SPACE–TIME MEASURES OF DEMAND FOR SERVICE: BRIDGING LOCATION MODELLING AND ACCESSIBILITY STUDIES THROUGH A TIME-GEOGRAPHIC FRAMEWORK

by
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REN, F., TONG, D. and KWAN, M.-P. (2014): 'Space–time measures of demand for service: bridging location modelling and accessibility studies through a time-geographic framework', *Geografiska Annaler: Series B, Human Geography* 96 (4): 329–344.

ABSTRACT. Demand for service in location modelling is often evaluated based on the spatial proximity of fixed and static reference locations of demand (e.g. home) to a facility, which ignores person-specific activity–travel patterns and the temporal changes in demand for service throughout the day. To address these limitations, this study draws upon recent developments in space–time measures of individual accessibility to explore the spatial and temporal structures of demand by considering individuals' space–time constraints and impact of existing urban structures. Based on a time-geographic framework, eight space–time demand measures were developed and compared with three conventional location-based demand measures for 12 hospitals through an empirical study conducted in Columbus, Ohio. The results show that geographic proximity between clients' home and facilities may not be an effective indicator for service demand, and conventional demand measures tend to underestimate potential demand for service in most situations. The study concludes that space–time demand measures that take into account people's activity-travel patterns in space–time would lead to better estimation of demand for service in most cases.

Keywords: demand for service, time geography, space–time constraints, space–time measures

Introduction

Identifying optimal locations for service provision has long been a concern for geographers and planners because it plays an important role in strategic planning for both private and public organizations (Church and Murray 2009). Various location models have been developed to locate different kinds of facilities, including emergency service facilities (Church and ReVelle 1974; Murray and Tong 2009), healthcare services (Gu *et al*. 2010), bank ATMs (Hopmans 1986; Min and Melachrinoudis 2001), motels (Kimes and Fitzsimmons 1990), and farmers' markets (Tong *et al*. 2012). Although location models may vary in their objectives, decision variables, and system parameters and constraints, the general paradigm of location models often includes one or more supply facilities and a set of spatially distributed clients for service (Brandeau and Chiu 1989). As such, an accurate assessment of demand for service is very important for planners to optimally locate facilities and determine their operation hours.

In location modelling, demand for service is often conceptualized in two ways: continuous and discrete. Continuous conceptualizations conceive demand to be distributed continuously over space and can exist at any location in space. Problems involving continuous demand distribution are often challenging in both model construction and problem solution (Murray and Tong 2007; Matisziw and Murray 2009). Alternatively, demand for service in most situations is conceptualized to be at discrete locations and often operationalized using discrete population centres such as the centroids of census tracts or block groups. Generating such centres involves certain level of aggregation of the overall population within the associated areal units (Fotheringham *et al*. 1995). As a result, individuals within the same areal unit are assumed to live at the same location.

To date, the most commonly used demand measures in location modelling are primarily *location-based*, where demand is evaluated based on the spatial proximity of reference locations of clients (e.g. home or distribution centres) to a facility (e.g. a grocery store or a plant). For example, the *p*-median model seeks the location configuration of *p* facilities that minimizes the total demand-weighed distance from all clients to their closest facilities (Hakimi 1964; ReVelle and Swain 1970). Most of the studies on service area delineation also assume that clients travel to the closest facility for service. For instance, Voronoi and weighted Voronoi diagram tessellations (Aurenhammer and Edelsbrunner 1984; Okabe *et al*. 1992) are two popular space decomposition approaches. For covering problems, the effective service range of a facility is usually determined based on a pre-specified travel distance or time. A client is considered as being "covered" by the facility only when the client is located within its service range.

These location-based measures are suitable for some situations where demands are fixed in space, such as locating warehouses or fire stations. However, they become less appropriate in other situations where clients do not travel to facilities from a single fixed location like home or a population centre. This is often true for retails (O'Kelly 1981), preventive healthcare services (Gu *et al*. 2010), and other facilities for discretionary activities like eating and shopping (Kwan 1999a, 1999b). In addition, demand is also affected by service quality that has many dimensions, including reliability of service, knowledge and skills to perform the service, service competence, security, courtesy, and others (Parasuraman *et al*. 1985).

Drawing upon recent developments in space–time measures of individual accessibility, this study examines the spatial (where clients come from) and temporal (when clients can possibly visit or use a facility) structures of demand by considering individuals' space–time constraints and the influence of existing urban structures through an empirical study. The rest of the article is organized as follows. The conceptual framework of how demand and supply interact in space and time will be discussed in the next section, which is followed by a review of space–time measures and modelling. The empirical study will then be introduced, including data collection, specification of space–time measures for demand, and analysis of results. Finally, the article concludes with a discussion of how the space–time demand measures might be used in location models.

Spatial and temporal distributions of demand and supply

Before discussing the demand measures developed in this study, it is necessary to revisit the conceptual framework of how the spatial and temporal distribution of demand can be defined in relation to that of supply. Past literature has suggested that spatial organization of urban opportunities and individual spatial movements are closely related and they form a 'circle of causality' (Anderson 1971, p. 360). This indicates that demand and supply are intertwined to shape each other's spatiotemporal patterns. From the perspective of supply facilities, they are often sited to achieve one of the following objectives: cost minimization (transportation cost in particular), demand satisfaction, profit maximization, and environmental concerns (Current *et al*. 1990). Spatial distribution of demand population needs to be considered directly or indirectly to reach these goals. For example, maximizing demand accessibility and reducing transportation cost could be measures of profit maximization. Further, "when clients could possibly visit where" is also a very important question in service provision planning. For instance, constrained by production and transportation cost, many farmers' markets usually operate for limited hours in a week (Tong *et al*. 2012). To find the locations of a set of farmers' markets that maximizes the patronage, the temporal windows in which demand can access a farmers' market need to be accounted for. Thus, both spatial and temporal distribution of these facilities depends on that of the demand population.

Meanwhile, demand distribution in space and time is not independent on the spatial and temporal distributions of supply facilities. In time geographic conceptualizations, individuals' spatial movements are restricted by various constraints, including capability constraints, coupling constraints, and authority constraints (Hägerstrand 1970). Coupling constraints restrict 'where, when and for how long, an individual has to join other individuals, tools, and materials to produce, consume and transact' (Hägerstrand 1970, p. 14). This indicates people's daily activity– travel is constrained by the spatio-temporal availability of alternatives for activity destinations (Kim and Kwan 2003). Thus, existing urban structures actually play a role in forming its own spatial distribution through affecting people's activity–travel patterns. For example, the downtown area in a city often attracts much travel due to the cluster of urban opportunities, which in turn potentially generates higher demand for the facilities in the area (Kwan 2000).

The interdependence between demand and supply suggests that the spatial and temporal demand distribution is determined by both individual accessibility/travel and existing urban structures. Location-based demand measures, however, assume demand is only generated at fixed locations (especially at people's home location), while ignoring the dynamic nature of demand distribution due to people's daily travel. In fact, activity–travel research has shown that more than half of urban trips consist of multi-purpose and multi-stop trip chains (Hanson 1980; Richardson and Young 1982; O'Kelly and Miller 1984; Kitamura *et al*. 1990; Arentze *et al*. 1994). The complexity of urban travel indicates that clients can combine various activities in a single trip, and therefore the spatial distribution of demand is not fixed (Chen and Kwan 2012).

Similarly, the temporal distribution of demand is not static due to the dynamics involved in individual travel. Summarizing demand by a single static value, such as the total number of households in the service range, thus fails to acknowledge that demand distribution varies in space and time in a highly complex manner.

The above discussion suggests that the conceptualization of demand in conventional location-based measures is not always appropriate for locating new supply facilities because demand is treated as temporally invariant and originated from spatially fixed population centres that are independent of supplies. To overcome the limitations of current demand measures, this study draws upon insights from the time-geographic approach, which is one of the six commonly used quantitative methods for analysing movement data (Long and Nelson 2013). The other five important methods include path descriptors, path similarity indices, pattern and cluster methods, individual–group dynamics, and spatial field methods. In the time-geographic framework, activities are differentiated with regard to the extent to which their locations and/or times can be changed easily. Activities whose locations and/or times cannot be changed easily (such as work and children pick-up/drop-off) are referred to as *fixed activities*, while others such as dining at a restaurant or grocery shopping are referred to as *flexible activities* (Lenntorp 1976; Burns 1979). Between any two consecutive fixed activities, which serve as the space–time pegs that constrain where and how much time an individual can spend, a *feasible* area within which a person could move freely can be identified (e.g. Miller 1991; Kwan 1998, 1999a, 1999b; Weber and Kwan 2002; Schwanen and Dijst 2003). This area is referred to as the potential path area (PPA) in the parlance of time geography. If a facility falls within this area, the person then could feasibly visit the facility and he/she becomes a potential demand. Conceptualizing demand for service as *feasible* visits to the facility overcomes the limitations of conventional demand measures by considering the impacts of person-specific constraints on the spatial extent in which clients may possibly move (Kwan 2013). It also takes into account the impact of the existing urban structures in that individual activity travel is dependent on the spatial and temporal distributions of supplies.

Developments in space–time accessibility measures

To develop demand measures based on this new conceptual framework, we draw upon the literature on space–time measures of individual accessibility (STAMs) (e.g. Lenntorp 1976; Burns 1979; Miller 1991; Kwan 1998; O'Sullivan *et al.* 2000; Wu and Miller 2001; Weber and Kwan 2002; Dijst *et al.* 2002; Kim and Kwan 2003; Casas 2007; Yu and Shaw 2008; Neutens *et al.* 2010a, 2011; Chen *et al.* 2011; Delafontaine *et al.* 2011). Unlike conventional contour measures (Wickstrom 1971; Hanson and Schwab 1987) and gravity-type indices (Ingram 1971; Handy 1993; Geertman and Ritsema van Eck 1995), space–time measures are capable of capturing the effects of person-specific space–time constraints and thus allow accessibility to vary even for individuals who live in the same household (Geurs and van Wee 2004).

A recent study by Neutens *et al.* (2010b) compares three types of STAMs both conceptually and empirically. Following Lenntorp's work (1976), the first type of STAMs evaluates accessibility by the number of the feasible opportunities or network length in the space–time prism (Kwan 1998; Weber and Kwan 2002). Since this approach treats accessibility in a dichotomous way (Ettema and Timmermans 2007), other important dimensions of accessibility, such as attractiveness of alternatives, are missing. The second type of STAMs is derived from Burns' utility-based framework for space–time measures (Burns 1979). Miller (1999) developed three standard space–time accessibility and benefit measures to evaluate accessibility as a utility function of activity duration, attraction of activity locations, and the travel cost to these locations.

Other utility functions have also been suggested in the literature. For instance, Ashiru *et al.* (2004) assume that the utility of engaging in an activity depends on timing, duration, and the intensity with which the activity is performed, while Ettema and Timmermans (2007) propose alternative utility functions to cope with the impact of uncertainty of travel time and travel information on accessibility. The third type of STAMs is an extension of Lenntorp's measures by considering certain qualities of the feasible opportunities. For example, the number of feasible opportunities can be discounted by the travel distance, replaced by the maximum duration that an individual can spend, or weighed by opportunity areas (Kwan 1998, 1999a; Neutens *et al.* 2010a). Further, the influencing factors of accessibility, such as opening hours of services and activity duration, have also been integrated into accessibility measures (Weber and Kwan 2002; Kim and Kwan 2003; Delafontaine *et al*. 2011; Neutens *et al*. 2012).

Although considerable developments have been made in time-geographic studies on individual accessibility in the past 15 years or so, there is no study to date that uses this powerful framework to advance demand measures for location modelling. While demand and accessibility are closely related because an individual cannot become a potential demand for a facility if the facility is inaccessible to him/her, there are significant conceptual and analytical differences between these two distinct notions. In location models, demand is examined from the perspective of facilities and is evaluated based on the number of potential (or feasible) visits by clients. In accessibility studies, accessibility is examined based on the perspective of individuals and is assessed by the number of feasible activities for the person in question at different facility locations. Although the effect of person-specific space–time constraints on interpersonal variations in accessibility has been widely recognized, its implications for demand evaluation in location models has not been explicitly examined to date.

To fill this gap in location modelling, five types of space–time demand measures are specified and compared with two types of location-based demand measures through an empirical study as described in the following section. In doing so, we attempt to highlight the urgent need for more appropriate conceptual frameworks in which spatiotemporal distribution of demand can be better captured for future location modelling studies. This study represents an initial attempt to bridge the space–time accessibility literature and the location modelling literature through a time-geographic framework. The problem it examines is significantly different from the problems addressed in either of these two literatures.

Data collection

The empirical study was conducted in Franklin County, Ohio, which consists of the city of Columbus and several other small cities. According to the 2010 US Census, the population of Columbus is approximately 1.8 million and is well mixed with different races and incomes. Due to its diverse demographics and geographies, Columbus is considered a "typical" American city for testing markets for new products (Wolf 2006). An activity–travel diary dataset was collected by Kwan and Ren in the study area between 2003 and 2004. The survey was originally developed to examine the impact of the Internet use on people's space–time constraints and activity-travel patterns. At the start of the data collection, screening packages were sent to 32 000 randomly selected household addresses in Franklin County. Eight hundred and seventy-five households agreed to participate and were sent a survey package that included the diary. The participants were asked to report their detailed activity travel in two designated days (weekdays only) and usable diaries from 376 individuals were used in this study.

Table 1. Testing locations.

Location ID	Hospital name
H1	Franklin County Hospital
H2	Columbus Community Hospital
H3	Lincoln Memorial Hospital
H4	Doctors Hospital
H5	Children's Hospital
H6	Central Ohio Psychiatric Hospital
H7	University Hospital East
H8	Mount Carmel East Hospital
H9	OSU Medical Center
H10	Riverside Methodist Hospital
H11	Harding Hospital
H12	Mount Carmel Saint Ann's Hospital

In addition to the information commonly collected in travel diary surveys – such as the purpose, location, and timing and duration of activities – information about the spatial and temporal fixity of participants' activities was also collected. Based on a scale of 1–5, participants were asked to rate the ease with which the location and time of all the reported activities could be changed, with 1 being the easiest and 5 being the most difficult. An activity was considered fixed if its spatial and temporal fixity ratings were greater than 3. The activities reported in the first-day diaries were used for implementing the space–time demand measures that are specified in the next section.

Participants included 248 women (65%) and 128 men who are couples with/without child(ren) or single parents with child(ren). Most of the participants are white (93%), highly educated (80% are college or graduate degree holders), work full time (63%), and rely on their own motorized vehicle (97%). Both the employment and household status of the participants indicate that most of them might experience

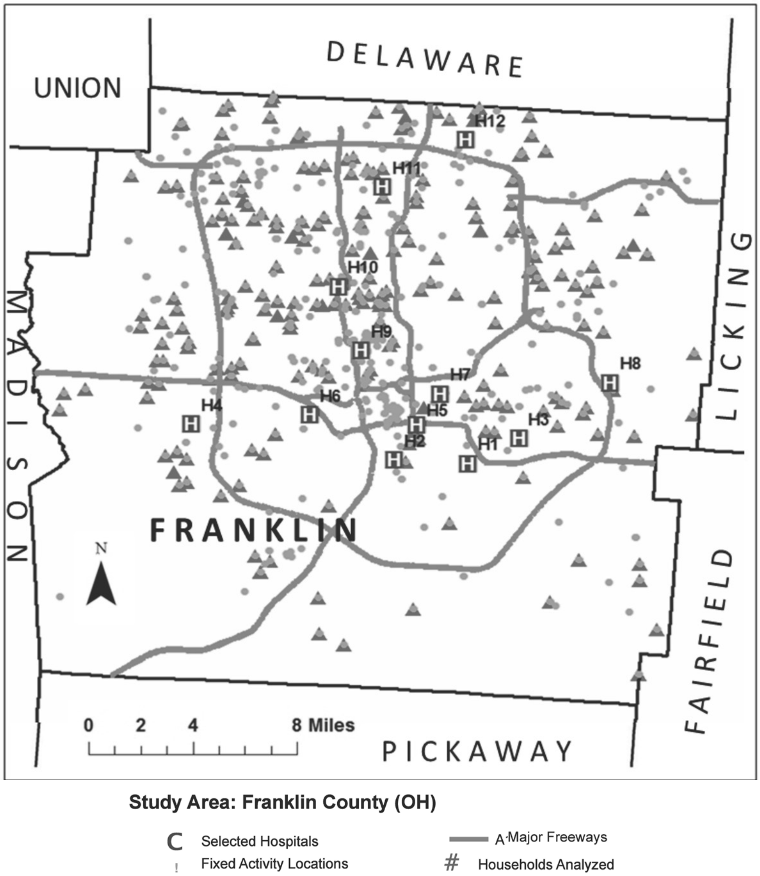

Figure 1. Locations of selected hospitals, spatially fixed activities, and the households participating in the survey in Franklin County, Ohio.
Source: map by authors based on data collected by Kwan and Ren in 2003 and 2004.

relatively high space–time constraints and therefore they are likely to combine multiple activities in a single trip to juggle both work- and household-related obligations. All activity locations were geocoded onto a detailed digital street network called Dynamap/2000 for computing travel times and service areas. The coordinate system used in the analysis is NAD 83 State Plane Coordinate System.

A set of twelve spatially dispersed hospitals in the study area was selected to serve as potential service facility locations (Table 1). Since the primary purpose of the study was to compare the demand patterns obtained using space–tine demand measures with those obtained using location-based measures, our focus is on their similarities and differences (which will not be affected by the type of public facilities examined) instead of the empirical meaning of the findings. We thus used hospitals mainly as an example because they are readily identifiable major public facilities in the study area that offer a wide range of health services to the population. As shown in Figure 1, most of these hospitals are located close to the centre of the Columbus Metropolitan Area while several of them are located closer to major suburban areas in the north, east, and west of the area. Figure 1 also shows that home locations and fixed activities of the participants are mainly distributed in the central and northern parts of the study areas where many job and commercial opportunities are located.

Specifications of the demand measures

Two forms of location-based demand measures and five types of space–time demand measures were specified to evaluate demand at the selected service locations. Table 2 summarizes the eleven demand measures derived from the seven types of demand measures. These demand measures are further explained below.

Table 2. Location-based and space–time demand measures.

Measure notation		Specifications
Location-based measures:	1. AREA5	The number of individuals living within the 5-minute travel zone from facility *j*
	2. AREA10	The number of individuals living within the 10-minute travel zone from facility *j*
AREA and NEAR	3. NEAR	The number of individuals whose home is closer to facility *j* than any other facilities
	4. NUM5	The number of individuals who can reach facility *j* within 5 minutes of travel given their space–time constraints
	5. NUM10	The number of individuals who can reach facility *j* within 10 minutes of travel given their space–time constraints
Space–time measures:	6. MAXDUR5	The amount of time (in hours) that individuals could spend at facility *j* within 5 minutes of travel given their space–time constraints
NUM, MAXDUR, DNUM, ST_NEAR, and NUM(*t*)	7. MAXDUR10	The amount of time (in hours) that individuals could spend at facility *j* within 5 minutes of travel given their space–time constraints
	8. DNUM5	The discounted number of individuals who can reach facility *j* within 5 minutes of travel given their space–time constraints
	9. DNUM10	The discounted number of individuals who can reach facility *j* within 10 minutes of travel given their space–time constraints
	10. ST_NEAR	The number of individuals to whom facility *j* is the nearest facility given their space–time constraints
	11. NUM(*t*)	The number of individuals who can reach facility *j* at clock time *t*

Specifications of location-based demand measures

Evaluating demand by service area (*AREA*). The first form of location-based demand measure (AREA) assumes that the effective service range of a facility is defined by a threshold travel cost and people who live within the range are the potential demand population.

For a facility at j, whether a participant, designated by p, is considered as a potential client is expressed by the following indicator function:

$$I_{p,j} = \begin{cases} 1 & if\ T_{p,j} < T_0 \\ 0 & otherwise \end{cases} \tag{1}$$

where $T_{p,j}$ = travel cost from p's home to j; T_0 = the threshold travel cost determining the service range. Assume that there are m individuals, the overall demand for the facility at j ($AREA_j$) is given by:

$$AREA_j = \sum_{p=1}^{m} I_{p,j} \tag{2}$$

In this study, a 5-minute service area and a 10-minute service area were implemented for all 12 hospitals. The numbers of participants who lived in these service areas were calculated as AREA5 and AREA10 respectively.

Evaluating demand by the nearest facility from home (*NEAR*). The second type of location-based demand measure (NEAR) assumes that people travel to the nearest facility from home. Considering a set of facilities designated by J, whether participant p is assigned to the facility at j can be expressed by:

$$I_{p,j} = \begin{cases} 1 & if\ d_{p,j} < d_{p,l}\ for\ all\ l \in J, and\ j \neq l \\ 0 & otherwise \end{cases} \tag{3}$$

where $d_{p,l}$ = travel cost between p's home and the facility at l. Assuming there are m individuals, the total number of participants assigned to j is then summarized as:

$$NEAR_j = \sum_{p=1}^{m} I_{p,j} \tag{4}$$

Specifications of space–time demand measures

Specifications of the space-time demand measures are based upon Lenntorp's space–time accessibility measures. However, unlike Lenntorp's measures that express accessibility in the form of feasible opportunities, the space–time demand measures implemented in this study present demand as a function of *feasible visits or clients*. Consider participant p, who conducted both fixed and flexible activities in a day. For any pair of consecutive fixed activity episodes, suppose the first fixed activity episode F_i at location i ended at time t_i, and the following fixed activity episode F_{i+1} at location i+1 started at time t_{i+1}. The space–time prism that contains all the space–time points (k, t) where the individual can reach during the time budget $t_{i+1} - t_i$ and within the maximum travel time T_o can be represented by the following expression (modified from Kwan and Hong 1998):

$$STP_i = \{(k,t) | t_i + T_{i,k} \leq t \leq t_{i+1} - T_{k,i+1} \text{ and } T_{i,k} \leq T_0\} \quad (5)$$

where k = a geographic location in the space–time prism; t = a time between the time budget $t_{i+1} - t_i$; $T_{i,k}$ = travel time from location i to location k; and $T_{k,i+1}$ = travel time from location k to the next fixed location i+1.

The projection of this 3D space–time prism onto a 2D geographic plane is potential path area (PPA). If there are n pairs of fixed activity episodes in this person's activity programme, n space–time prisms and a set of PPAs can be obtained. The aggregation of these PPAs is called the daily potential path area ($DPPA_p$), which includes all the possible activity locations the person could visit within the desirable travel time in a day. Based on this theoretic definition of DPPA, the following space–time demand measures are specified.

Evaluating demand by the number of clients (*NUM*). The first space–time measure (NUM) is similar to AREA. However, instead of defining the service area of a facility by a specified travel zone from a fixed location, we consider whether the facility is accessible to an individual given his/her specific space–time constraints, which is expressed by the following indicator function:

$$I_{p,j} = \begin{cases} 1 & if\ j \in DPPA_p \\ 0 & otherwise \end{cases} \quad (6)$$

Assume that there are m individuals under examination, and the potential demand at j (NUM_j) is then evaluated by the total number of potential clients who could reach it within a specified travel cost T_0:

$$NUM_j = \sum_{p=1}^{m} I_{p,j} \quad (7)$$

In this study, the travel costs of 5 minutes and 10 minutes to each hospital were imposed, and the corresponding measures are designated as NUM5 and NUM10 respectively.

Measuring demand by activity duration (*MAXDUR*). The second space–time measure (MAXDUR) takes activity duration as another important indicator of demand for service. For example, the duration that a customer can spend at a farmers' market may affect his/her spending. In situations like these, demand would be better measured by activity duration than by the binary indicator of whether the person can feasibly visit the market. Although a customer's space–time constraints may allow him/her to visit a market multiple times in a day, only the visit that has the maximum activity duration is considered as people normally will not visit the same service facility more than once.

Based on the previous definition of PPA, the amount of time that p can stay at facility location j during any time budget $t_{i+1} - t_i$ is then expressed by:

$$DUR_{p,i,j} = \begin{cases} (t_{i+1} - t_i) - (T_{i,j} + T_{j,i+1}) & if\ j \in PPA_{pi} \\ 0 & otherwise \end{cases} \quad (8)$$

Assume that the activity programme consists of n pairs of fixed activity episodes. His/her demand for service at j is then expressed by the maximum value of all the activity durations at j ($MAX_i(DUR_{o,i,j})$). The overall demand at facility j considering all the m individuals is then evaluated by the sum of the individual's maximum activity duration:

$$MAXDUR_j = \sum_{p=1}^{m} MAX_i(DUR_{p,i,j}) \quad (9)$$

For the purpose of comparison, both 5-minute and 10-minute travel constraints were enforced as well, which are designated by MAXDUR5 and MAXDUR10 respectively.

The formulations of NUM and MAXDUR only

model demand without adjusting for supply. When there are multiple facilities providing similar service in a PPA of person p, competition among these facilities may reduce the chance that each facility will be visited. This issue has been raised in the studies of accessibility to healthcare where the classic gravity measures ignore the competition among individuals for the same healthcare facility. Joseph and Bantock (1982) modified the classic gravity measures by discounting the healthcare facilities with the total population that fall in their service areas. Following a similar reasoning, the third space–time measure for demand at facility j, DNUM, considers the influence of multiple facilities by discounting potential clients.

Measuring demand by discounted number of clients (*DNUM*). Destination choice among multiple facilities is affected by various factors, including travel cost, individuals' preference, and service quality. Since this study is not intended to develop service-specific demand measures, it only considers distance, the common discounting factor of demand for all services. Other variables that can measure service quality should be integrated into the following equation in the future. For example, for grocery stores, the floor space and retail sales may be used in combination with distance to adjust for the attractiveness of supply.

Assume that there are a set of facilities that person p could possibly visit during the time budget $t_{i+1} - t$i. The chance that participant p interacts with any of these facilities is assumed to be determined by travel cost; people are more likely to visit the facility that requires less travel. The probability that p would travel to the facility at j can be formulated as:

$$PROP_{p,i,j} = \begin{cases} \frac{1/f(d_{i,j})}{\sum_{l \in PPA_{i}} 1/f(d_{i,l})} & if\ j \in PPA_{pi} \\ 0 & otherwise \end{cases} \quad (10)$$

where $d_{i,l}$ = travel cost from location i to facility l in PPAp_i; and $f(d_{i,l})$ = distance decay function that can take on different forms. Given n pairs of fixed activity episodes, we only consider the maximum probability that p visits the facility at j, $MAX_i(PROP_{p,i,j})$. Compared with the binary indicator, $I_{p,j}$, in Equation (6), $MAX_i(PROP_{p,i,j})$ can be considered a discounting factor with its value ranging between 0 and 1, indicating the effect of competition from nearby facilities. For m individuals, the overall potential demand for service at facility j is then evaluated by the sum of discounted clients:

$$DNUM_j = \sum_{p=1}^{m} MAX_i(PROP_{p,i,j}) \quad (11)$$

Similar to the implementation of previous space–time measures, two DNUM measures (DNUM5 and DNUM10) were operationalized in the empirical study, and the inverse distance friction function with a power of 2 was used. In accessibility research, negative exponential and inverse distance functions are often used and the choice of distance friction parameters varies with applications. According to Luo and Wang (2003), the power of 2 is in the reasonable range for measuring accessibility to healthcare facilities.

Evaluating demand based on the nearest facility from activity locations (*ST_NEAR*). The fourth space–time demand measure we propose, namely ST_NEAR, is a counterpart of NEAR, but takes into account individuals' space–time constraints when seeking the nearest facility. Specifically, ST_NEAR assumes that participant p would visit the nearest facility from F_i during the time budget $ti_{+1} - t_i$. For n pairs of fixed activity episodes, there may be multiple nearest facilities that p could visit during the n time budgets, among which the one that requires the minimum travel is considered as the nearest facility for p. Therefore, ST_NEAR is similar to NEAR by assigning each participant to his/her nearest hospital; however, home is not the only travel origin and participant p may not be assigned to any hospital if none of the hospitals can be reached given the space–time constraints.

Measuring temporal variations in demand for service (*NUM*(t)). So far, the four proposed space–time measures evaluate the spatial structure of demand by considering individual activity–travel behaviours, but all with a single value. The last space–time measure, NUM(t), focuses on measuring the temporal changes in demand. The temporal structure of demand at facility location j is evaluated by the number of potential clients to whom location j is accessible at any clock time t within a desirable travel cost. Participant p is considered a potential client for facility j at time t if t falls in his/her earliest arrival time at j and his/her latest departure time at j for any time budget $t_{i+1} - t_i$, which is shown by the following indicator function:

$$I_{p,t,j} = \begin{cases} 1 & if \;\; t_i + T_{i,j} \le t \le t_{i+1} - T_{j,i+1} \;\; and \; T_{i,j} < T_0 \quad for \; i = 1 \ldots n \\ 0 & otherwise \end{cases} \tag{12}$$

where $T_{i,j}$ = travel time from location i to facility j; $T_{j,i+1}$ = travel time from facility j to the next fixed location i+1; n = the number of pairs of fixed activity episodes in p's activity programme. If there are m individuals, the total number of potential clients to whom facility at j is accessible at time t can be computed as:

$$NUM_{t,j} = \sum_{p=1}^{m} I_{p,t,j} \tag{13}$$

It is obvious that $NUM_{t,j}$ is not a single static value, but is a function of time t and varies at different times in a day; the changes in $NUM_{t,j}$ indicate the temporal structure of demand for service at facility location j. A 10-minute travel cost was used in the empirical analysis.

Analysis of demand measures

A total number of 4478 activities reported in the first-day diaries were included in the analysis, among which 661 time budgets ($t_{i+1} - t_i$) were flexible activities performed by 314 participants. Three types of comparisons were conducted. First, the relationships between the ten generalized demand measures were analysed using Pearson's correlation coefficients and paired t-tests. Second, the spatial patterns of demand population derived from these measures were compared with a focus on NEAR vs ST_NEAR and NUM vs NUM5. Lastly, the temporal changes in demand at the selected hospitals were examined using the demand measure NUM(t).

Relationships among the demand measures

The results of the generalized demand measures are summarized in Table 3, where the value columns present the numerical values of different measures and the rank columns indicate the ranking of the amount of demand for each of the 12 hospitals. By visually examining the ranking in the table, we can easily identify discrepancies between these measures. For example, NEAR places H5 (Nationwide Children's Hospital) as the second last on the ranking, while ST_NEAR ranks the same hospital the fifth. This is reasonable because H5 is located in the downtown area where relatively few participants lived but many urban opportunities in the downtown area could facilitate participants' multi-purpose trips.

To allow a more comprehensive comparison between different measures, the relationships among these demand measures were first examined with the Pearson correlation coefficient (Table 4).

Table 3. Analysis results of location-based and space–time demand measures.

Hospi-	AREA5		NUM5		MAXDUR5		DNUM5		AREA10		NUM10		MAXDUR10		DNUM10		NEAR		ST_NEAR	
tals	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank	value	rank
H1	10	8	14	8	22	8	3.3	11	35	11	71	9	149	9	7.4	12	3	12	1	12
H2	7	9	38	4	64	5	12.3	7	56	7	119	5	288	5	16.9	9	8	10	8	10
H3	16	3	18	7	39	6	11.9	8	43	8	75	8	160	8	14.4	10	20	6	18	8
H4	14	4	13	9	22	8	13.0	6	59	6	52	10	124	10	39.3	3	60	3	41	3
H5	11	7	50	2	99	2	21.5	3	67	5	133	2	317	2	25.2	6	6	11	31	5
H6	0	12	2	12	1	12	1.3	12	30	12	77	7	181	7	9.0	11	11	9	2	11
H7	19	2	50	2	95	3	19.5	4	70	4	133	2	316	3	27.2	5	16	6	22	6
H8	2	11	6	11	17	11	6.0	10	38	10	38	11	89	11	18.4	8	41	5	15	9
H9	13	6	76	1	169	1	50.9	1	78	3	138	1	353	1	55.0	2	14	8	55	2
H10	14	4	21	6	36	7	17.5	5	86	2	125	4	312	4	35.4	4	85	1	35	4
H11	27	1	31	5	71	4	31.0	2	112	1	99	6	194	6	60.1	1	69	2	65	1
H12	2	10	9	10	21	10	9.0	9	43	8	38	11	83	12	21.8	7	43	4	19	7

Source: authors' calculations.

Table 4. Pearson correlation coefficients for the demand measures.

Correlation	AREA5	NUM5	MAXDUR5	DNUM5	AREA10	NUM10	MAXDUR10	DNUM10	NEAR	ST_NEAR
AREA5	1	0.438	0.441	0.559	0.801**	0.456	0.355	0.665	0.333	0.698
NUM5		1	0.988**	0.858**	0.554	0.834**	0.838**	0.534	–0.302	0.504
MAXDUR5			1	0.909**	0.567	0.774**	0.776**	0.595	–0.263	0.572
DNUM5				1	0.744*	0.638	0.635**	0.848**	0.090	0.828**
AREA10					1	0.600	0.540	0.881**	0.526	0.871**
NUM10						1	0.987**	0.370	–0.197	0.340
MAXDUR10							1	0.348	–0.202	0.309
DNUM10								1	0.535	0.980**
NEAR									1	0.544
ST_NEAR										1

* p.<0.05; ** p.<0.01
Source: authors' calculations.

Normality of the data was tested using one-sample Kolmogorov–Smirnov test, and the results indicate none of the measures significantly deviate from the normal distribution.

As shown in Table 4, the second type of location-based measure, NEAR, seems to be the most distinct measure as it is the only one that has no significant correlation with any other demand measures at p = 0.01. Among the three 5-minute space–time measures (NUM5, MAXDUR5 and DNUM5), NUM5 and MAXDUR5 have the strongest correlation (r = 0.988), which may be because both of them do not consider the effect of competition. A similar and stronger pattern is observed for the 10-minute space–time measures. This is because the 10-minute constraint yields larger PPAs that likely allow more facilities to compete for customers. Hence, the discounting effect of nearby facilities on DNUM10 is greater than that on DNUM5, resulting in a greater departure of DNUM10 from NUM10. As for ST_NEAR, it has significant correlations with both DNUM10 (r = 0.980) and DNUM5 (r = 0.828), which may be because all of them mostly favour the nearest facility.

In addition to correlations among the demand measures, their similarities were also examined using paired t-tests (Table 5). Since it is only meaningful to compare measures with the same measurement unit, MAXDUR5 and MAXDUR10 are not compared with other measures. Several observations can be made from Table 5. First, demand estimation is significantly affected by the permitted travel cost

Table 5. Paired t-tests for the demand measures.

Difference in mean	AREA5	NUM5	MAXDUR5	DNUM5	AREA10	NUM10	MAXDUR10	DNUM10	NEAR	ST_NEAR
AREA5	0	–16.08*	–	–5.18	–48.50**	–80.25**	–	–16.25**	–20.08*	–14.75**
NUM5		0	–	10.90*	–32.41**	–64.16**	–	–0.175	–4.00	1.33
MAXDUR5			0	–	–	–	–159.16**	–	–	–
DNUM5				0	–43.31**	–75.06**	–	–11.07**	–14.90	–9.56*
AREA10					0	–31.75**	–	32.24**	28.41**	33.75**
NUM10						0	–	63.99**	60.16**	65.50**
MAXDUR10							0	–	–	–
DNUM10								0	–3.82	1.50
NEAR									0	5.33
ST_NEAR										0

Note: difference in mean is calculated by subtracting column from row.
* p<0.05; ** p<0.01
Source: authors' calculations.

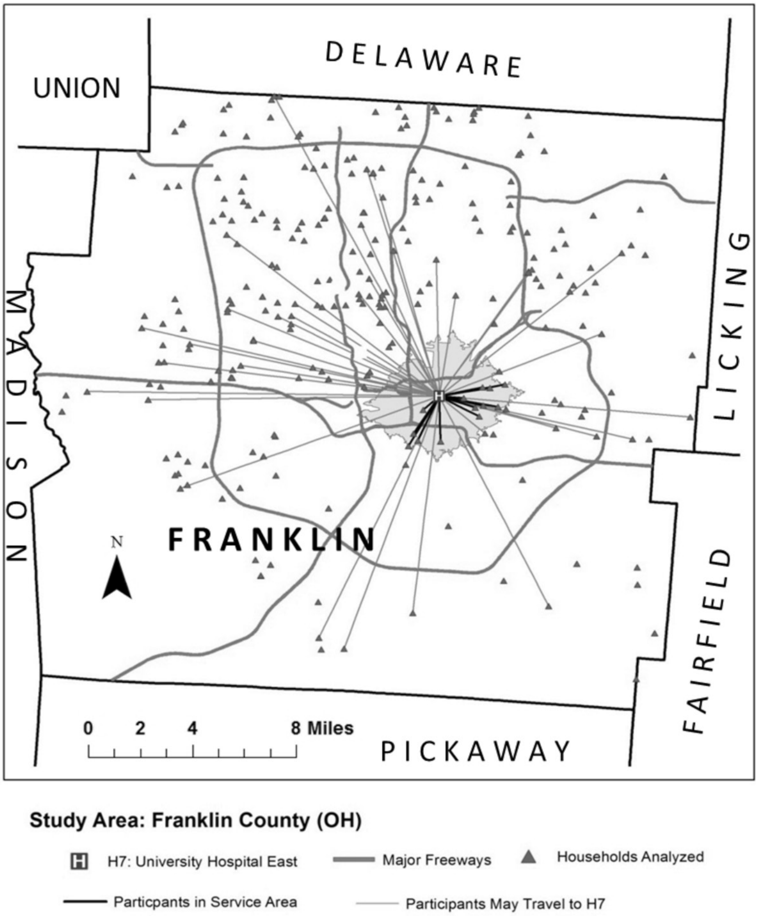

Figure 2. Comparison between AREA5 and NUM5.
Source: map by authors based on data collected by Kwan and Ren in 2003 and 2004.

and the competition effect of nearby facilities. For example, the overall activity duration at the 12 hospitals evaluated by MAXDUR5 (a 5-minute measure) is about 159 hours less than that calculated by MAXDUR10 (a 10-minute measure). Compared with the clients evaluated by NUM5 (which does not consider competition), each hospital on average would serve about 10 clients less than that given by DNUM5 (which considers competition).

Second, compared with NUM5 (NUM10), AREA5 (AREA10) provides significantly smaller estimated demand, indicating the conventional service area measures tend to underestimate potential demand population for service in most situations. However, in an extreme case where all the participants were highly constrained such that very few of them could move freely, the conventional measure would then overestimate the potential demand. Third, evaluation made by NEAR is larger than that made by ST_NEAR. Although the overestimation is not significant in this study, NEAR will always provide equal or greater demand evaluation compared with ST_NEAR. This is because NEAR can always assign every individual to the nearest facility, while ST_NEAR only assigns the individuals to the nearest facility when their activity programmes can accommodate such visits.

Spatial patterns of demand population

Besides the differences in the numerical values, the space–time and location-based measures also yield very different spatial distributions of demand assignment. Figure 2 compares the participants who may travel to H7 (the University Hospital East), where the darker lines represent the participants estimated

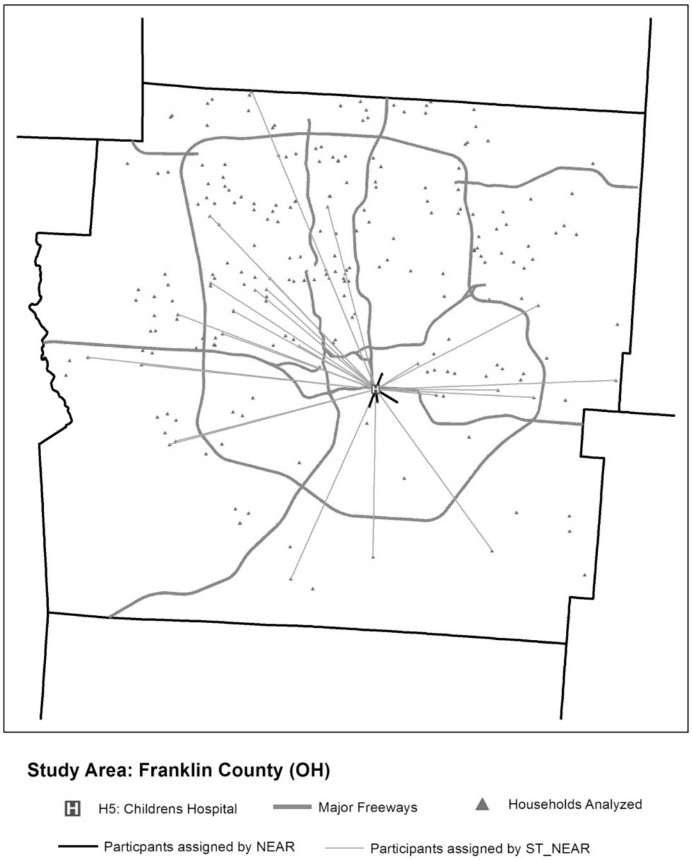

Figure 3: Participants assigned to H5 by NEAR and ST_NEAR.
Source: map by authors based on data collected by Kwan and Ren in 2003 and 2004.

by AREA5 and lighter lines indicate the demand calculated by NUM5. The geographic extent of all the potential clients for H7, indicated by NUM5, is much larger than that measured by AREA5. Most of the participants who could feasibly visit H7 actually lived outside the travel zone, which confirms that the spatial structure of service demand at a facility greatly depends on urban residents' activity–travel patterns and the urban structure.

Similarly, Figure 3 shows the different assignments of participants to H5 (Children's Hospital) prescribed by NEAR and ST_NEAR. The darker lines represent the assignment made by NEAR, and the lighter lines indicate the assignment by ST_NEAR. Two very distinct spatial configurations are observed: all the participants assigned to H5 by NEAR have been assigned by ST_NEAR to a hospital different from H5. This means that participants to whom H5 is the nearest hospital from home could visit another one with less travel cost when combining the trip with other activities. This in turn suggests that geographic proximity between home and facilities may not be an effective indicator for service demand evaluation.

Temporal variations in demand for service

Figure 4 shows the changes in the number of participants who could visit the 12 hospitals within 10 minutes of driving by minute. The general trend of all the curves suggests that potential demand is not static, but varies at different times of the day. H9 (the Ohio State University Medical Center) is highlighted by heavier lines in light colour in the figure to illustrate the pattern of temporal variations in demand. Generally, demand peaks around 9 am, 12 pm, 4 pm and 7 pm, while troughs are around 7 am, 10 am, 3 pm and after 9 pm. This overall pattern seems reasonable. For example, adults, who are not single, are often busy with getting the family ready for work and/or school at the beginning of the day and need to do some household chores in the

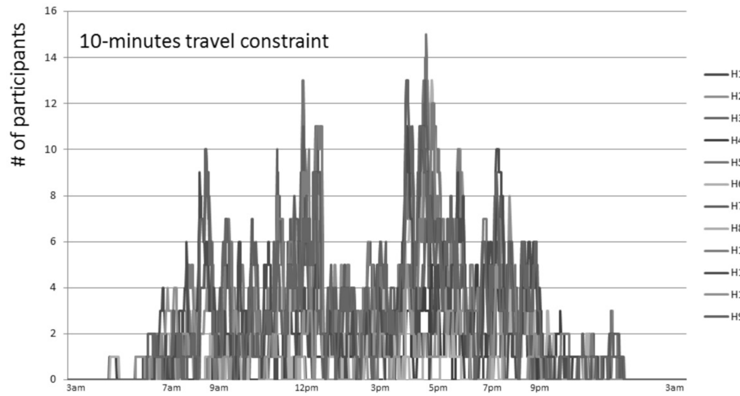

Figure 4: Temporal variations in number of potential clients.
Source: authors' calculations.

evening or prefer to relax at home. Therefore, the intensity of visits to the 12 hospitals is expected to be low during these two periods. In other time periods of the day, people tend to have greater freedom to choose places and times for lunch and some household/personal/leisure activities like shopping right after work and dinner.

Understanding the temporal structure of demand for service will be particularly useful for developing strategies to determine optimal operating hours when planning time-dependent services, such as farmers' markets and government offices with limited opening hours (e.g. Neutens *et al.* 2010a). For example, based on the 2000 Census Transportation Planning Package demographic and commuting data, Tong *et al.* (2012) developed a new location model for siting farmers' markets in Tucson, Arizona by explicitly addressing the spatial-temporal variation in demand. Taking into account the option of combining farmers' market visits with commuting trips, the empirical study showed that, compared with the classic model (the *p*-median problem), the new model identifies optimal farmers' market sites and hours of operation with a reduction in overall consumers' travel by as much as 11 per cent.

Conclusion

In this study, we examined 11 location-based and space–time demand measures for 12 hospitals and explored the differences and similarities among them through an empirical study conducted in Columbus, Ohio. While distinctive patterns of differences and similarities among the measures were observed, the focus of the study is on exploring why these measures yield different results and what implications they would have for location modelling. Meanwhile, the findings are not particular to any kind of service facilities such as hospitals, because the same conclusion will be reached even with a set of hypothetical service locations.

Compared with the location-based measures, the space–time demand measures were constructed based on a time-geographic framework in which an individual is defined as a potential demand for a facility when he/she can feasibly visit the facility under a specific urban environment and given his/her space–time constraints. In this framework, geographic proximity to a facility from a fixed reference location such as home is not the only influential factor for demand evaluation; instead, space–time constraints and current urban structure largely define the spatial and temporal distribution of demand. In doing so, demand population is no longer temporally invariant and spatially fixed. For example, ST_NEAR ranks Nationwide Children's Hospital in the downtown area much higher than NEAR. This is because diverse urban opportunities in the downtown area attract many spatial movements, which in turn increases the potential demand for a facility in the area.

The two very distinct demand distributions suggested by these two measures indicate that demand evaluation will be more realistic if variations in individual space–time accessibility are considered, which goes beyond the simple evaluation of how far one's home is from the nearest service facility. Failure to consider dynamic individual activity–travel patterns and urban structures can result in a spatial structure of demand that deviates significantly from the true demand structure. This can be a real and major problem in the context of public service provision, and there is thus an urgent need to revisit conventional demand measures by taking into account individual space–time constraints and the existing urban structure (Kwan 2013).

Further, the operational formulations of the space–time demand measures not only allow us to better evaluate demand for service, but also have important implications for developing better site selection strategies. For example, NUM measures the ability of a group of individuals to visit facility *j* by a binary indicator, which can be used in a covering problem where demand is modelled as either covered or not covered. When demand varies substantially over time during the day, NUM(*t*) can be used since it explicitly considers temporal variations in demand. It should be noted that when these measures are used for siting multiple facilities, some adjustments are required to address duplicate counting. For example, the sum of NUM5 for each hospital was 541; however, only 170 distinct participants could travel to these locations after the duplications were removed. To handle this issue, specific constraints need to be constructed in the corresponding location model to eliminate the redundant counting. In addition, some of these measures are constructed on the similar ground; for example, NUM and ST_NEAR are indeed special cases of DNUM, and MAXDUR and NUM are built in the same way. These measures can be incorporated in location models by re-identifying the corresponding closest facilities or re-evaluating the associated travel distances (times). Such incorporation often does not involve development of new location models. However, the time-dependent measures might require the construction of new models, as shown in Tong *et al.* (2012).

Although this article has stressed the limitations of location-based demand measures, it by no means suggests discarding those measures. In fact, location-based and space–time measures have their own strengths and weaknesses. Location-based measures are easy to implement with existing public datasets, which is a significant benefit for practical applications. In addition, this type of measure is suitable for evaluating services that are largely affected by distance, such as cellular towers. On the contrary, space–time measures have better explanatory and predictive power on demand evaluation, but face the challenges of relying on disaggregate activity–travel data. However, due to the wide adoption and rapid development of location-aware devices such as smart phones, collecting human movement data with high positional and temporal accuracy has become more feasible (Kwan 2012). This presents enormous opportunities for future research that will benefit both activity–travel research and location modelling. Further, other dimensions of people's choice behaviour are missing in our conceptual framework, including personal preference and specific attributes associated with a service facility (business level, size, etc.). In terms of personal preference, past literature on choice modelling and behavioural geography has shown that people have spatial preference or locational aversion, and their perceptions and attitudes to the environment significantly influence their spatial behaviour as well as their space–time prism (Isard and Decey 1962; Gärling and Golledge 1989; Ben-Akiva and Boccara 1995; Arentze and Timmermans 2005; Chen and Kwan 2012; Scott and He 2012). How to incorporate people's spatial choice behaviour into the conceptual framework to refine the demand distribution in space and time points to an important avenue for future research.

Acknowledgements

The data used in this paper were collected with a grant from the US National Science Foundation's Information and Technology Research (NSF/ITR) Program (BCS-0112488) to Mei-Po Kwan. The comments of the anonymous reviewers and editors on the manuscript are gratefully acknowledged as well.

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