure-based activity spaces (see Figure 3.1b).
3.3.2 Accessibility Measure

Accessibility has been considered one of the most basic and valuable of concepts in the fields of geography, transportation and urban studies (Krizek, 2003). Accessibility can be used as a way to measure potential interactions individuals may have with spatially distributed opportunities. Accessibility connects people’s movements and transportation to urban land uses (Páez et al., 2012; Wachs and Kumagai (1973) noted that accessibility is perhaps the most important concept in defining and explaining urban forms.
Over time, a variety of accessibility measures have been developed. These may be classified into two broad categories: location-based accessibility and individual-based accessibility (Geurs and van Wee, 2004; Horner and Downs, 2014). For detailed reviews of accessibility measures, interested readers are referred to Handy and Niemeier (1997), Geurs and Ritsema van Eck (2001), Geurs and van Wee (2004) and Páez et al. (2012). Among others, cumulative opportunity measures and gravity-based measures are the most widely used location-based accessibility measures (Geurs and van Wee, 2004; Horner and Downs, 2014).

In this study, to emphasize varied effects of spatial proximity on accessibility, we chose to focus on the gravity-based accessibility measures. Compared with cumulative opportunity measures that treat all opportunities falling within a specified travel distance/time cut-off equally, the gravity-based measures account for the distance decay effect by using an impedance function defined based on travel distance, time or cost. The underlying assumption of the distance decay effect is that the farther an opportunity, the less accessible it is to an individual, and vice versa.

Equation (1) describes a general form of a gravity-based accessibility measure (Hansen, 1959). For individual \( i \) and opportunities \( j \), accessibility \( A_i \) is computed as:

\[
A_i = \sum_j w_j f(c_{ij})
\]  

(1)

where \( w_j \) is attractiveness, quantity or importance of opportunity \( j \); \( f(c_{ij}) \) is an impedance function; and \( c_{ij} \) is the travel cost between \( i \) and \( j \), usually measured by travel time or distance. The negative exponential form is one of the most commonly used impedance functions (Handy and Niemeier, 1997):

\[
A_i = \sum_j w_j e^{-\theta c_{ij}}
\]  

(2)

Here \( \theta \) is a distance decay coefficient reflecting the strength of distance as an obstacle to travel. A higher value of \( \theta \) means that accessibility decreases more rapidly as distance increases.
Similar to many other accessibility measures, the equation given in (2) also suggests that nearby opportunities contribute more to the overall accessibility than distant ones.

In recent years, issues have been raised concerning the conventional location-based accessibility measures that assume individuals will always originate their trips from a fixed location, usually home. For example, Bhat et al. (2007) reported that at least 30% of trips made by workers were not home-based in the Boston metropolitan region. An assumption of all trip being home-based may not correspond well with people’s actual movements in space-time, and therefore individual-based accessibility measures have thus been developed. Kwan (1998) proposed an individual-based accessibility measure that assumed individuals are mobile in space with no fixed location of trip origin. In this study, we extended location-based accessibility to account for the variation due to an individual’s movement based on the sub-activity spaces delineated in Figure 3.1 and differentiated accessibility calculations between workers and non-workers.

For non-workers, accessibility is computed based on the shortest travel from home to an opportunity location, which is similar to the conventional location-based measure. Based on the sub-activity spaces given in Figure 3.1, in addition to the home-based sub-activity space, workers may take the advantage of the other two sub-activity spaces to access opportunities from workplace or along the commute. Similar to the home-based accessibility measure, the workplace-based accessibility can be computed assuming trips originate from the workplace.

For the commute-based accessibility, we used the scheme proposed by Golledge and Stimson (1997) and developed a conditional accessibility measure to assess the ease to reach various potential opportunities while accounting for the two “anchor points” of workers’ daily travel: home and workplace. An illustration is also given in Figure 3.2. For a potential opportunity \( j \), we computed the travel time difference between the work commute \( t_{hk} \) and the trip with the additional stop at the opportunity \( j \) \( (t_{hj} + t_{jk}) \). Equation (3) gives a formula that can be used to
calculate the travel time $c_{ij}$ specified in Equation (2) as a way to quantify the additional travel effort needed for making a stop at opportunity $j$ conditional on the workplace at $k$ and home at $h$.

$$c_{ij}(h, k) = t_{hj} + t_{jk} - t_{hk} \quad (3)$$

Where $h$ and $k$ are home and workplace, respectively; $j$ represents a potential opportunity along the commute. $t_{hj}, t_{jk}, t_{hk}$ are the shortest travel time between $h$ and $j$, $j$ and $k$ and $h$ and $k$ respectively. $c_{ij}(h, k)$ is individual $i$’s additional travel time due to the visit at $j$, conditional on the workplace at $k$ and home at $h$.

![Figure 3.2 An illustration of additional travel for potential opportunities along a commute](image)

### 3.3.3 Activity Classification

In this study, we focus on non-work activities as opposed to work activities for both workers and non-workers. In the literature, non-work activities, compared with work activities, have yet to be fully studied. Zhang (2005) provided several reasons for the under-studied status of non-work activities. One is the longstanding focus within the planning community on work commutes given that these trips are usually associated with peak-period congestion and the highest accident rates. Another reason is the greater challenge of dealing with the less regular and more
diverse non-work activities. Various non-work activities may affect travel differently. In terms of spatial distribution, they also tend to be more spread out than work activities.

While examining urban opportunities, in this study we only focus on activities that take place outside home. While mostly following the activity classification scheme used by the NHTS (see the next section for details), we break down non-work activities into six categories: shopping, dining, medical, leisure, gasoline-buying and school. Our shopping category mainly accounts for shopping activities for goods, including groceries, clothing, hardware and so on. The dining activity is limited to dining out at restaurants only. The medical category mainly consists of doctor visits, and trips to dental services and pharmacies. The leisure category involves a variety of recreational/entertaining locations such as parks, fitness centers, bars, casinos and others. The gasoline-purchasing activity includes only fueling personal vehicles at gas stations. The gasoline-purchasing category was a sub-category of the shopping class defined by the NHTS scheme, however, we suspect that gasoline-purchases may have unique characteristics compared with other shopping activities. The school activity is only for people who are students, rather than those employed or carrying out other activities at schools.

3.4 Empirical Study

Pima County, Arizona, which is coterminous with the Tucson Metropolitan Statistical Area, was selected as our study area. The main dataset we used is the 2008 Add-on National Household Travel Survey (NHTS). Observations in this dataset were mainly found in the City of Tucson, given that the majority of the county’s population is concentrated in the city.

The data were collected based on an interview-based method, where participants were asked to report their travel information in a day. A typical time frame defining a survey day starts at 4:00 AM and ends at 3:59 PM of the following day (Santos et al., 2011). Within the 24-hour time
frame, each individual’s travel and activity participation history was recorded in detail, including trip origin and destination, travel distance, trip purpose, time duration of activities and mode of transportation.

The entire dataset consists of 4777 individuals in 2361 households, which accounts for about 0.5% of the county population. A data filtering process was performed to exclude individuals who had incomplete trip sequences (did not start or end at home locations), this resulted in a final selection of 3118 individuals in 1877 households.

Table 3.1 summarizes a selected number of socio-demographic characteristics of the individuals included in this study.

<table>
<thead>
<tr>
<th>Table 3.1 Socio-demographic profile of the selected individuals</th>
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<tbody>
<tr>
<td><strong>Employment Status</strong></td>
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<tr>
<td>Worker</td>
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<tr>
<td>Non-worker</td>
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<tr>
<td><strong>Age Group</strong></td>
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<td>0-64</td>
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<td>65+</td>
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<td><strong>Gender</strong></td>
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<td>Female</td>
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<td><strong>Driver Status</strong></td>
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<tr>
<td>Driver</td>
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<tr>
<td>Non-Driver</td>
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Land use parcel data were used to identify potential opportunities available for various activities. The data were obtained from the Pima County GIS portal. Using the property use code manual provided by the county, we extracted opportunity locations for shopping, dining, medical services, leisure, gasoline-purchasing and school activities based on the activity classification scheme discussed in Section 3.3.3. Neighboring parcels based on a 500-meter search distance with the same owner and service type were consolidated to reduce redundancy.
In this study, we used the parcel size to approximate the possible attractiveness of a potential opportunity, \( w_j \) for dining, shopping, and medical services, where larger sites usually indicate higher capacities of providing the relevant services. Considering the substantial variation in size across these three types of urban opportunities, we also normalized all the weights based on the opportunity size distribution for each activity type. For leisure, gasoline-purchasing, and school activities, we assigned an equal weight to each opportunity because size might be less appropriate to indicate attractiveness for these activities, and no other information is available for determining the attractiveness level.

In total, 14,704 activity locations and 4,987 opportunities were geocoded for the six activity categories. Figure 3.3 maps all the urban opportunities identified. Dining, shopping, and gasoline-purchasing activities are more uniformly distributed than the medical, school, and leisure counterparts. Moreover, some opportunities tend to be concentrated in the central area, such as medical, shopping, and dining opportunities, whereas others are more balanced between central and peripheral areas, such as leisure, gasoline-purchasing, and school opportunities.
For each individual, activity spaces were generated separately for different activity types. The activity space generation algorithm introduced in Li and Tong (2016) was implemented using Python 2.7 and ArcGIS 10.31’s geoprocessing library Arcpy. A street network dataset obtained from the Pima County GIS portal was relied upon to facilitate the network-based activity space generation. As a result, 4473 activity spaces were generated.

Figure 3.4 shows an example of two leisure activity spaces (home-based and commute-based) and one shopping activity space (home-based) generated for an individual in the survey.
Accessibility scores were computed for all six types of non-work activities using equation (2). For the distance decay coefficient $\theta$, recent empirical studies suggested a range from 0.1 to 0.2 for urban areas (Handy and Niemeier, 1997; Shen, 1998; Kwan, 1998; El-Geneidy and Levinson, 2006). In this study, 0.2 was chosen because it gave a more realistic model of the distance decay effect, considering the geographical scale and other spatial characteristics of the study area.

Accessibility computation was performed using the network-based travel time (in minute). Workers and non-workers were treated differently when measuring accessibilities considering the additional two sub-activity spaces workers have.

Table 3.2 presents the descriptive statistics for the two sets of variables: area of activity space ($km^2$) and accessibility score.

<table>
<thead>
<tr>
<th>Area of Activity Space</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dining Activity Space</td>
<td>731</td>
<td>0.022</td>
<td>2079.131</td>
<td>176.011</td>
<td>318.522</td>
</tr>
<tr>
<td>Shopping Activity Space</td>
<td>1638</td>
<td>0.000+</td>
<td>3339.383</td>
<td>189.773</td>
<td>380.610</td>
</tr>
<tr>
<td>Medical Activity Space</td>
<td>283</td>
<td>0.617</td>
<td>2482.997</td>
<td>334.522</td>
<td>493.891</td>
</tr>
<tr>
<td>Leisure Activity Space</td>
<td>1147</td>
<td>0.000+</td>
<td>2538.385</td>
<td>221.370</td>
<td>408.536</td>
</tr>
<tr>
<td>Gasoline-purchasing Activity Space</td>
<td>112</td>
<td>0.098</td>
<td>3339.383</td>
<td>296.813</td>
<td>612.821</td>
</tr>
</tbody>
</table>
As Table 3.2 shows, on average, medical activity spaces account for the largest area, followed by gasoline-purchasing, leisure, shopping and dining activity spaces; the smallest are school activity spaces. This indicates a great variability of travel ranges across different types of non-work activities. Moreover, the level of variation within each activity type is also noteworthy. The highest standard deviation of gasoline-purchasing activity spaces indicates that individuals tend to have a highly varied spatial travel range for gasoline purchases. Comparatively, school activity spaces appear to have less variation.

Figure 3.5a shows the distribution of areas of activity spaces for all the six categories. In particular, we can identify a bimodal activity space distribution for most of the activity types, where the local maximums are found at smaller activity spaces (< 40 $km^2$) and larger activity spaces.
(>200 km²). Figure 3.5b gives a frequency distribution of the accessibility scores for the six activity types. It shows that the majority of the accessibility scores are under 20 for most of the activity types except for shopping accessibility, which exhibits bimodal distribution peaked around 20 and 100.

According to the mean accessibility scores in Table 3.2, shopping has the highest value; leisure and gasoline-purchasing activities are among the lowest. Based on our calculation, accessibility is a combined function of attractiveness and spatial distribution of opportunities. A low accessibility score may be due to its notably smaller overall quantity of service opportunities compared with others (e.g. gasoline-purchasing vs shopping). The spatial distribution matters. For example, although leisure opportunities have the second largest number among all activity types, the opportunities tend to spatially clustered throughout the urban area (see Figure 3.3). This led to a relatively low accessibility score of leisure.
3.5 Analysis and Results

3.5.1 Model Estimation

Figure 3.6 shows a scatter plot of activity space and accessibility for each activity type. A visual examination of Figure 3.6 suggests a general negative relationship between activity space and accessibility. That is, activity space generally becomes smaller with improved accessibility. Moreover, this relationship appears to be non-linear across all six activity types. After testing various nonlinear functions, including power, exponential, logarithmic, inverse and logistic, we found that the logarithmic model gave the best goodness of fit. Considering that area of activity space is non-negative, the logarithmic model is revised to a truncated form, as follows:
\[ S_{it} = \begin{cases} \beta_t - \sigma_t \ln A_{it} & A_{it} < e^{\beta_t / \sigma_t} \\ 0 & A_{it} \geq e^{\beta_t / \sigma_t} \end{cases} \]

where \( i, t \) represent individual and activity type respectively; \( S_{it} \) denotes the size of individual \( i \)'s activity space of activity type \( t \); \( A_{it} \) is individual \( i \)'s accessibility to potential opportunities of activity type \( t \); \( \sigma_t \) is the accessibility decay parameter of activity type \( t \); and \( \beta_t \) is a constant.

Similar to the idea of the distance decay effect, model (3) attempts to describe how travel territory (activity space) shrinks with greater accessibility. According to (3), activity space \( S_{it} \) decreases with \( A_{it} \), and when \( A_{it} \) gets close to the critical value \( e^{\beta_t / \sigma_t} \), \( S_{it} \) approaches zero.

The decay coefficient \( \sigma_t \) may differ among various types of activities. The larger \( \sigma_t \), the more rapidly activity space \( S_{it} \) declines with accessibility. \( \beta_t \) is the size of the activity space when \( A_{it} = 1 \), reflecting the range an individual is willing to travel when accessibility is low (see Figure 3.5b). The modeling fit was found to be significant for each activity type \( t \) at the 0.01 significance level.

Table 3.3 summarizes the model estimation results.

<table>
<thead>
<tr>
<th>Activity</th>
<th>( \beta_t^* )</th>
<th>( \sigma_t^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dining</td>
<td>376.857**</td>
<td>79.709**</td>
</tr>
<tr>
<td>Shopping</td>
<td>467.181**</td>
<td>78.911**</td>
</tr>
<tr>
<td>Medical</td>
<td>609.942**</td>
<td>118.347**</td>
</tr>
<tr>
<td>Gasoline-purchasing</td>
<td>390.626**</td>
<td>96.308**</td>
</tr>
<tr>
<td>Leisure</td>
<td>295.767**</td>
<td>47.790**</td>
</tr>
<tr>
<td>School</td>
<td>184.246**</td>
<td>23.073**</td>
</tr>
</tbody>
</table>

**: significant with a p-value < 0.01
Figure 3.7 illustrates the activity space decay curves based on the $\beta_t^*$ and $\sigma_t^*$ estimates in Table 3.3:

As illustrated by Figure 3.7, activity spaces generally decrease with accessibility $A_{it}$. The decay effect is particularly strong where accessibility is low ($A_{it} \leq 20$). When $A_{it} > 20$ the decline of activity space becomes less substantial, especially when $A_{it} > 100$, which is where most of the curves become stable. In addition, the constant $\beta_t$ and rate of decay $\sigma_t$ tend to vary across various types of activities.

Table 3.3 and Figure 3.7 show that medical activities have the highest $\beta$, which indicates that when medical accessibility is low individuals tend to travel more for medical services. Medical activities also have the highest $\sigma$, resulting in the most sharply declining curve. An examination of the spatial distribution of medical services might help explain the results. According to Figure 3.3, medical services are largely clustered in space. As Figure 3.5b shows, 47% individuals’ medical accessibility scores are considered low ($A_{it} < 20$). Therefore, a considerable proportion of the
population with low medical service accessibility will need to travel more extensively (high $\beta$) to access medical services. However, the steepest slope of the medical activity curve in Figure 3.7 suggests that, if available, people may still prefer to choose medical services that are more accessible.

Gasoline-purchasing activities have a moderate $\beta$ and the second highest $\sigma$, which are as expected. Unlike other activities such as shopping, dining or medical, gasoline-purchasing activities are more frequently performed as a “side” activity linked to other main activities. Therefore, fueling nearby or along trips to other destinations is common, which also explains the high value of $\sigma$. Although the number of gas stations is the smallest among all the activity opportunities, the moderate $\beta$ may be due to the relatively uniform distribution of gas stations across the region (see Figure 3.3) so that all people have a reasonable accessibility to gas stations.

Shopping and dining activities have similar $\sigma$’s that are comparatively high, suggesting some impacts of accessibility on the travel ranges of shopping and dining. However, compared to gasoline-purchasing services that could be considered relatively “homogenous” among different providers, shopping and dining services may differ in variety and service qualities. Therefore, individuals’ preferences and other factors may have a greater effect on service location choices. This may explain why shopping and dining activities are less affected by accessibility, compared to gasoline-purchasing and medical counterparts. Although both shopping and dining activity spaces decay similarly with accessibility, noticeable differences can be observed in Figure 3.7, where shopping activities tend to have larger activity spaces when accessibility level is low ($\beta$). This might be because in addition to daily groceries, the category of shopping activities also include shopping at department stores and malls, which have limited availability and often require farther travel than daily groceries.

With the wide availability of leisure opportunities, it occurs the spatial extent of travel for leisure purposes is less affected by accessibility. This might be that besides accessibility, choices
of locations for leisure activities could be highly subject to personal preferences. Similarly, accessibility to schools has a smaller effect on school travel. In this study, we included all schools in one’s neighborhood when evaluating the accessibility score. However, not all the schools are suitable for the individual. For example, although a nearby and large school such as a university provides educational services, it might not be appropriate for all non-college students and therefore will not help reduce travel. It is worth noting that school activities have the smallest $\beta$, that is, travel to school is the least among all the activities when the accessibility level is low. This suggests that students tend to go to the nearby schools when no alternatives are available in the neighborhood.

### 3.5.2 Effect of Employment Status

As discussed earlier, workers and non-workers may exhibit different travel behavior when engaging in non-work activities. Unlike non-workers whose trips are assumed to always start at homes, workers have the option of initiating travel from non-home places such as workplace or anywhere along a work commute. On the other hand, due to work duties, workers might be more spatially and temporally constrained that allows less flexibility for them to participate in non-work activities. It is, therefore, worthwhile to examine how the relationship between accessibility and activity space varies between non-workers and workers, so we divided the sample population into two sub-groups: workers and non-workers.

Table 3.4 shows the statistics of activity space size and accessibility score by employment status; Table 3.5 lists the percentages of workers’ home-based, workplace-based and commute-based non-work activity spaces for each of the six activity types.

| Table 3.4 Descriptive statistics of activity space and accessibility by employment status |
|---------------------------------|--------|--------|--------|--------|--------|
| Area of Activity Space          | N      | Minimum | Maximum | Mean   | Std. Deviation |
| Worker                          |        |         |         |        |                 |


The model fitting procedure described in the previous section was repeated for both workers and non-workers.
Table 3.6 summarizes the model fitting results. Based on the model parameter estimates, Figure 3.8 shows a comparison of fitted curves between worker and non-workers for all the six activity types.

### Table 3.6 Model estimation results for workers and non-workers

<table>
<thead>
<tr>
<th>Activity</th>
<th>Worker</th>
<th>Non-Worker</th>
<th>All individuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dining</td>
<td>377.896**</td>
<td>371.522**</td>
<td>376.857**</td>
</tr>
<tr>
<td></td>
<td>76.963**</td>
<td>81.334**</td>
<td>79.709**</td>
</tr>
<tr>
<td>Shopping</td>
<td>388.639**</td>
<td>504.764**</td>
<td>467.181**</td>
</tr>
<tr>
<td></td>
<td>56.767**</td>
<td>93.039**</td>
<td>78.911**</td>
</tr>
<tr>
<td>Medical</td>
<td>570.304**</td>
<td>619.652**</td>
<td>609.942**</td>
</tr>
<tr>
<td></td>
<td>109.546**</td>
<td>121.014**</td>
<td>118.347**</td>
</tr>
<tr>
<td>Gasoline-purchasing</td>
<td>281.367*</td>
<td>430.281**</td>
<td>390.626**</td>
</tr>
<tr>
<td></td>
<td>66.025*</td>
<td>96.206**</td>
<td>96.308**</td>
</tr>
<tr>
<td>Leisure</td>
<td>357.064**</td>
<td>276.908**</td>
<td>295.767**</td>
</tr>
<tr>
<td></td>
<td>64.408**</td>
<td>43.911**</td>
<td>47.790**</td>
</tr>
<tr>
<td>School</td>
<td>383.350*</td>
<td>153.295*</td>
<td>184.246**</td>
</tr>
<tr>
<td></td>
<td>72.158*</td>
<td>18.266*</td>
<td>23.073**</td>
</tr>
</tbody>
</table>

*significant with a p-value < 0.05; **significant with a p-value < 0.01
Both Table 3.6 and Figure 3.8 show that, with an increase of accessibility, the dining, shopping and gas activity spaces of workers decayed less rapidly than those of non-workers when accessibility level is high. This suggests that workers’ activity spaces for these activities tend to be less sensitive to accessibility when more accessible opportunities are available. We found that the less sensitivity of workers to accessibility was mainly due to the activities performed along commute trips. As summarized in in Table 3.5, numbers of commute-based sub-activity spaces account for considerable proportions of shopping, dining and gasoline-purchasing activity spaces generated (30%, 20% and 48% respectively). For the three types of activities, we noticed that workers’ commute-based accessibility scores are 4 to 8 times greater than the home-based counterparts. However, their commute-based activity spaces are only 1 to 3 times smaller than the home-based activity spaces. It’s worth noting that non-workers’ gasoline-purchasing activity
spaces are about 1.5 times larger than those of workers when accessibility is low (see the $\beta$ values in Table 3.6), which we did not observe from shopping or dining activities. This may suggest that when accessibility level is low, workers tend to choose the most accessible gas stations, resulting in much smaller activity spaces.

Comparatively, we found that the effect of medical accessibility on travel range does not exhibit a significant variation between workers and non-workers. Although commute-based sub-activity spaces account for over a quarter of all the medical activity spaces (see Table 3.5), it did not bring more flexible choices to workers, due to the spatial concentration of medical services in the city area (also see Figure 3.3).

Compared to non-workers, workers’ leisure and school activity spaces are more strongly associated with accessibility. As Table 3.6 shows, workers’ $\sigma$’s are significantly greater than those of non-workers for leisure and school activities, resulting in more rapid declines of the activity space curves as seen from Figure 3.8. A possible explanation is that such activities tend to have long-duration which are less likely to be performed after work. Based on the survey data, over 80% of workers’ leisure and school trips were home-based. Given the limited time budget, workers tend to choose nearby services for after work leisure and school activities.

### 3.5.3 Effect of Trip Chaining

In addition to employment status, trip chaining behavior may also have an important role in affecting the relationship between accessibility and travel. So far, accessibility to opportunities was measured from home, workplace, commute trip or combined. The implication here is that travel only stems from those instances, which might be true if only one non-work opportunity is to be visited along the entire trip. In the real world, people may combine multiple stops (with possibly multiple purposes) into a single trip, and such trip chaining behavior accounts for a considerable
share of the total trips made daily (Mcguckin and Murakami, 1995; Primerano et al., 2007). When taking into account trip chaining behavior, accessibility could become very complex. For example, when planning for a home-based trip, if an individual were to link a new activity A to a planned activity B (either before or after), the final locational choice of activity A could be influenced by the locations of both home and B.

We focus on an examination of how trip chaining behavior affects the relationship between accessibility and urban travel. As in Primerano et al. (2007), we categorized trips into two types, namely, simple trips and complex trips. A simple trip contains a single stop (either home-stop-home, workplace-stop-workplace or workplace-stop-home). When multiple stops are chained along a trip, the trip becomes complex.

Table 3.7 lists the percentages of simple and complex trip-based activity spaces for each of the six activity types.

| Table 3.7 Complex trip-based and simple trip-based activity spaces in the Tucson metro database |
|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| Simple trip-based | Complex trip-based |
| Number | Percentage (%) | Number | Percentage (%) |
| Dining | 294 | 40.2 | 437 | 59.8 |
| Shopping | 573 | 35.0 | 1065 | 65.0 |
| Medical | 126 | 44.5 | 157 | 55.5 |
| Leisure | 696 | 60.7 | 451 | 39.3 |
| Gasoline-purchasing | 29 | 25.9 | 83 | 74.1 |
| School | 390 | 66.1 | 200 | 33.9 |

Table 3.7 indicates that dining, shopping, gasoline-purchasing and medical activities are more likely to be performed through complex trips. For example, the majority of gasoline-purchasing activities (74.1%) were chained with other activities, whereas leisure and school activities are more often associated with simple trips. For each of the six activity types we repeated the model fitting process for complex and single trips. These results are summarized in Table 3.8.
As Table 3.8 shows, among the six categories, β’s and σ’s of complex trips are consistently greater than those of simple trips, suggesting that the travel range of complex trips is more sensitive to accessibility than that of simple trips. This noticeable difference due to trip chaining is as expected. With multiple stops being added, complex trips are often longer due to visits to multiple opportunities. If given the same time budget, choosing the more accessible opportunities along a complex trip may be essential for successfully performing all the activities.

### 3.6 Discussion

Empirical results presented in previous sections have shown that accessibility to non-work opportunities have varying effects on travel ranges across different activity categories. Higher accessibilities to medical, shopping, dining and gasoline-purchasing opportunities are strongly associated with smaller activity spaces and, therefore, less travel. However, the negative relationship between accessibility and travel seems less substantial for school and leisure activities.
From a service provision planning point of view, our findings suggest that increasing spatial accessibilities to medical, shopping, dining and gas services may help significantly reduce urban travel. This strategy might be especially effective for medical services, which tend to be unevenly distributed in space, because travel to these services was found to be most sensitive to accessibility.

Variation in the accessibility-trip relationship was also found to vary with employment status. Due to additional options brought by non-home-based travel, workers may choose to perform shopping, dining and gasoline-purchasing activities on commutes (shopping, dining and gasoline-purchasing) or around their workplace. Given such flexibility, workers’ activity spaces seem not as sensitive as those of non-workers to spatial accessibility. On the other hand, due to limited time budget, workers tend to choose more accessible school and leisure opportunities than non-workers. Having knowledge of the differences between workers and non-workers, more effective urban travel reduction strategies can be formulated by treating the two groups differently.

Personal trips have become increasingly complex—in part due to trip-chaining behavior. This study shows that trip chaining incorporated complex travel might be more sensitive to spatial accessibility. With the trend toward more complex trips being made on a daily basis (Mcguckin and Murakami, 1995; Primerano et al., 2007), improvement of accessibility to mixed-type of opportunities may help further encourage trip chaining and result in overall travel reduction. However, further research is needed examining at what accessibility level and to what extent trip chaining can help significantly reduce urban travel.

One limitation of this study relates to the travel survey dataset used. Our survey data only contain one-day travel information. To gain more insights into the accessibility-travel relationship, a longer observation period with more detailed non-work activity categories would be desirable. For example, in this study the shopping activities at grocery stores, department stores, hardware stores, malls and others are grouped into one category despite their varying travel related characteristics such as daily needs, duration and travel-budget required. If finer categories were
available, more insights might be gained as to how travel for the activity of each sub-category varies with accessibility. Also, the very broad definition of leisure activities might have led to a less accurate assessment of the effect of accessibility on travel. Moreover, the land use parcel data used in the study has its limitations. For instance, schools can only be classified by land owners, such as state-, county-, city- and private-owned with no other information. This may result in an overestimation of the accessibility score for the school opportunity as some schools might not be suitable for all the individuals in the neighborhood.

Similar to most existing location-based accessibility approaches, accessibility in this study is measured based on home, workplace or commuting trips. Nevertheless, when trip chaining is involved in a trip, as we already pointed out, accessibility might not be only subject to the trip origins, but also to stops that have been or are to be visited on the trip. Therefore, a new accessibility measure that also accounts for possible visits to multiple stops/opportunities on the complex trip simultaneously remains for future research. We anticipate significantly more computational resources will be needed for computing such an accessibility measure.

3.7 Conclusion

In this study, we examined the effect of accessibility on urban travel. To account for the complexity of individuals’ urban travel, we proposed a new accessibility measure based on the important “anchor” points of people’s activity-travel to account for accessibility differences along commuting trips. Based on a real-world dataset, activity spaces of six non-work activity types were generated to examine the impact of accessibility on urban travel. Analysis results suggested a negative relationship between accessibility and activity space. More importantly, such an association varies across different activity types.
We also explored the roles of employment status and trip chaining behavior in shaping the accessibility-travel relationship. The empirical results showed that workers’ spatial extent of travel might be less affected by improved accessibility when non-home trips are heavily relied upon to perform activities, but might be more subject to accessibility if the majority of trips are home-based. In addition, the spatial extent of complex trips due to trip chaining was found to be more sensitive to spatial accessibility, compared to simple trips.

Our findings provide useful insights to aid policy makers and urban planners in their efforts to reduce urban travel. Our study suggests that benefits that could be gained by improving accessibility may vary among different types of urban opportunities and different population groups.
CHAPTER 4
ACCESSIBILITY MAXIMIZATION FOR FACILITY SITING: AN INCORPORATION
OF ACTIVITY SPACE AND TRIP CHAINING

4.1 Introduction

Identifying the best location(s) for service provision has long been a concern for urban and regional planners. Location modeling has been widely recognized as an important tool for supporting locational decisions in both the private and public sectors (Church and Murray, 2009). Over time, a range of location models have been developed to facilitate placement of various types of service facilities. In public sector applications, location models have been called upon for siting fire stations (Toregas et al., 1971; Schilling et al., 1980), nature reserves (Saetersdal et al., 1993), school districts (Heckman and Taylor, 1969), public health services (Horner and Tayler, 1979) and others. In private sector applications, models have been developed to locate farmer’s markets (Tong et al., 2012), ATMs (Min and Melachrinoudis, 2001), commercial franchises (Current and Storbeck, 1994), cellular towers (Kalvenes et al., 2005) and wireless devices (Shillington and Tong, 2011).

In location modeling, one common objective has been to site facilities so that they are most accessible to their demand populations. Among others, travel cost (distance, time, etc.) has been widely used in these models to evaluate accessibility of alternative spatial configurations of facilities. Such an accessibility evaluation is often performed based on demand at fixed locations, usually individuals’ residences (Tong et al. 2012). This may contradict the empirical evidence in travel behavior research that suggests that travel for acquiring services also commonly originates from non-home locations, such as workplaces or schools (Mcguckin et al., 2005, Primerano et al., 2007). Moreover, due to the increasing frequency of multi-stop (and possibly multi-purpose) trip
chaining behavior, facility siting efforts could be more effective if more realistic travel behavior is considered (Suzuki and Hodgson, 2005; Berman and Huang, 2007; Tong et al. 2012). Therefore, the fixed, home-based accessibility evaluation widely used in the current location models needs to be improved to more accurately account for complex travel behavior and the associated locational choice making.

In addition, activity space may play an important role when an individual evaluates the accessibility of alternative sites/destinations (Gesler and Meade, 1988; Sherman et al., 2005; Wong and Shaw, 2011; Farber et al., 2012; Martinez et al., 2014; Patterson and Farber, 2015). Activity space describes the spatial extent that an individual covers over a certain time period (Schönfelder and Axhausen, 2004). Studies showed that opportunity locations found within one’s activity space would be considered more “accessible” than those outside the activity space, regardless of the actual travel distances involved (Nemet et al. 2000; Sherman et al. 2005). However, individuals’ activity spaces have not been considered when location models are used to search for the most accessible facilities.

Some empirical studies have recognized the limitations of the current location models. For example, in addition to home-based travel, a few studies have examined commute-based trip chaining for facility siting (Hodgson 1981; Tong et al., 2012). However, little effort has been made to consider other types of trip chaining, as well as the role of people’s activity spaces. To fill these research gaps, we propose a new facility location model that incorporates more general trip chaining travel behavior and people’s activity spaces into locational decisions.

The remainder of the article is organized as follows. In next section, a literature review is provided on location modeling and activity space in the context of accessibility maximization. This is followed by the introduction of a new multi-objective accessibility based facility location model. The model is then applied to an empirical study with results discussed. Conclusions and discussion are given in the last section.
4.2 Literature Review

Location modeling has been widely used to support the locational decisions for various types of facilities (Murray, 2010). When searching for “good” facility locations, sites that are the most accessible are often of the highest interest. Accessibility is therefore widely relied upon for evaluating the potential benefits/efficiency of alternative facility sites. Accessibility is often evaluated based on travel distance/time, with the widely adopted assumption that spatial interaction or reachability of a service facility decreases with the travel distance/time needed to reach an opportunity (Levinson, 1998). The p-median problem (PMP) represents one of the most widely used location models; it aims to achieve the minimal system-wide travel distance from demand to the closest service facility. Hakimi (1964) introduced the problem and ReVelle and Swain (1970) provided the first mathematical formulation. Consider the following notation:

- $j$: index of potential facility locations and the entire set is $J$
- $i$: index of demand and the entire set is $I$
- $p$: number of facilities to locate
- $d_{ij}$: travel distance from $i$ to $j$
- $x_j = \begin{cases} 1 & \text{if facility is chosen to be located at } j \\ 0 & \text{otherwise} \end{cases}$
- $y_{ij} = \begin{cases} 1 & \text{if demand } i \text{ is assigned to the facility at } j \\ 0 & \text{otherwise} \end{cases}$

The p-median problem (PMP) can be formulated as

\[
\text{Minimize} \quad \sum_i \sum_j d_{ij} y_{ij} \tag{1}
\]

s.t. \[
\sum_j y_{ij} = 1 \quad \forall i \tag{2}
\]

\[
y_{ij} \leq x_j \quad \forall i, j \tag{3}
\]

\[
\sum_j x_j = p \tag{4}
\]

\[
x_j, y_{ij} \in \{0,1\} \tag{5}
\]
Objective (1) minimizes the overall travel distance. Constraints (2) specify that each demand is assigned to one facility. Combined with the objective function (1) that aims to minimize the total travel distance, Constraints (2) ensure that demand is always assigned to the closest facility available. Constraints (3) state that a facility can be visited only if it is selected for siting. Constraints (4) specify that $p$ facilities will be located. Constraints (5) impose binary restrictions on the decision variables.

The travel distance/time based cost described in the PMP is the most widely used proxy for accessibility assessment (ReVelle and Eiselt, 2005; Church and Murray, 2009). The maximal accessibility is achieved through seeking facilities that minimize the overall system-wide travel distance/time. The PMP has also been extended to consider service capacity and stochastic demand, and others (Daskin, 2008). The PMP and its variants have been widely applied to support locational decisions. Examples include health centers (Horner and Tayler, 1979; Syam and Côté, 2010), distribution centers (Nozick and Turnquist, 2001), airports (Horner, 1980; Min et al., 1997), recreational facilities (Robertson, 1978; Goodchild and Booth, 1980). A number of decision support packages based on the PMP and its variants have been developed, such as the PLACE suite (Goodchild and Noronha, 1983), the UDMS (Robinson, 1983), a spatial decision support system (SDS) (Densham and Rushton, 1991) and ArcGIS’s location-allocation analysis module.

However, some important assumptions made in the classic PMP and some of its variants may be less realistic when these models are used to achieve the goal of maximal accessibility. For example, in the PMP it is often assumed that people originate their travel at home locations and always choose the facility that is closest to home. Such an assumption might not necessarily be true in reality (Tong et al., 2012). Activity travel studies showed that individuals may also initiate their travel from other important locations such as school or workplace. According to some empirical findings in the literature, non-home-based trips account for over 30% of all daily trips (Mcguckin et al., 2005; Primerano et al., 2007; Santos et al., 2011). In addition, trip chaining travel behavior,
which refers to the phenomenon of making one or multiple stops before reaching a destination, has been found to become increasingly common in recent years. It has been found that 30% to 70% of daily trips made are multi-stop multi-purpose trips (Mcguckin et al., 2005; Primerano et al., 2007; Santos et al., 2011). As a result, travel to a service facility could be part of a chained trip where accessibility might be a function of many activity stops that need to be made on the trip.

Some attempts have been made to incorporate multi-stop (and perhaps multi-purpose) trip making into facility location modeling. For example, Suzuki and Hodgson (2005) and Berman and Huang (2007) extended the PMP to allow people to visit two or more types of facilities on a single trip. However, no other stops (activities) are considered except for the facilities to be sited, and the models proposed only account for home-based trips whereas other trip instances are ignored. Efforts have also been made to account for trips chained with the daily commute. In a day care center location problem, Hodgson (1981) noted that travel for dropping off children at day care centers is often chained with other major activities, and he proposed a PMP variant that minimizes the total work commute deviation due to potential day care center visits. When looking for the best spatial configuration of farmers’ markets, Tong et al. (2012) considered both home-based single purpose trips and commute-based chained trips to evaluate the accessibility of potential market demand. Their approach also considered temporal variation of demand due to the limited time availability of farmers’ markets.

In addition to chained commute trips, we note that a substantial amount of other types of chained trips exists. According to the report of 2001 National Household Travel Survey (NHTS), only 20% of chained trips made in the U.S. were along commuting routes. Therefore, a full consideration of trip chaining travel behavior should also include non-work trips.

Another important notion that is highly related to accessibility is activity space. Activity space is “a 2-dimentional area consisting of locations that have been frequented during a period of time” (Schönfelder and Axhausen, 2004). Incorporating activity space into accessibility evaluation
has been widely recognized (Gesler and Meade, 1988; Sherman et al., 2005; Wong and Shaw, 2011; Farber et al., 2012; Martinez et al., 2014; Patterson and Farber, 2015). A number of activity space measures have been developed. Patterson and Farber (2015) and Ren (2016) give comprehensive reviews of the existing activity space approaches. Sherman et al. (2005) suggested that activity space can be used as an alternative approach to study accessibility. Individuals may often use their mental “activity space” to evaluate accessibility to opportunities. Opportunities found within an individual’s activity space may be perceived as “near and familiar” and those located outside the activity space are “far and unfamiliar,” regardless of the actual distances involved. In an empirical study, Nemet and Baily (2000) showed that more visits are associated with service providers located within one’s activity space. Therefore, presence of opportunities within one’s activity space may serve as an important dimension for accessibility evaluation (Patterson and Farber 2016). Although studies have suggested the effectiveness of service provision when coinciding with individuals’ activity spaces (Shannon and Spurlock 1976; Cromely and Shannon 1986), to our knowledge, very little effort has been made to integrate activity space into facility location modeling.

The classic p-median problem has the potential to be extended to incorporate a more realistic accessibility assessment that considers more general multi-stop trip chaining behavior and the role of individuals’ activity space. In this study, building on the PMP, a multi-objective location model is developed to explicitly incorporate conventional home-based travel cost, activity space, and trip chaining travel behavior. In doing so, spatial accessibility can be more realistically modeled when determining the optimal sites for service provision.

4.3 Methodology
In this section, a multi-objective location model is introduced for accessibility maximization. Additional notation includes:

\( k \): index of activities and the entire set is \( K \)

\( e_{ikj} \): individual \( i \)'s additional travel due to visit to \( j \) after activity \( k \)

\[
  z_{ikj} = \begin{cases} 
  1 & \text{if individual } i \text{ visits facility } j \text{ after performing activity } k \\
  0 & \text{otherwise}
  \end{cases}
\]

\[
  b_{ij} = \begin{cases} 
  1 & \text{if facility } j \text{ is within individual } i \text{'s activity space} \\
  0 & \text{otherwise}
  \end{cases}
\]

As we discussed before, in addition to travel cost, activity space may serve as a critical factor when an individual evaluates accessibility. Compared with travel cost (distance, time), activity space often plays a more important role in determining accessibility and therefore affecting people’s locational choices (Kwan, 1998; Nemet et al. 2000; Sherman et al. 2005). In many cases, opportunities falling within one’s activity space are considered more accessible than those located outside the activity space (Nemet et al. 2000; Sherman et al. 2005). As Figure 4.1 shows, given two opportunities A and B that provide the same level of service, although travel cost (distance, time) from individual \( i \)'s home to opportunity A seems less than to opportunity B, the individual may consider B more accessible than A. This is because the opportunity at B is located in the person’s activity space and thus is more likely to be visited in his/her daily routine. In this regard, accessibility can be measured by an evaluation of the presence of service opportunities within one’s activity space, as noted by Patterson and Farber (2015).
Figure 4.1 An illustration of the relationship between activity space and accessibility

Based on the evaluation of whether an opportunity falls in one’s activity space, the first objective is formulated in (6) below.

Objective 1: Maximize \( \sum_{i} \sum_{j} b_{ij} x_j \)  

(6)

Objective function (6) maximizes the total activity space-based accessibility, by summing up the number of potential facilities falling within each individual’s activity space. A binary parameter \( b_{ij} \) was introduced to denote the spatial relationship between potential facilities and activity spaces. In particular, if a potential facility location \( j \) falls within the activity space of individual \( i \), then \( b_{ij} \) equals to one. Otherwise, \( b_{ij} \) is zero. Each individual’s activity space-based accessibility links activity space with the spatial distribution of opportunities. To maximize overall accessibility, facilities that can be found within the largest number of people’s activity spaces will be selected.

The second major extension of accessibility maximization that we are proposing involves consideration of trip chaining travel behavior. In this study, a full spectrum of trip chaining
including both commute-based and non-commute-based trips is accounted for. As Figure 4.2 illustrates, with trip chaining behavior being considered, travel to a service facility can possibly occur at any stop along the entire trip, in addition to the fixed home location. The objective function of trip chaining based accessibility maximization is presented in (7).

![Figure 4.2 An illustration of a potential travel deviation for a visit to a facility from a chained trip](image)

Objective 2: Minimize

\[
\sum_i \sum_k \sum_j e_{ikj} z_{ikj}
\]  

(7)

In objective function (7), \(e_{ikj}\) denotes the excess travel cost involved due to a visit to \(j\) after performing activity \(k\) on a chained trip. Similar ideas of modeling excess travel can be found in Hodgson (1981) and Tong et al. (2012). The following example in Figure 4.3 illustrates the concept of “excess travel.” Suppose an individual is traveling along a planned trip that involves multiple activities (stops). After completing a certain activity \(k\), prior to the next activity \(k+1\), the individual decides to make an additional visit to a facility at \(j\). This results in a deviation from the original route from \(k\) to \(k+1\). The additional travel cost due to the visit to \(j\) can be derived by subtracting
travel distance/time between $k$ and $k+1$ ($c_{k,k+1}$) from combined travel cost of $k$ to $j$ and $j$ to $k+1$ ($c_{k,j} + c_{j,k+1}$).

Figure 4.3 Excess travel due to a visit of facility $j$ on a chained trip

As in the original PMP, the importance of home-based demand for services is important. For example, studies showed that home-based single stop trips account for a considerable proportion (20% to 50%) of total trips made (Mcguckin et al., 2005; Primerano et al., 2007; Santos et al., 2011) suggesting that the tendency to visit a facility directly from home is fairly high. In the new accessibility maximization location model, it is reasonable to include the home-based accessibility component as described in the classic PMP. Thus, the third objective is identical to (1):

$$\text{Objective 3: Minimize } \sum_i \sum_j d_{ij} y_{ij}$$

Objective function (8) minimizes the total travel cost $d_{ij}$ between homes and potential facilities. Additional model constraints are presented as follows:
Constraints (9) and (10) ensure that only one facility can be visited via a multi-stop chained trip or a home-based single purpose trip, respectively. Constraint (11) is the same as (4), specifying the total number of \( p \) facilities to locate. Constraints (12) and (13) specify that a facility can be visited through a chained trip or a home-based single purpose trip only if the site is selected. Constraints (14) are binary integrity constraints.

Overall, the three proposed objectives (6), (7) and (8) aim at achieving accessibility maximization from different angles. The first objective seeks to maximize the total accessibility based on the spatial relationship between the distribution of facility sites and people’s current activity spaces. The second and third objectives focus on minimizing the overall travel cost between demand and potential service to approximate accessibility, either from home or stops along a chained trip. By accounting for all the three components, accessibility is expected to be maximized in a more realistic sense compared to the classic PMP.

### 4.4 Application

The new location model was applied to site service facilities (e.g., restaurants, post offices, day care centers, etc.) in the Tucson Metropolitan Statistical Area, which is coterminous with Pima County, Arizona (see Figure 4.4). The 2008-National Household Travel Survey (NHTS) add-on...
data were used to generate service demand and activity spaces. For each survey participant, the dataset provides detailed information in terms of activity location, activity duration, travel distance/time, travel sequence and mode use within a 24-hour time frame. The entire dataset contains 4,777 travelers (about 0.5% of the population in Pima county), 1,659 of whom outside of the study area were excluded. As a result, a total of 3,118 individuals were accounted for in the study. Home-based fixed demand was derived from 3,118 home locations of all individuals. In addition to home locations, 14,705 non-home activity locations along chained trips were used to measure the accessibility addressed by Objective 2 as specified in (7).

In this study, we used one of the most widely used activity space approaches, the standard deviational ellipse (SDE) (Yuill, 1971), to generate individuals’ activity spaces. SDE is an ellipse that captures the smallest area encompassing activity locations with a certain probability (e.g., 68%, 95%, etc.). Applications of the SDE activity space approach can be found in Buliung and Kanaroglou (2006a), Miranda-Moreno et al. (2012), Schönfelder and Axhausen (2004), Serman et al. (2005) and Järv et al. (2014). In this study, the SDE was chosen to construct activity spaces because of its robustness (Järv et al. 2014) and easy implementation (Sherman et al., 2005). In Python with Arcpy geoprocessing library, each individual’s activity space was generated from observed activity locations. Figure 4.5 shows a SDE drawn for an individual in the survey dataset, where 95% of observed activity locations were encompassed by the activity space.

A total of 50 candidate sites for facility siting was selected based on a number of criteria, including population density, road network and urban land-use form (also see Figure 4.4). The number of facility to site \( p \) was set to 10. A road network dataset was obtained from Pima County GIS portal, and ESRI’s network analyst extension was used to compute travel costs in (7) and (8).
Given a multi-objective model with possibly conflicting objectives, it is very likely that no optimal solution exists that can optimize all objectives simultaneously. For a multi-objective model,
the scalar concept of “optimality” can be replaced with the notion of “Pareto optimality,” which refers to a condition that a solution’s performance on one objective cannot be further improved without sacrificing at least one other objective (Duh and Brown, 2007; Yeung and Man, 2011). The determination of Pareto optimality involves the identification of non-dominated (also known as non-inferior) solutions. According to Cohon (1978), a solution x is considered to be dominated/inferior if there exist other solutions that can be as good as x in terms of all objectives, and for at least one objective, is strictly better than x.

A number of approaches have been developed to obtain non-dominated solutions. Among others, the weighting method is a widely used approach (Cohon, 1978; Farhan and Murray, 2008). The weighting method collapses multiple objectives into a single objective with a set of weighting coefficients associated with each objective.

Using the weighting method, a single-objective function of our model can be formatted as:

\[
\text{Maximize: } w_1 f_1 - w_2 f_2 - w_3 f_3 \quad (15)
\]

where

\[
f_1 = \sum_i \sum_j b_{ij} x_j, \quad f_2 = \sum_i \sum_k \sum_j e_{ikj} z_{ikj}, \quad f_3 = \sum_p \sum_j d_{pj} y_{pj} \quad ; \quad w_1, w_2, w_3 \text{ are weighting coefficients indicating relative importance of } f_1, f_2 \text{ and } f_3.
\]

Also note that Objectives 2 and 3 with minimization goals have been transformed into problems with maximization goals by multiplying -1.

By changing the weight combinations, different sets of non-dominated solutions could be generated (Cohon, 1978). To find the most desirable solution(s), decision makers need to rely upon their expert knowledge to make the selection of weights. Choices of weights can be determined by factors such as the type of facilities of and decision makers’ own preferences. Alternative solutions could also be compared for different subjectively determined weightings.
We note that objectives specified in (6), (7) and (8) have different magnitudes and are in different units. We standardized the objective functions to make sure they are comparable. A normalization scheme introduced in Grodzevich and Rmanko (2006) was adopted in this paper, which is shown as follows:

\[ f' = \frac{f - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}} \]  \hspace{1cm} (16)

where \( f' \) is normalized objective function, \( f_{\text{min}} \) and \( f_{\text{max}} \) are the lowest and highest values that the objective function can reach. The normalized combined objective function is presented below:

Maximize: \[ W_1 \frac{f_1 - f_{1\text{min}}}{f_{1\text{max}} - f_{1\text{min}}} - W_2 \frac{f_2 - f_{2\text{min}}}{f_{2\text{max}} - f_{2\text{min}}} - W_3 \frac{f_3 - f_{3\text{min}}}{f_{3\text{max}} - f_{3\text{min}}} \]  \hspace{1cm} (17)

After applying the normalization scheme, all sub-objective function values are found in the range \([0,1]\). In particular, \( f_{1\text{max}}, f_{2\text{min}} \) and \( f_{3\text{min}} \) can be derived by solving each single-objective problem individually. To obtain \( f_{1\text{min}}, f_{2\text{max}} \) and \( f_{3\text{max}} \), we solved a large number of combined multi-objective problems with different weights to approximate the theoretical minimum (maximum) of the objective function values when the other two objectives are considered. With a total sum weight of 10, decision makers are offered a range of choices for the relative priority for each objective. For example, a combination of 5, 4, 1 for \( w_1, w_2, w_3 \) indicates that relative importance of the associated objective is 50%, 40% and 10% respectively.

A number of model instances were coded in Python and solved by IBM’s commercial optimization software CPLEX 12.6. Solution results were then exported to GIS for analysis and display. Using a PC with Intel i7 processor and 16 GB RAM, exact solutions were successfully generated within a reasonable amount of solution time as shown in Table 4.1 for thirteen non-dominated solutions with a range of weight combinations assigned (p=10). The first three columns
show different configurations of $w_1, w_2, w_3$ with a sum of 10 (except the first three rows). The fourth, fifth and sixth columns report normalized objective function values associated with the three objectives. Iterations and solution time (in seconds) are listed in the last two columns.

### Table 4.1 Non-dominated normalized solutions ($p=10$)

<table>
<thead>
<tr>
<th>$w_1$</th>
<th>$w_2$</th>
<th>$w_3$</th>
<th>Objective 1</th>
<th>Objective 2</th>
<th>Objective 3</th>
<th>Iterations</th>
<th>Time (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>28059</td>
<td>489.73</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>-</td>
<td>26854</td>
<td>524.83</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>51</td>
<td>523.64</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>1</td>
<td>0.92</td>
<td>0.65</td>
<td>0.55</td>
<td>18518</td>
<td>524.05</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>2</td>
<td>0.87</td>
<td>0.52</td>
<td>0.42</td>
<td>35</td>
<td>517.61</td>
</tr>
<tr>
<td>7</td>
<td>2</td>
<td>1</td>
<td>0.81</td>
<td>0.35</td>
<td>0.37</td>
<td>21663</td>
<td>687.28</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>3</td>
<td>0.78</td>
<td>0.28</td>
<td>0.27</td>
<td>21096</td>
<td>572.41</td>
</tr>
<tr>
<td>6</td>
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<td>2</td>
<td>0.76</td>
<td>0.24</td>
<td>0.25</td>
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<td>590.59</td>
</tr>
<tr>
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<td>3</td>
<td>0.70</td>
<td>0.17</td>
<td>0.16</td>
<td>20206</td>
<td>517.55</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>3</td>
<td>0.68</td>
<td>0.14</td>
<td>0.16</td>
<td>49</td>
<td>595.84</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>5</td>
<td>0.63</td>
<td>0.12</td>
<td>0.13</td>
<td>51</td>
<td>523.98</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>2</td>
<td>0.42</td>
<td>0</td>
<td>0.09</td>
<td>69</td>
<td>527.51</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>6</td>
<td>0.26</td>
<td>0.01</td>
<td>0.02</td>
<td>41</td>
<td>527.08</td>
</tr>
</tbody>
</table>

As Table 4.1 shows, each objective function value ranges from 0 to 1. The first three rows in Table 4.1 provide solutions for the scenarios where only one objective is in effect while ignoring the two others (with a weight of 0). This is equivalent to solving each normalized single-objective problem individually. Each solution provides the best value possible for the corresponding objective function. In particular, when only Objective 1 is in effect, the maximal value it can achieve is 1. In contrast, due to the negative relationships imposed on Objective 2 and 3 in the combined objective function (see (15)), the theoretical maximal values that the two objective functions can achieve are 0.

With different weight combinations being applied, values of the three objective functions may vary accordingly. In general, a larger weight results in greater influence of the associated objective, and vice versa. Such an influence is evaluated from the objective function values. A higher objective function value of Objective 1 and lower objective function values of Objectives 2,
3 indicate greater influences of the corresponding objectives. According to Table 4.1, a decrease of Objective 1 value leads to decrease of values of the two other objectives (but increased influences). This exhibits a significant conflicting relationship between Objective 1 and Objectives 2 and 3.

The relationship between Objectives 2 and 3, however, seems more complex. As Table 4.1 shows, Objective 2 and 3 are positively related to each other, that is, when one is influential (with smaller objective value), the other is influential as well, and vice versa. Furthermore, it is common to see a crossed boosting effect between the weights assigned to the two objectives. For example, with a weight combination of 2, 6, 2, although the weight assigned to Objective 3 is fairly low ($w_3 = 2$), the objective is still fairly influential with an objective function value of 0.09. This may be due to the effect of a large weight assigned to Objective 2 ($w_3 = 6$).

It is worth noting that the proposed location model allows an individual to visit different facilities via home and a chained trip. In other words, the restriction of one demand (individual)-one facility enforced in the PMP has been relaxed. This brings a great flexibility for the individual to decide which facility to visit, depending on his/her actual trip choice (single purpose trip or multi-purpose trip or both).

Figure 4.6 illustrates an individual’s potential travel to two selected facilities based on a solution. The travel originated from both home and a chained trip. The individual is assigned to facility 4 if the travel starts from home. However, if the individual travels via a chained trip, the nearest selected facility 7 is assigned to the individual. As a result, the individual is provided with two options of facilities to acquire services, which is more flexible than the single choice provided by the PMP.
Figure 4.6 An illustration of potential travel to optimal facilities from home and from a chained trip

Figure 4.7 displays the selected facility sites by solving each objective individually. From the map of spatial configurations of the selected facility sites, one can gain a deeper understanding of the relationships among the objective functions. Figure 4.7a, 4.7b and 4.7c depict model solutions after solving single Objective 1, 2 and 3 individually. Based on the solutions by solving Objective 1 only, all selected sites are concentrated in the urban center, with no facility located in suburban areas (see Figure 4.7a). Figure 4.7b maps solutions obtained by solving Objective 2 alone. The figure shows that although 6 out of 10 facilities are still found in the central area, 4 sites are located in the peripheral areas as well. The distribution of selected facility sites obtained by solving single Objective 3, shown in Figure 4.7c seems more dispersed compared with the results in the first two single-objective solutions.
Figure 4.7 Site selection results when solving each objective individually ($p=10$)

Figure 4.7 indicates that the geographical locations of the selected sites of solving the three objectives become gradually dispersed. To explain this spatial pattern, it would be helpful to refer to Figure 4.8, where density surfaces of aggregated activity spaces, non-home activity locations...
and home locations are generated and displayed. The majority of activity spaces are concentrated in the central urban area (see Figure 4.8a), suggesting that a significantly higher proportion of the daily activities of the population are performed in the central area. Therefore, it is reasonable to see the selected facility sites all located in the central area, where the overall number of individuals’ activity spaces containing the selected facilities is maximized. By contrast, Objective 3 only accounts for potential travel originating from homes, which are also densely distributed in certain areas on the outskirts in addition to the central areas (see Figure 4.7c). Therefore, while solving the problem with Objective 3 alone, the importance of the peripheral residential home locations may result in the selected sites to be more dispersed from the city center. On the other hand, Objective 2 considers all non-home activity stops that have been chained on trips when measuring accessibility. The non-home activity stops, compared with home locations, are more centrally clustered (see Figure 4.8b and 8c). This also explains the less dispersed solutions by Objective 2 only when compared with those by Objective 3 only. For example, candidate site 14 is shown as selected in Figure 4.7c (Objective 3) but not in Figure 4.7b (Objective 2). According to Figure 4.8c, the site is located in a major residential area where notably high home density is found. However, in terms of non-home activity locations, the density seems not high enough in the neighborhood of the candidate site (see Figure 4.8b), which might explain why it is not shown as selected in Figure 4.7b.
Figure 4.8 Density maps

a: Activity space density

b: Non-home activity stop density

c: Home density
In short, Objective 1 produces solutions that prefer central urban areas, whereas Objective 3 gives solutions that prefer residential areas, which may include substantial suburban areas. Sites based on Objective 2 seem to be located between these two. Therefore, the spatial trade-offs among the three objectives can be conceptualized as a trade-off between “urban center” and “suburban areas.” Based on the actual type of facilities and decision makers’ own preferences, different weightings can be assigned to the three objectives. Figure 4.9 shows a set of model solutions by adopting a weight combination of $w_1 = 4$, $w_2 = 3$ and $w_3 = 3$. Due to the relatively equal weight assigned to the objectives, the geographical configuration of the selected facility site exhibits a balance between the central and suburban areas.

![Figure 4.9 Model solutions ($w_1 = 4$, $w_2 = 3$ and $w_3 = 3$, $p=10$)](image-url)
4.5 Discussion and conclusion

In this study, we developed a location model to address three aspects of accessibility maximization. The first objective ensures the number of facilities contained by the total number of individuals’ activity spaces is maximized. The other objectives consider two different types of travel (home and trip chaining) that have been commonly realized in the real world. In fact, fixed home-based demand accounted for by Objective 3 can be very influential considering that a significant proportion of daily trips originate from homes and are single purpose. In addition, people’s daily trip-making behavior, especially trip chaining, suggests alternative options for individuals to access service facilities. Objective 2 presents a means to assess accessibility linked to such travel behavior. On account of all three aspects of accessibility maximization, the new model provides a more realistic and comprehensive approach for determining the optimal spatial configuration of facility locations.

With respect to potential applications of each objective, we discuss a number of real-world examples. As for Objective 1, our empirical results suggest that it favors central urban locations, so possible applications of the objective could be public services or certain commercial facilities such as theaters, central parks and shopping centers, which might bring more convenience to the public when located in urban centers. Due to the focus on residential areas in Objective 3, community or neighborhood oriented services such as community centers, home cleaning services, laundry stores and grocery stores could be good applications. Objective 2, on the other hand, values visits that could take place along on a trip with other activities, and such travel is often for pursuing side or discretionary activities”. In this regard, site selections for fast food restaurants, automobile services and gas stations could be properly addressed using this objective.

The weighting method used for solving the model offers a range of flexibility for decision makers to compare and evaluate the relative importance for each objective. In general, Objective 1 maintains a direct competing/conflicting relationship with Objectives 2 and 3. Our empirical study...
shows that for the individuals included in the survey the sites selected based on a higher weight assigned to Objective 2 (3) can also benefit Objective 3(2). This indicates that sites selected that are accessible to residential areas also tend to be accessible along the chained trips individual make in our study area, although for an individual traveler, the facility assigned to the individual based on the home travel might be different from the one based on a multi-stop chained trip. However, whether such a relationship remains true for other study areas remains unknown.

Although the model is capable of capturing potential travel to a service facility occurring on a chained trip, the accessibility measured based on individual i stopping at each activity location is still limited. It is possible that travel for a potential service could take place at any point along the trip, which would involve many more locations than only the activity sites k. For example, it is common for people to make decisions to visit gas stations or coffee shops while traveling, without planning beforehand. In this case, any point along the trip can be considered as an origin of potential travel to facility j. One solution to the problem is to modify the way excess travel distance is calculated in Objective (2) In Objective (2) the additional travel distance $e_{ijk}$ only measures the travel between activity location pairs of $k$ and $k+1$ and facility $j$. If one is interested in accounting for any point $x$ between $k$ and $k+1$, it will result in infinite $e_{ijk}$ to be computed. A discretization strategy could be applied to compute $e_{ijk}$ on average.

In this study, we are more interested in the spatial aspects of demand and service facilities and we have mainly focused on how and where demand originates for obtaining services. We note that temporal variability of demand and service facilities might also be important. Tong et al. (2012) incorporated time frames (e.g., morning and afternoon, weekdays and weekends) for demand modeling. Further, demand may also vary over the course of the day. This is particularly critical for certain public facilities that are available with limited hours of operation, such as post offices,
libraries and food assistance stations. More efforts are needed for developing models to fully incorporate the temporal characteristics of demand associated with service hours of facilities.

The activity space-based accessibility measure approach in this study has room for further improvement. Although the cumulative measure is the most intuitive way of modeling accessibility and easy to implement (Horner et al., 2015), the binary notion used in Objective 1 to evaluate the accessibility of service facilities falling within in the activity spaces may be less realistic in the real world. Accessibility among multiple candidate facility sites falling in one’s activity space may need to be differentiated as opposed to be treating equally in Objective 1. For example, given a set of candidate facilities in the activity space, accessibility could be evaluated in a more refined way based on the likelihood of visits. Some more sophisticated activity space approaches, such as density based activity spaces (Schönfelder and Axhausen, 2004), can be used to help compute the likelihood.

This research has a great potential to incorporate big data reflecting individual’s space-time travel behavior. With the emergences of GPS enabled applications and geo-tagged social media data, such as Facebook check-ins, geo-tagged tweets and four square check-ins, studies of travel behavior are provided with an unprecedented opportunity to include much larger samples of the total population than with traditional survey-based datasets and to take advantage of greatly enhanced data resolution (Patterson and Farber, 2015). Temporal dynamics of activity travel can be tracked using the temporal information (time stamps) provided in these data sources. As a result, space-time travel trajectories extracted from these data can be used as data input to the location model proposed in this article. Future research can be developed to exploit the advantages of the new data sources based on our modeling framework. Some modifications of the model, however, may be required to better incorporate such new data.
CHAPTER 5
CONCLUSION

Research on urban travel has been a continued interest in geography, transportation planning and urban studies. Compared to the traditional trip based approach, the activity based approach offers a better understanding of the motivation underlying travel, that is, activity participations. Urban activity travel takes place in space and time, therefore it is worthwhile to position the research body in the context of time geography framework. By doing so, details of the activity travel programs could be fully revealed. Activity space presents a useful tool in describing the actual (realized) travel of individuals. Despite a variety of activity space approaches have been introduced in the literature, the time geography based activity space deserves our attention considering it unique ability to situate individuals’ activity travel in the perspective of time and space, as opposed to only accounting for the spatial dispersion of activities.

Major issues of the time geography based activity space relate to the possible overestimation of the areas included as well as the underestimation of the complexity of urban travel, especially when trip chaining behavior is considered. To address the issues, in the first essay, the time-geography based activity space approach is extended by incorporating urban structure and more detailed urban travel instances. As a result, spatial extents of urban travel can be more accurately drawn, where our first contribution to the literature resides.

Using the enhanced activity space approach incorporating space and time, in the second essay, the relationship between accessibility to urban opportunities and urban travel was investigated. Such a relationship has been generally understood in the literature, indicating improved level of accessibility is often associated with reduced travel. However, whether and how
the effect varies among different activity types is still under-researched. The main contribution of
the study lies in providing an empirical study to enrich the literature. The study suggests that the
effect of accessibility varies among various activity types. In addition, employment status (worker
vs no-worker) and trip chaining behavior are also accounted for when examining the accessibility-
travel relationship. The research findings provide valuable implications for urban travel reduction
policies and practices.

Activity space and trip chaining behavior have a great potential to be applied in location
modeling. In the third essay, attention is paid to location models that focus on maximizing spatial
accessibility. To fill in the gaps in the literature, the classic p-median problem (PMP) is extended
by incorporating trip chaining behavior as well as activity space. The new model provides two
additional means of measuring accessibility in addition to the home-based accessibility measure
conceived in the PMP. By adding two more objectives and solving the problems in a weighting
manner, the new location modeling approach offers a great flexibility to decision makers when
selecting new facility locations.

This research has a great strength to be further bridged to studies of activity-travel for the
aging population. Nowadays, population aging has become a global issue that many countries are
experiencing. With the growing elderly population (age over 65), our society needs to
accommodate this trend properly. Particularly, efforts need to be made in a timely manner to meet
the growing transportation demands of the elderly, whose travel behavior could be very different
from their younger counterparts in many aspects. The premise behind any effective actions lies in
a thorough understanding of elderly’s activity-travel. The activity space model developed in chapter
two can be used to examine the travel characteristics of the elderly. A series of statistical analysis
can be conducted to assess impacts of social-economic status of the elderly on their activity spaces
considering various travel purposes (e.g., travel for food services, health services, recreational
services, shopping services) when compared with younger adults. As a result, insights are expected
to be gained with respect to effectiveness and efficiency of the existing transportation and urban infrastructures for serving the elderly population.

Constructing activity spaces is very data intensive and data availability represents one of the challenges in the activity space research. In fact, empirical studies on human activity spaces are relatively lagged compared with theoretical development due to the lack of long-term travel behavior data. Recently, emerging location-aware data sources have been receiving growing attentions in activity-travel research, including smartphone data, mobile call data, smart card data, GPS data and social media data, which can be recognized as varieties of so called “big data”. Big data has a number of advantages such as better resolution, larger sample sizes, and relatively less expensive to obtain. This brings an unprecedented opportunity to the activity-travel research. The current research has a great potential to couple with these new data sources. However, a challenge is that big data has known issues such as uncertainty, missing information, sample bias and low quality. In my future research, I also plan to address some of these issues.

As I already pointed out, time variability is also worthy of attention when building activity spaces. In this essay, activity spaces were constructed based on the travel made in 24 hours. It’s commonly believed that people’s travel behavior may vary between different periods (e.g. weekdays vs weekends,). Therefore, activity spaces need to be able to couple with the temporal variations. Furthermore, a further study might involve an examination of the aggregated activity spaces of a sample population based on different time intervals to gain insights into the overall spatio-temporal travel dynamics of the population. However, such an analysis requires data of a vast population coverage and with long-term observations. Such requirement might not be easily fulfilled unless the big data source discussed above can be properly utilized. The computation effort to process the massive data and generate activity spaces could pose another challenge to the future research.
REFERENCES


