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Urban Mobility and Activity Space

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Abstract

Recent theoretical and methodological advances in urban sociology, including spatially located data, provide new opportunities to consider the joint influence of mobility and place in urban social life. This review defines the concept of activity space, describes its origins in urban sociology, and examines the extent to which activity space approaches advance sociological research in four substantive domains—spatial inequality and segregation, social connectedness and engagement, crime and offending patterns, and health and health-related behavior. It next describes the evolution of methods for location tracking and new approaches that hold promise for maximizing urban mobility and activity space contributions. It then discusses how location data may be augmented to enhance our sociological understanding of the structure, meaning, and implications of the places people visit or traverse in daily life. We close with new directions for activity space research, emphasizing how such work could enable comparative contextual research.

BACKGROUND

Space and place have been fundamental concerns of sociology since the inception of the discipline. In classical urban sociological theory, the city was described as a "mosaic of little worlds" (Park 1915, p. 608), with the flow of urban dwellers through these social worlds contributing to a macrolevel urban metabolism. However, sociological research in the Chicago School tradition has focused largely on describing the uniqueness of the "little worlds," or neighborhoods, and assessing their social implications, rather than considering mobility across these settings and the consequences of such movement (e.g., Sampson 2012, Shaw & McKay 1942).

Research on neighborhoods rarely incorporates information about structural or social characteristics of locations where individuals spend time outside of their own residential neighborhoods (Diez Roux & Mair 2010, Matthews & Yang 2013). Current research often makes the assumption that the residential context is the most consequential social space, even though the long tradition of time-use research suggests that individuals spend substantial portions of their waking hours outside of their home or residential environments (e.g., Hamermesh et al. 2005). Individuals commonly move beyond their residential neighborhoods for daily activities and social interaction, and characteristics of this broader range of geographic contexts may have direct consequences for individual outcomes such as health, economic attainment, social engagement, and victimization. Moreover, this very movement between and among social environments creates a dynamic that cannot be captured when neighborhood influences are conceptualized using data on a single neighborhood per individual.

Recent theoretical and methodological advances, including spatially located data collection and the analysis of geotagged digital trace data, hold promise for a more expansive sociological understanding of the joint influence of mobility and place in urban context. In this review, we describe urban mobility and the concept of activity space, which encompasses the spatial contexts in which individuals conduct their daily activities, including but not limited to the residential neighborhood (Browning & Soller 2014, Cagney et al. 2013). We discuss the origins of this concept in geography, and how activity space is now incorporated in sociological studies of contemporary urban life. We draw attention to four substantive areas within sociological research that have employed activity space concepts and methods—social inequality and segregation, social connectedness and engagement, crime and offending patterns, and health and health-related behavior—and we consider how attention to urban mobility and activity space is reshaping these subfields. Because methodological advances have been essential to the development of the concept of activity space and its import in sociological research, we describe the evolution of methods for location tracking and extend our summary to the augmentation of these data to enhance their sociological value. After considering some key limitations and analytic challenges, we conclude with new directions in the field and a brief example to illustrate how an activity space approach can shed light on enduring sociological questions about urban social life.

ACTIVITY SPACE

The notion of activity space has its roots in geographic research and refers to the spatial patterns of routine activity, wherein regular events occur with distinctive rhythms, tempos, and timings (Golledge & Stimson 1997). It is a spatiotemporal construct that captures the set of places individuals encounter as a result of their routine activities in everyday life (Browning & Soller 2014, Cagney et al. 2013). Tasks, obligations, social engagement, and tastes may draw people out of, and potentially far from, their residential context. Activity spaces therefore include—but are typically not limited to—individuals' residential areas. Activity spaces also vary across individuals in geographic span as well as in the structural, physical, and social features contained within them.

Activity space approaches recognize that relevant social spaces often emerge through the dynamics of individuals' movement between and among neighborhood areas. The spatial turn in late-twentieth-century social scientific research led to an intense focus on the assessment of neighborhood effects on individual outcomes. This research considers social factors such as neighborhood composition (e.g., age structure), the concentration of poverty or affluence, characteristics of the local built environment, and factors such as the neighborhood service environment (Subramanian et al. 2006). Social disorganization theory has been a guiding framework for this literature, elaborating a process through which compositional and collective characteristics of a neighborhood, including concentrated poverty, residential instability, and racial/ethnic heterogeneity, weaken social connections among neighbors and reduce community involvement. This, in turn, reduces social cohesion, informal social control, and the combined notion of collective efficacy—considered as neighborhood-based contextual properties (Sampson 2012, Sampson & Groves 1989, Sampson et al. 1997). Research in sociology and related fields has been particularly focused on the implications of neighborhood social context for a range of factors, including child well-being, educational and economic outcomes, and individual and population health. In this way, neighborhood effects research provides grounding for the characterization of the physical and social context within activity space, and examination of their consequences for urban social life.

The consideration of activity space provides a way to connect early theoretical conceptualizations of mobility within urban contexts and the contemporary focus on residential neighborhood effects. Residential context is, of course, consequential apart from exposure to it (e.g., home values, local institutions or services), but if time spent in space is theoretically meaningful, then expanding our view beyond residential neighborhoods to consider activity spaces may shed new light on a wide range of social processes. For example, activity space approaches allow us to examine the extent to which individuals are exposed to their residential neighborhoods, compared with other areas of the city or region, and to account for within-neighborhood heterogeneity in patterns of mobility. By attending to the spatial contexts in which individuals conduct their daily activities and the areas they traverse, the concept of activity space allows us to consider the effects of exposures to heterogeneous social spaces that are outside of the residential neighborhood. Indeed, early ecological models of urban sociology envisioned metropolitan residents as encountering and coping with a wide range of social environments as they moved around the city [e.g., Burgess 1925, Simmel 1971 (1903)].

ACTIVITY SPACE IN SOCIOLOGICAL RESEARCH

We focus on four key substantive areas of sociological research that have begun to employ activity space approaches—spatial inequality and segregation, social connectedness and engagement, crime and offending patterns, and health and health-related behavior. In this review we focus on the literature in sociological outlets but also include literature from related disciplines (e.g., computer science) if the approach has implications for sociological research. We expand our catchment group of articles to include those that described methods such as activity settings, space-time scan, spatial mobility, routine activities, activity fields, and neighborhood activity spaces. We also include select findings from outside the US context.

Spatial Inequality and Segregation

Extensive research documents spatial inequality and racial/ethnic segregation in the residential context (Krysan & Crowder 2017, Massey et al. 1987), but less is known about segregation in spaces of daily activities. Spatial inequalities and segregation in activity spaces may contribute to inequalities in access to resources and shape patterns of intergroup interaction. At the same time, daily routines of commuting, working, schooling, and other activities may change the composition of urban areas across the course of the day (Ellis et al. 2004). Activity space research in geography, for instance, has begun to consider how spaces beyond residential areas are occupied and used by different groups (Wong & Shaw 2011).

Groundbreaking sociological research on segregation and spatial inequality in activity spaces has been conducted using data from the Los Angeles Family and Neighborhoods Study (LA FANS). LA FANS was one of the first population-based surveys to assess activity space using respondents' reports of frequently visited locations, including children's schools and places of work, shopping, and worship. These data provide striking evidence that spatial inequalities long studied at the neighborhood level also extend to activity spaces. For example, Jones & Pebley (2014) observe greater heterogeneity in racial/ethnic composition of individuals' activity spaces compared with their residential areas. However, they also find considerable racial/ethnic segregation across individuals' activity spaces—African Americans tend to visit locations with a higher proportion of African American residents, while Latinos similarly visit spaces with a higher proportions of Latinos. Research in geography similarly finds that levels of segregation differ between residential and work locations, pointing to variations across racial/ethnic groups and gender.

Segregation across activity spaces also intersects with inequalities in exposure to environmental disadvantage. Krivo et al. (2013) use data from LA FANS to show that socioeconomic disadvantage in residential areas is strongly associated with disadvantage in nonresidential areas across racial and ethnic groups; however, they also find that African Americans and Latinos spend time in more disadvantaged areas compared with whites, even when living in economically comparable neighborhoods. Recent research by Q. Wang et al. (2018) uses geocoded Twitter messages from nearly 400,000 individuals over the course of 18 months to examine sociodemographic differences in travel patterns and neighborhood isolation. These authors find that black, Hispanic, and white individuals exhibit comparable levels of activity space span and number of destinations; however, those living in primarily black and Hispanic neighborhoods are significantly less exposed to non-poor or white middle-class neighborhoods. In another recent study using the same data, Phillips et al. (2019) track travel patterns and develop measures of the concentration of individual visits between neighborhoods and the equity in neighborhoods' visits to quantify the structural connectedness of cities.

Other studies have highlighted structural inequalities in activity spaces among the young and old, potentially more influential or vulnerable stages of life. For example, York Cornwell & Cagney (2017) use Global Positioning System (GPS) tracking of older adults in New York City to show that black and Latino older adults, as well as those with fewer years of education and lower incomes, have greater exposure to poverty within their activity spaces. Other studies have compared structural characteristics in residential neighborhoods and activity spaces. For example, in a study of young adults in Montreal, Canada, Shareck et al. (2014) find exposure to area-level material deprivation to be greater in nonresidential activity spaces than in residential space for individuals with lower levels of education. Taken together, these studies suggest that spatial inequalities within activity spaces may be an underexplored source of racial/ethnic and socioeconomic inequality—and, in particular, for life course processes such as the transition to adulthood and aging across racial/ethnic and socioeconomic groups.

The study of activity spaces has also yielded important insights around resource accessibility and economic attainment. In their study of prisoner reentry and employment, Sugie & Lens (2017) reveal the importance of employment opportunities in daytime activity space locations. Using a smartphone-based study of recently incarcerated men, the authors find that daytime travel to more job-accessible areas is a means of compensating for job-impoverished features of residential areas.

Other research has similarly highlighted the relevance of temporal patterns in the composition of individuals' activity spaces. In a series of studies examining segregation in Estonia, Silm & Ahas (2014) found that during the daytime different ethnic groups are more likely to share city space, whereas nighttime is characterized by greater ethnic segregation. In this sense, the characteristics of daytime activity spaces may be relevant for processes of both economic attainment and social exchange.

Social Connectedness and Engagement

Sociological research emphasizes the role of shared spatial contexts for the cultivation of social relationships and the structure of social networks (Small & Adler 2019). However, few studies have explicitly considered how social networks influence individuals' activity spaces or how activity spaces are shaped by features of individuals' social connections. In one exception, a study using call data records in Jiamusi, China, examines linked activity spaces—that is, the degree to which an individual's activity space overlaps with the activity spaces of his or her telephone contacts. The authors find greater overlap among individuals' first- and second-degree network members' activity spaces than what would be expected at random (Wang et al. 2015), suggesting that a spatial component may underlie patterns of close social ties. This finding is consistent with a long line of sociological research that has emphasized the relevance of shared spaces in the formation and maintenance of network ties (Fischer 1982, Small & Adler 2019), even after accounting for advances in communication that would seem to make space less relevant for social relationships (Cairncross 2001, Mok et al. 2010).

Social networks may also be relevant to explanations of how environmental exposures and peer groups affect individual behavior, including health-promoting and health-risk behavior. For example, Mason et al. (2015) find that among adolescent boys, but not girls, having a more protective peer network lessened the association between risk of substance use in activity space locations and individual substance use. Other research finds that the degree to which pairs of households share multiple activity locations is inversely associated with youth substance use, delinquency, and sexual activity (Browning et al. 2015). These studies support the idea that sociospatial overlap among residents has important implications for youth behavior and well-being.

Shared activity spaces may also play an important role in community cohesion. Browning et al.'s (2017a,b) research on eco-networks—two-mode networks that indirectly connect individuals through their shared activity spaces—suggests that shared activity spaces may be a source of neighborhood social organization, trust, and social capital. This research links eco-networks to neighborhood-level outcomes, finding that neighborhoods with higher-intensity eco-networks have lower levels of property and violent crime (Browning et al. 2017a). The degree to which eco-networks include multiple households (extensivity) and multiple locations (intensivity) is positively associated with collective efficacy and intergenerational closure within the neighborhood (Browning et al. 2017b).

In a similar vein, Williams & Hipp (2019) use the notion of third places to consider how spaces outside of home and work facilitate neighbors' interaction and, in turn, neighborhood cohesion. They find that third places are key facilitators of interaction and cohesion, but only among residents in the very poor strata of neighborhood economic status. Further research is needed to examine the implications of neighborhood socioeconomic disadvantage and characteristics of activity spaces for social interaction and cohesion.

Crime and Offending Patterns

Place and person–place interaction have been central to understanding crime. Brantingham & Brantingham (1981), in their influential crime pattern theory, explicitly theorize that criminals search for potential targets within their awareness space, defined as the "area normally within the visual range of the activity space" (Brantingham & Brantingham 2008, p. 84). Awareness space includes frequent locations (nodes) such as one's home, workplace, school, and recreational locations, as well as paths connecting those nodes. As a result of the offender's spatial knowledge of such locations, crime is predicted to occur when their awareness space intersects with opportunities to engage in crime. Recent studies in support of this theory indicate that rioters are more likely to engage in disorder close to their homes and areas covered by their activity spaces (Baudains et al. 2013) and offenders are more likely to offend in areas near their current and former homes (Bernasco 2010), family members' homes (Menting et al. 2016), and locations that they have previously targeted (Lammers et al. 2015).

Prior research focused on the spatial link between offenders' prior crime locations and a select sample of locations they go to frequently, but more recent studies have begun to examine real-time activity patterns among reoffenders (Rossmo et al. 2012), terrorists (Griffiths et al. 2017), and populations at risk for victimization (Malleson & Andresen 2015). Findings from several recent studies reveal complexities in the relationship between activity space and offending patterns. Bichler et al. (2011) compare the distances traveled by offenders to delinquent and nondelinquent locations. Their findings reveal that delinquent hangouts are substantially farther away than expected by scholars who have assumed that criminal activity takes place nearer routine activity spaces. By drawing on returning prisoners' use of activity spaces, Leverentz (2019) finds that most of returning prisoners' daily activities take place outside of the neighborhood area and that they experience a great deal of geographic instability due to a lack of stable housing and supportive social network connections. Other research reveals that gangs sort into activity spaces (i.e., set space) that are characterized by lower levels of social control and lower levels of surveillance by residents and police (Tita et al. 2005).

Situational Action Theory, along with its innovative space-time budget survey, is one of the first efforts in criminology to systematically track adolescents' activity patterns and spatial exposures (e.g., structural characteristics, companionship) (Wikström et al. 2012). Retrospectively collecting hour-by-hour information on activities (e.g., truancy, substance use) and spatially located settings (e.g., location and companionship) allows the dynamics of person–environment interactions to be measured. Recent scholarship has considered how characteristics of particular locations interact with an individual's propensity for offending (Simons et al. 2014, Wikström et al. 2012). For example, using the space-time budget, Wikström et al. (2010) find that the influence of exposure to crime-prone settings on offending varies with a person's propensity for crime. In related research, Simons et al. (2014) find that youth exposure to adversity is associated with criminogenic knowledge structures and, in turn, selection into criminogenic activity spaces, which heightens the probability of offending. In terms of altering the likelihood of crime, Graif et al. (2019), using employment-based commuting data, suggest that exposure to more advantaged work environments represents potential opportunities for residents of more disadvantaged areas to connect to external resources and organizations that are not available in their residential environments. These resources and services could then contribute to an increase in social cohesion and trust in their residential neighborhoods, and ultimately to a reduction in residential crime (Graif et al. 2019). In this sense, commuting patterns may represent channels for individuals living in more disadvantaged urban neighborhoods to overcome the disadvantages of institutional isolation (Wilson 1987).

Health and Health-Related Behavior

Studies of individual health outcomes have used activity space measures to elicit novel insights into the spatial determinants of physical and mental well-being. Most of this research considers features of individual activity space alongside aspects of the residential neighborhood to understand the extent to which routine activity in nonresidential spaces influences individual health. Extending the now-sizable literature that has explored the relationship between residential neighborhood socioeconomic disadvantage and health, several studies have considered the implications of exposure to disadvantage within activity spaces. For example, Inagami et al. (2007) found that accounting for activity space exposures revealed a stronger association between residential neighborhood disadvantage and health. And several studies suggest that the association between residential neighborhood disadvantage and health is conditioned by characteristics of activity spaces (Colabianchi et al. 2014, Inagami et al. 2007, Sharp et al. 2015, Vallée et al. 2011). For example, individuals living in more socioeconomically disadvantaged residential neighborhoods are more likely to report worse self-rated health when they spend time in less disadvantaged areas. At the same time, individuals living in less disadvantaged residential neighborhoods report poorer health when their activity spaces include exposure to more disadvantaged areas (Sharp et al. 2015).

Recent research has begun to expand beyond structural characteristics to consider how health may be related to characteristics of the built environment within and outside of the residential neighborhood. A longitudinal study in France has identified several features of nonresidential environments such as green space, fresh food stores, walkability, and physical decay that are consequential for cardiovascular risk factors including body mass index and waist circumference, blood pressure, and recreational walking (Chaix 2009, Chaix et al. 2012). Other research among low-income housing residents of New York City finds that individuals whose activity spaces have high levels of noise complaints have significantly lower blood pressure, perhaps suggesting that more active areas increase the likelihood of social and physical engagement (Tamura et al. 2017).

Other studies point to the role of local and nonlocal resources in shaping individuals' exposure to residential and nonresidential areas. For example, research by Ivory et al. (2015) shows how individuals' desire to maintain an active lifestyle leads them to construct their own activity spaces in ways that are conducive to physical activity. Individuals' assessments of the walkability of their residential neighborhood, for example, led them to either seek opportunities for physical activity in their own neighborhood or travel elsewhere. Similar push-and-pull dynamics may underlie routine activity and mobility patterns in seeking fresh food, health care, and other health-related resources. Indeed, researchers document significant differences in aspects of foodscape exposure, including access to grocery stores and restaurants, across individuals' residential and nonresidential spaces (Hurvitz & Moudon 2012, Kestens et al. 2010, Zenk et al. 2011).

These insights may be especially relevant for people at more sensitive stages of the life course, such as children and older adults (Cagney & York Cornwell 2018, Loebach & Gilliland 2016). Adolescents, for example, may be particularly vulnerable to levels of physical activity and risky behavior; researchers have begun to adopt more spatially and temporally sensitive data collection methods to account for the wide range of contextual exposures that may contribute to increasing levels of childhood obesity. These include the use of Geographic Information System and other spatial methods (Matthews 2012), as well as survey-based assessments of relevant environmental exposures that extend beyond adolescents' neighborhood boundaries (Colabianchi et al. 2014). Active commuting between home and school, for example, has been identified as a potentially important contributor to youth physical activity (Rainham et al. 2012). Using an activity space approach to measure youth exposure to alcohol and tobacco outlets also provides a more accurate assessment of this type of exposure than do home-, school-, or census tract–based measures (Basta et al. 2010, Lipperman-Kreda et al. 2015). The use of an activity space approach may be especially important to consider in studies of high-risk adolescents, for whom frequency of substance use and mental health problems are key determinants of the level and locations of risky activity space (i.e., places where youth are most likely to partake in risky or dangerous activities) (Mason & Korpela 2009). That said, research indicates that neighborhood locations that promote adolescent physical activity also tend to be areas with higher crime, where youth may be more likely to be at risk of victimization or offending (Robinson et al. 2016). This result draws attention to the idea that, just like residential neighborhoods, activity spaces contain bundles of resources, exposures, benefits, and risks, and, as such, they likely have multifaceted effects on health.

METHODOLOGICAL APPROACHES

The four subsections above provide guidance for a summary assessment of the range of methodological approaches used to capture urban mobility and location information and, when possible, to augment through data linkage, algorithmic data processing, and so forth. Drawing on these varied approaches is critical to research in sociology, since theory can often suggest different spans of influence and levels of analysis.

Location Data

The growth of social scientific interest in activity spaces, patterns of urban mobility, and exposures to settings outside of the residential neighborhood goes hand in hand with methodological developments that provide researchers with unprecedented access to individuals' daily lives. In the past two decades, advances in geolocation techniques, new communication technologies, and growing participation in social media have opened up new opportunities for the assessment of activity space. In this section and in **Table 1**, we synthesize a wide range of approaches to locating individuals or tracking their locations in real time, and consider their relative strengths and limitations. We use the table as a foundation for the discussion below, which describes the evolution of activity space approaches and considers their potential for sociological research on urban mobility.

Survey methods. Empirical studies of urban mobility have traditionally relied on surveys that collect information on individuals' routine trips or activities, in addition to their sociodemographic characteristics. Early survey-based assessments relied on self-reported mobility. For example, respondents might be asked to estimate the time they spend within certain life space zones, defined as areas radiating out from their household (Baker et al. 2003), or to list or map the locations they visit within a typical week (Gibson et al. 2015), places that are important to them (Townley et al. 2009), or places where they carry out particular tasks or activities (Sherman et al. 2005).

LA FANS pioneered the collection of self-reported activity space locations, as mentioned above (Jones & Pebley 2014). Travel diaries take a more expansive approach by asking respondents to report all movements for the previous day or a future day. For example, the National Household Travel Survey has been collecting national transportation data for nearly a half-century, in support of travel behavior models and transportation planning. Travel surveys have been applied to a variety of fields, including those that examine human mobility (e.g., Jiang et al. 2012). This approach, and extensions that incorporate information about corresponding activities and person–environment interactions (i.e., space-time budget studies), can be fruitful sources of activity space data, although data collection is demanding for the respondent and can introduce error based on recall or misestimation of future activity.

GPS tracking. A recent extension of activity space research involves the use of GPS location–based tracking via smartphones or other geolocation devices that can be worn or carried by respondents for a specified period of time. Because the tracking is passive, the data are less likely than self-report or survey-based assessments to suffer from biases due to respondent recall or reporting. Observations from continuous tracking also allow greater precision in estimations of exposure to

Table 1 Methodological approaches to capturing location data[a]

Instrument[b]	Substantive fields and studies	Unit and sample	Spatiotemporal resolution[c]	Sociodemographic information	Contextual information[d]	Volume and scale	Key limitations
Survey methods							
Transportation or travel surveys	Human mobility (Jiang et al. 2012) Crime (Boivin & D'Elia 2017) Spatial inequality (Jones & Pebley 2014, Krivo et al. 2013) Health (Sharp et al. 2015, Vallée et al. 2011) Social connectedness (Browning et al. 2017a,b; Williams & Hipp 2019) Spatial accessibility (Kestens et al. 2010)	Survey sample of individuals	Low: individuals' whereabouts of activity-by-activity or hour-by-hour resolution	Rich: augmented by surveys	Limited: comprehensive travel behavior (especially transportation surveys) but little contextual information	Limited sample size and volume Limited geographic scale (e.g., one city) Short time frame (1–2 days or "routines")	Not dynamic (a snapshot): updated at low frequency Incomplete or inaccurate: trips often "imagined" retrospectively or prospectively Onerous for respondent High cost
Space-time budget	Crime (Hoeben & Weerman 2014, Wikström et al. 2012)	Survey sample of individuals	Moderate: individuals' hour-by-hour whereabouts (geocoded to census units) and corresponding activities	Rich: augmented by surveys	Rich: continuous assessment of activities and environs	Limited sample size and volume Limited geographic scale Limited time frame (e.g., one week)	Not dynamic: updated at low frequency Incomplete or inaccurate: trips often retrospectively collected Onerous for respondent High cost
GPS tracking							
GPS tracking of persons and surveys	Tourist behavior (Asakura & Iryo 2007) Activity satisfaction (Dong et al. 2018) Segregation (Zhang et al. 2019) Human mobility (Palmer et al. 2013) Health (Kwan et al. 2019, Tamura et al. 2017) Crime (Rossmo et al. 2012) Aging (York Cornwell & Cagney 2017) Spatial accessibility (Lipperman-Kreda et al. 2015, Sugie & Lens 2017)	Survey sample of individuals	High: precise coordinates location at certain sampling rates (a few seconds to a few minutes) or geofenced (e.g., 20 m) Continuous tracking	Rich: augmented by surveys	Rich: augmented by additional surveys or EMAs	Same as above	Not dynamic: updated at low frequency Onerous for respondent if additional survey required High cost

(*Continued*)

Table 1 (*Continued*)

Instrument[b]	Substantive fields and studies	Unit and sample	Spatiotemporal resolution[c]	Sociodemographic information	Contextual information[d]	Volume and scale	Key limitations
GPS tracking of vehicles (e.g., taxicabs, trucks, personal cars)	Traffic (Lima et al. 2016) Human mobility (Gan et al. 2019, Li et al. 2012) Urban boundaries (Rinzivillo et al. 2012) Business survival (D'Silva et al. 2018)	Selective of certain types of vehicles and their users	High: precise coordinates at a high sampling rate Continuous tracking	Limited: augmented by surveys (less common in practice)	Little to none (require additional surveys)	Moderate sample size and volume Moderate geographic scale Time frame varies by study High between-study variation regarding volume and scale	A special type of mobility Incomplete trip: only trips by certain vehicles ("last miles" missing) Vehicle as unit: data collection is vehicle based or trip based Limited contextual information (e.g., actual activities, companionship, purpose)
Big data							
Transportation data							
Big transportation data (e.g., smart card)[e]	Human mobility (Hasan et al. 2013, Sun et al. 2013) Urban structure (Roth et al. 2011)	Public transportation users	Low: located to transportation stops Irregular tracking depending on public transportation use	Limited: linkable to personal account from card system	Limited (e.g., travel mode)	Large volume Limited geographic scale (e.g., one city) Long time frame	A special type of mobility Incomplete trip: only trips by certain vehicles ("last miles" missing) Sometimes trips only partially captured (e.g., card not required for exiting) Limited contextual information (e.g., actual activities, companionship, purpose)
Mobile phone data							
CDRs	Human mobility (González et al. 2008, Song et al. 2010, Widhalm et al. 2015) Location identification (Ahas et al. 2010) Disaster response (Bengtsson et al. 2011)	Phone users (often of a particular carrier or multiple carriers)	Moderate: cell tower reception area (typically 0.15 km^2 urban to 15 km^2 rural) Irregular tracking depending on phone-use frequency	Little to none (exception: Yuan et al. 2012, in which basic demographic characteristics are linked)	Little to none	Large volume Large geographic scale Long time frame	Uneven spatial resolution: Resolution depends on the distribution of cell towers Unrepresentative: phone users not representative Phone using behavior not continuous in space-time (e.g., duration of stay unknown)

(*Continued*)

Table 1 (*Continued*)

Instrument[b]	Substantive fields and studies	Unit and sample	Spatiotemporal resolution[c]	Sociodemographic information	Contextual information[d]	Volume and scale	Key limitations
	Epidemic transmission (Le Menach et al. 2011, Wesolowski et al. 2012) Residential mobility (Wesolowski & Eagle 2010) Social network (Wang et al. 2011) Crime (Griffiths et al. 2017, Song et al. 2019) Segregation (Silm & Ahas 2014)						Potential systematic between-person, between-context, or between–time frame variations in phone use Uncertain accuracy: accuracy depends on the workload of nearby cell towers Requires sky environment and auxiliary transmitters Privacy concerns
LBSM							
Twitter	Human mobility (Hawelka et al. 2014, Luo et al. 2016) Crime (Malleson & Andresen 2015) Disaster response (Wang & Taylor 2014) Urban boundaries (Yin et al. 2017) Social events (Gabrielli et al. 2014) Segregation/integration (Dong et al. 2019, Phillips et al. 2019, Shelton et al. 2015, Wang et al. 2018)	Geolocated social media users (e.g., Twitter users who geotag tweets)	High: precise longitude and latitude coordinates Irregular tracking depending on geotagging behavior	Moderate: from user profile and messages	Limited: from messages	Large volume Large geographic scale Long time frame	Unrepresentative: social media users highly selected Social media use not continuous in space-time (e.g., duration of stay unknown) Potential systematic between-person, between-context, or between–time frame variations in social media use Social media use highly selective (e.g., geotagged photo posting) Low percentage of geotagged messages (e.g., Twitter <10%) Privacy concerns
Foursquare	Human mobility (Noulas et al. 2011) Business survival (D'Silva et al. 2018) Urban boundaries (Cranshaw et al. 2012)						
Flickr	Mobility growth (Daggitt et al. 2016)						
Others (e.g., Google Latitude, Weibo)	Human mobility (Ferrari & Mamei 2011, Zhang et al. 2016)						

(*Continued*)

Table 1 ***(Continued)***

Instrument[b]	Substantive fields and studies	Unit and sample	Spatiotemporal resolution[c]	Sociodemographic information	Contextual information[d]	Volume and scale	Key limitations
Financial transaction data							
CCRs	Human mobility (Hawelka et al. 2014, Lenormand et al. 2015) Segregation (Dong et al. 2019)	Bank card users (often of a particular financial institution or multiple institutions)	High: precise coordinates location or addresses Irregular tracking depending on card-use frequency	Moderate: from bank user account (e.g., basic demographic information and home locations)	Limited: from financial spending behaviors	Large volume Large geographic scale Long time frame	A special type of mobility Unrepresentative: card users not representative Card using behavior not continuous in space/time (e.g., duration of stay unknown) Potential systematic between-person, between-context, or between–time frame variations in card use Privacy concerns

[a]Only the two most recent papers per substantive field are shown in the table. Other, more restricted forms of data approaches, such as commuting flows (used in Graif et al. 2019) and data extracted from residential and offense history (used in Lammers et al. 2015, Menting et al. 2016), are not included.

[b]The methods introduced in this table are by no means exhaustive. Other data approaches include locations from email IP addresses, Bluetooth, Wi-Fi signals, and bank notes (see the section titled Other Data Opportunities for descriptions).

[c]Spatiotemporal resolution refers to the typical time interval and spatial distance between two consecutive records.

[d]Contextual information refers to information related to the observed movement: travel mode, speed, trip purpose, actual activities involved, companionship, and immediate environment, among others.

[e]In some cases, public transportation data cannot be linked to individual travelers. We discuss only transportation records that can be linked to individual users who repeatedly use public transportation (e.g., users of Chicago Ventra Card and London Oyster Card). In cases where individual users cannot be identified, the data are essentially transportation volume or commuting flow data. Examples include single-ride tickets and flight and ferry records. Nevertheless, such data have been found useful to predict epidemic transmission and intercity connectivity.

Abbreviations: CCR, credit card record; CDR, call detail record; EMA, ecological momentary assessment; GPS, Global Positioning System; LBSM, location-based social media.

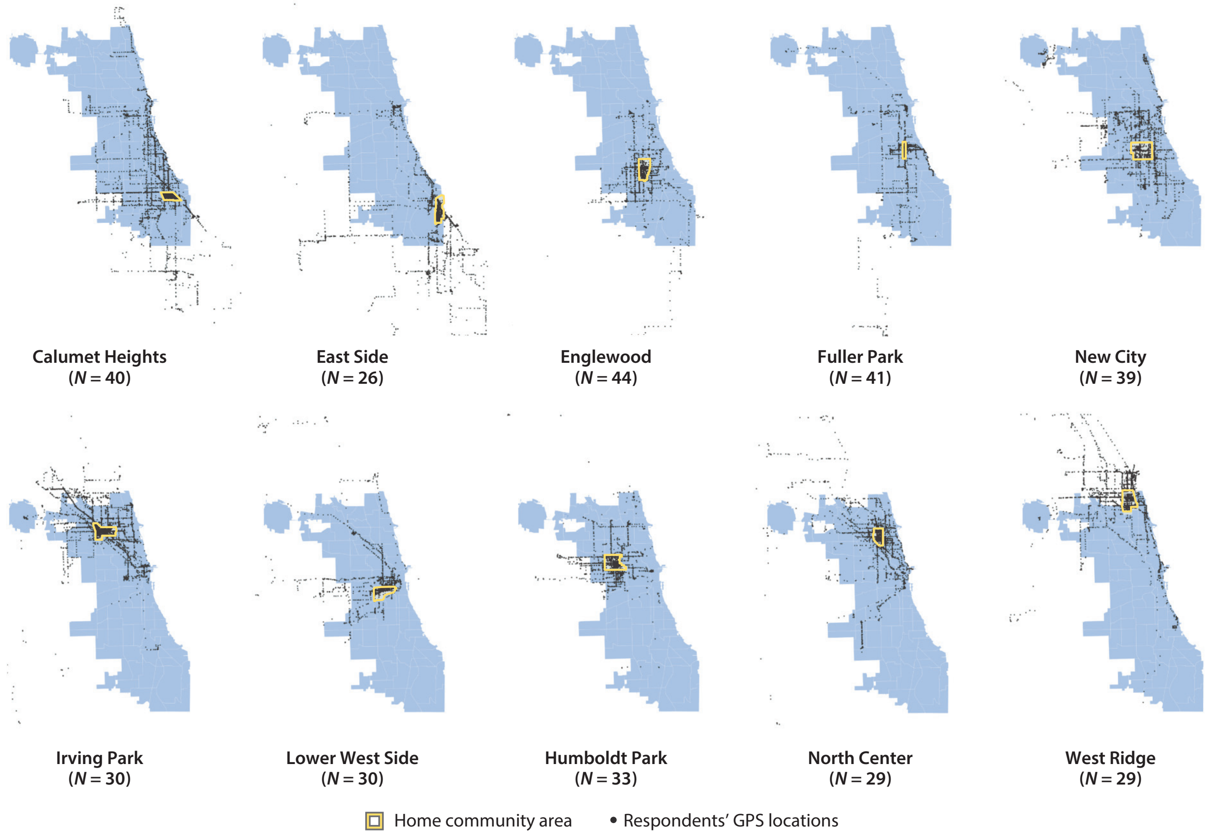

Figure 1

Chicago Health and Activity Space in Real Time (CHART) wave 2 data (2019).

particular areas or conditions compared with approaches that capture only select locations. Studies using GPS trackers rather than smartphones are able to capture locations in very short time intervals such as every 1 or 5 seconds and typically have longer battery life than smartphones, reducing the potential for data loss (Wan & Lin 2016, Wan et al. 2013, Zenk et al. 2011). However, the use of smartphones for GPS tracking allows collection of additional contextual data such as ecological momentary assessment (EMA) data, which we discuss below. When combined with data from a social survey, GPS tracking of activity spaces provides new opportunities to consider how urban mobility varies across social groups and how this may contribute to inequalities in access to resources or exposure to risks.

Figure 1 displays data from Chicago Health and Activity Space in Real Time (CHART), a study of 450 older adults in 10 Chicago neighborhoods. These data suggest very different activity space patterns by neighborhood; for instance, those who live north appear to gravitate north (e.g., North Center), while those who live south appear to head south more often (e.g., Calumet Heights). They also imply that the pattern of dispersion is somewhat racialized. The south and west sides of Chicago are primarily African American, and the north side primarily white; thus, activity space patterns track to some degree with the racial and ethnic composition of the communities of origin (Cagney 2016).

GPS tracking devices installed in vehicles may also allow examination of intraurban population flows. Tracking devices are increasingly installed in vehicles such as taxicabs, trucks, car-share vehicles (e.g., Uber, Lyft), and private cars. Similar to GPS tracking of individual persons, vehicle tracking provides fine-grained footprints of vehicles' whereabouts, which can be indicative of persons' whereabouts but also important in itself for understanding traffic patterns and urban activity hubs (e.g., Gan et al. 2019, Lima et al. 2016, Rinzivillo et al. 2012). However, because the data are vehicle based, they typically provide only a snapshot of mobility for a select group and for only one form of movement.

Transportation. A large volume of transportation data has emerged and is growing significantly. Many cities have implemented smart card systems, in which public transit users register for an account and use their cards to pay for rides. Data from smart cards allow continuous tracking of travel on public transit; customers are identifiable and may be linked to personal characteristics registered on the card account. Such data may be particularly useful for studying human mobility (Hasan et al. 2013, Sun et al. 2013) and urban activity patterns (Roth et al. 2011, Zhong et al. 2014). However, these data often lack information about the ultimate destination and provide little contextual detail about riders or the purpose of their travel. This approach is also more accurate in densely populated areas with more extensive public transit.

Mobile phones. The increasing use of mobile phones makes locations derived from these phones a good proxy for human activity. A major type of such data is call detail records (CDRs) from carriers. Whenever a call, text, or data-use request is made, carriers register the location of the device for billing purposes. The actual locations of the device are approximated by the locations of cell towers to which the device is connected. Typically, Voronoi polygons are used to approximate cell towers' reception areas such that each phone call record corresponds to a single cell tower.

Tracking users' transitions across high-resolution cell tower reception areas allows for inference of their locations. CDR data have a number of advantages, including generally high spatial resolution, temporal continuity, large spatial coverage, and low cost. As a result, CDR data have been widely used in a range of research areas, including human mobility (González et al. 2008), disaster response (Bengtsson et al. 2011), epidemic transmission (Le Menach et al. 2011), social connectedness (Wang et al. 2015) and crime (Song et al. 2019). However, spatial resolution is substantially lower outside of urban areas (de Montjoye et al. 2013), and trajectories are recorded on the basis of phone use rather than actual movement.

Location-based social media. Another recent advance stems from location-based social media (LBSM) platforms that incorporate a location dimension (i.e., geographic coordinates) into social media content such as texts and photos. For instance, Twitter allows users to geotag their tweets, Flickr users can provide locations for the photographs they post, and Foursquare invites users to check in to various venues, ranging from private homes to tourist attractions. Other LBSM examples include Google+ and Weibo, China's major online social networking and microblogging platform.

The wide use of social media, with millions of active and sporadic users producing billions of geolocated social media items, makes LBSM a rich source of georeferenced data. LBSM has the potential to offer massive volumes of data across large spatial and temporal scales, along with sociodemographic information from user profiles and contextual data gleaned from the content of text or photos. LBSM has been extensively applied in social scientific studies to understand phenomena such as crime (Malleson & Andresen 2015), disaster response (Wang & Taylor 2014), mobility growth (Daggitt et al. 2016), urban boundaries (Yin et al. 2017), and social segregation and integration (Phillips et al. 2019, Q. Wang et al. 2018).

Financial transactions. Another form of data employed in social science research includes transaction records from financial institutions, often referred to as credit card records (CCRs). Georeferenced location data of the business where the transaction is made is often included with customers' spending information. Sociodemographic characteristics such as age, gender, occupation, and home locations are sometimes identified for each record. Massive volumes of transaction records are generated by active users on a daily basis. In the United States alone, 123.5 billion credit or debit card transactions were made in 2017, and the number is rising (Gerdes et al. 2018). Some studies have harnessed CCR data to investigate human mobility patterns (Lenormand et al. 2015) and economic segregation (Dong et al. 2019).

Other data opportunities. In related research, Brockmann et al. (2006) infer the statistical properties of human movement patterns by tracking and analyzing the circulation of half a million US bank notes. In another study that combines geolocated Yahoo! email IP addresses and surveys, Zagheni & Weber (2012) observe that female international migration has been increasing at a faster pace than male. Other studies have used Wi-Fi signals in combination with GPS traces to investigate the mobility of university students (Sapiezynski et al. 2015) and Bluetooth devices in combination with smartphones to identify student interactions and, over time, complex social systems (Eagle & Pentland 2006). These new approaches can be more widely employed to improve the temporal resolution of location data collection.

Augmenting and Contextualizing Location Data

The various sources of location data described above allow mapping of individuals' everyday activity spaces and intraurban mobility patterns. However, as discussed above, sociological inquiry extends beyond documenting where people are located to the consideration of the social structure, meanings, and implications of the places they visit or traverse. In this section, we focus on methods and subsequent data that are—or could be—combined with location data collection to provide new insight into sociological questions about how space and the social environment shape individual outcomes.

Neighborhood effects research has developed a variety of approaches to characterizing the residential neighborhood which could be extended to research on activity space. For example, research linking neighborhood context to individual outcomes often operationalizes the neighborhood as an administratively defined spatial unit such as a census tract. Administrative data on the composition and structural characteristics of the tract (e.g., poverty rate, racial/ethnic composition, residential turnover) are then used as indicators of the physical and social context of the neighborhood (Sampson 2012). Activity space locations could similarly be assigned to tracts, or smaller units such as block groups, enabling estimation of their physical and social contexts that individuals encounter in their daily lives—and characteristics of these locations could be directly compared with those of the residential tract.

Activity space data could also be overlaid with information about the availability of institutional resources such as health care clinics, fresh food stores, senior centers, and amenities like parks and fitness centers, which may have implications for social engagement and health. New sources of administrative and big data from cities allow for unprecedented exploration of residential and nonresidential contexts. For example, activity space data may be linked to the locations of crime and calls for city services (e.g., fixing potholes, rodent infestations). Urban sensing projects, such as Array of Things in Chicago (Catlett et al. 2017), also provide exciting opportunities to capture fine-grained variation in urban environmental conditions such as traffic, weather, noise, and particulate matter. When coupled with activity space data, this information could lend insight into individuals' real-time exposures to stressors, hazards, and risks.

In addition to characterizing where individuals spend time, we might also consider why they go to particular locations and what they do there. Daily mobility patterns are likely a product of both preferences and selection into (or away from) a particular location, as well as of structural constraints that restrict or direct individuals' mobility (e.g., transportation routes). Researchers have recently begun to develop algorithms that may shed light on these factors by estimating, on the basis of continuous location tracking, individuals' modes of transportation and identifying locations that individuals visit and those that they simply pass through (Wan & Lin 2016, Wan et al. 2013). Some LBSM approaches offer contextual data that can be gleaned from users' engagement, such as posts on Twitter or Flickr. However, information availability is uneven across users and posts.

EMAs can also provide an additional layer of information for characterizing activity spaces by drawing on respondents' reports of types of activities and destinations. EMAs are research tools akin to short, momentary surveys that capture participants' self-reports of their activities, surroundings, and subjective or affective states. Early EMA studies used paper diaries completed at specified times or when prompted by a pager, but smartphone-based EMA collection brings greater flexibility in timing and a reduction in recall bias, response error, and nonresponse (Trull & Ebner-Priemer 2009). In the context of location-based data collection, and GPS tracking in particular, the collection of EMAs can provide insight into why individuals visit particular places, what they do there, whether they are alone or with others, and how they feel.

The ability to capture individuals' real-time social interactions within particular locations enables consideration of interrelationships between social networks and social context. EMAs provide one means of gathering this type of information, by asking respondents to report on whether they are with someone or interacting with others. Other innovative approaches include the use of sociometers, or wearable sensors that passively measure interpersonal interactions, including the proximity and dialogue between individuals (Choudhury & Pentland 2002, 2003, 2004). Social media users can also signal or tag individuals who they are with at a given moment and location, generating networks among individuals and locations. Likewise, overlaying activity locations of multiple individuals enables large-scale studies of social connectedness among geographic areas and the assessment of similarities in mobility patterns across individuals. For instance, Toole et al. (2015) find high levels of similarity in the mobility patterns of more proximal individuals who are socially connected to one another in comparison to randomly selected individuals. Overlaying venue check-in information from apps such as Foursquare can also provide insight into how location choices are shaped by friends' choices (Colombo et al. 2012).

Finally, the ability to examine locations and travel patterns begs the question of how individuals experience those places—including their physical, emotional, and physiological reactivity—in real time. The simultaneous collection of location and health-related measures can provide information on aspects of the social environment (and individual perceptions) and how they contribute to variation in well-being. Repeated EMAs, for example, can reveal fluctuations in symptoms such as those indicative of stress response (e.g., pain, fatigue, worry) over the course of the day. Passively collected patient-generated mobility data coupled with mobile health applications can collect individuals' momentary feelings of stress and pain, as well as cognitive awareness (e.g., Adams et al. 2014, Murnane et al. 2016). Other researchers have used wearable devices such as smartwatches to examine cognitive, psychological, and behavioral changes. For example, the BoostMeUp smartwatch intervention captures how individuals perceive their own heart rate and related emotions (Costa et al. 2019). When these forms of real-time data collection on individual well-being are linked with location or activity-based data, there is opportunity to better understand how environmental factors, including activity, task, and venue, shape individual short- and long-term health. These data could also be used to link recent findings about racial and sociodemographic differences in social environmental exposures and activity spaces to address questions about the contribution of these environmental factors to health disparities.

LIMITATIONS

Activity space approaches, with the use of the data and location approaches described above, represent a turning point in research on context and its implications. Like any other conceptual and methodological undertaking, awareness of limitations in the approach enhances our ability to interpret findings and identify directions for further development.

Research on activity space brings a number of challenges around data collection. One key limitation is that location tracking could lead respondents to alter their behavior—potentially avoiding locations that they might otherwise visit, or changing their patterns of mobility to reflect a more active daily life. The increasing prevalence of smartphones may also help alleviate this concern, as carrying a smartphone is seen as less novel or less of an imposition. However, comfort with tracking via smartphone, app-based administration of surveys, or wearable sensors may vary by group. The user behaviors of other location data approaches such as LBSM and phone calls may also vary by group. For instance, those with limited resources to own and use a smartphone, those with an impairment (e.g., vision), or those with fewer years of education may not engage with the technology as readily.

A second and related concern is that most activity space research has followed respondents over a limited duration (e.g., one week), making broader patterns—not contingent on weekly actions—difficult to identify. A third limitation stems from practical concerns around study administration and implementation. Providing respondents with smartphones and/or data plans increases the cost of data collection, and technological expertise is required for the development of apps or protocols that elicit geographic locations and administer surveys. Fourth, activity space and location data more generally can be big and difficult to store, clean, and analyze. Data systems will likely improve, but researchers must be attentive to data infrastructure to get the most out of this form of data collection. Fifth, and critically, are concerns related to privacy. The tension between data generation and privacy has been addressed in the literature, but the practical matters of data sharing and permissions continue to be fraught (de Montjoye et al. 2013, 2015).

Turning to analytic challenges, missing data introduce an additional limitation. The problem is commonly observed in person- or vehicle-based GPS tracking data, often with low sampling rates due to the cost of data collection and battery drain. The easiest and standard prediction method is to compute the mean coordinates based on a pair of consecutive coordinates as the unobserved location, that is, the linear interpolation method in space and time (e.g., J. Wang et al. 2018). When the moving object is supposed to be on existing road networks, map-matching algorithms can be used to interpolate missing data points and reduce noise (with the accuracy of interpolation methods increasing with the sampling rate). This missing data issue is more often a problem for big mobility data. Data from mobile phones, social media, transportation services, and credit card use are available only when a user engages with corresponding activities. The extent to which such movement traces inferred from big data are representative of individual daily movement remains to be assessed.

Finally, research on neighborhood context more broadly has been beset by issues of selection (Chaix et al. 2013, Wodtke et al. 2011). Neither the forms of data collection we describe above nor the methods surrounding them fully obviate that concern. In fact, some introduce new forms of selection (e.g., Twitter). Still, we view the granular nature of these data, the potential for data linkage, and the temporal nature of many as providing insight into how and to what extent spatial context, apart from residential location, might bear influence.

NEW DIRECTIONS

Activity space approaches represent a turning point in scholarship on urban social and physical context. The theory allows scholars to conceive of spatial influences in a manner not anchored to a residential address and more responsive to the notion of exposure. The attendant methods then provide a way to more effectively address when and how urban residents move through their larger communities, what draws them out, and what might keep them closer to home.

We suggest eight points to consider as the field advances and as activity space concepts and methods become more commonplace in sociological pursuits. First, we need more research devoted to social networks and social relationships, and how they may intersect with, or be contingent on, activity space. We see potential, through social surveys, in examining individuals nominated as close network members with those who respondents find themselves with on a day-to-day basis. On a related note, intergenerational relationships, for instance, would be important to examine in the context of overlapping activity space patterns; family interaction in time and space could be understood in a manner more advanced than typical time-use studies would allow.

Second, we need scholarship that more fully engages in comparative research. Research that simultaneously examines both rural and urban activity space contexts, for instance, could provide insight into the increasing bifurcation of social life across these two contexts. If, for instance, typical activity spaces restrict the opportunity to interact with others who may offer alternative social and political points of view, then the exercise of revisiting perspectives is not encouraged.

Third, a life course perspective on activity spaces would further enhance our understanding of environmental influence by age and life stage. Life course theory attends to the timing and sequencing of places inhabited, and how that might intersect with age. Relatedly, it is reasonable that early activity space research focused more readily on early and later lives, but attention across the life course is essential. Working-age adults, for instance, spend a significant share of their days in occupational settings, but those physical and social exposures are often not incorporated into contextual research.

Fourth, attention to virtual places is critical, in terms of how they may both supplant certain destinations and, potentially, draw people to new locations or activities. Research on the role of virtual social interaction in terms of social network engagement is equivocal (e.g., Quan-Haase et al. 2017); it is not yet clear how virtual interaction affects other forms of social engagement.

Fifth, we emphasize the continued and critical importance of social surveys. We still need to understand how people think and feel and how they perceive their social and physical environments. EMA methods, for instance, provide an important form of in-the-moment reactions and moods that are coincident with the current environment. These methods can be combined with more traditional social surveys, which document such indicators as household structure, social network composition, and economic status, to provide a more effective understanding of well-being in context.

Sixth, activity space approaches can draw on other data sources to allow detailed assessment of the physical, ambient, or social characteristics of locations. For example, online repositories of municipal data increasingly provide information on locations of crime, reported potholes, and other civic concerns. Researchers have developed methods using Google Street View to "audit" neighborhood environments, allowing estimation of local disorder, vacancies, construction, and other characteristics of the built environment (Mooney et al. 2014). These sources could be fruitfully combined with activity space data and, in some instances, provide additional information related to time of day, which is often consequential for choices about activity and travel. Sensor-based sources of data, such as Chicago's Array of Things (Catlett et al. 2018), have allowed activity space data to be combined with data on air quality, temperature, and traffic congestion. This richness of environmental quality information provides an unprecedented opportunity to characterize the physical and social environment people navigate each day.

Seventh, sociological inquiry of activity space is deeply rooted in the study of neighborhood effects, as noted above, but attention to modification and innovation around statistical modeling is essential. Of primary interest for neighborhood effects research is the idea of how an individual's (level 1) outcomes are shaped by neighborhood (level 2) characteristics. Hierarchical linear models are employed to address the dependencies between observations from the same neighborhood (Raudenbush & Bryk 2002). Unlike the standard neighborhood effects scenario, in which each individual observation belongs to only one neighborhood, activity space research approaches recognize the importance of nonresidential contexts. One solution to this multiple membership data structure challenge is to use multiple membership models (Hill & Goldstein 1998), which employ a weighting procedure to account for the extent of exposure. A second potential way to capture travel trajectories is social sequence analysis, which processes respondents' intricate travel behavior and exposure contexts as sequences of events (for a full introduction to social sequence analysis, see Cornwell 2015). We note that empirical research in activity space research is still developing. Statistical models of this form are typically used for small- or moderate-sized samples; the extent to which these methods can address challenges of big and complex location data is relatively unknown. For example, the multiple membership model would require a weight for each neighborhood visited. Given the nature and density of travel trajectories, membership structure will be rather complex.

Finally, theoretical refinement is critical. We argue that explicit attention to exposure shifts our lens from residential location (allowing, for instance, a better understanding of the lives of those who do not have a fixed residential address), but more attention to its impact on urban theory is warranted. For instance, these data can inform the timing and duration of exposure, but little has been made of that contribution. We also note that the activity space conceptualization would benefit from a more formal consideration of the role of institutions in shaping activity spaces, as well as greater attention to local, or perhaps larger, political forces that could inform activity spaces and the way we interpret their patterns and change over time.

SUMMARY AND ENDURING QUESTIONS

The intent of this review is to define activity space, discuss its origins, and review its applications in sociological scholarship, with attention to urban mobility. It is also our charge to take stock of the body of activity space research and to assess its current status, potential, challenges, and opportunities. We have focused on four substantive areas in which urban mobility/activity space concepts have been employed, as well as the range of location and augmentation approaches meant to enhance its contributions. We believe that activity space theory and methods represent a critical turn in urban sociological scholarship, and one that will continue to help us describe, predict, and understand the nature and context of social interaction in urban context.

What are the major questions we can now answer? We close with one example. As Krysan & Crowder (2017) suggest, activity space approaches allow for a better understanding of how racial and ethnic groups cross racial boundaries. With the rich and varied activity space data, potentially coupled with methods such as EMA, we can more readily understand whether residents are drawn to another neighborhood for amenity needs (e.g., groceries), friend or family interaction, or institutional resources (e.g., church, medical care). City residents may depart a segregated context and move through a more integrated one, but the setting they actually spend time in may be compositionally similar to the community of origin. Activity space approaches will allow us to understand propinquity in a manner unprecedented, and may therefore provide insight into relationships across racial groups, and social interaction and exchange more broadly.

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LITERATURE CITED

Adams P, Rabbi M, Rahman T, Matthews M, Voida A, et al. 2014. Towards personal stress informatics: comparing minimally invasive techniques for measuring daily stress in the wild. In *Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare* (*PERVASIVEHEALTH 2014*), pp. 72–79. New York: ACM

Ahas R, Silm S, Järv O, Saluveer E, Tiru M. 2010. Using mobile positioning data to model locations meaningful to users of mobile phones. *J. Urban Technol.* 17(1):3–27

Asakura Y, Iryo T. 2007. Analysis of tourist behaviour based on the tracking data collected using a mobile communication instrument. *Transp. Res. A* 41(7):684–90

Baker PS, Bodner EV, Allman RM. 2003. Measuring life-space mobility in community-dwelling older adults. *J. Am. Geriatr. Soc.* 51(11):1610–14

Basta LA, Therese S, Richmond TS, Douglas J, Wiebe DJ. 2010. Neighborhoods, daily activities, and measuring health risks experienced in urban environments. *Soc. Sci. Med.* 71(11):1943–50

Baudains P, Braithwaite A, Johnson SD. 2013. Target choice during extreme events: a discrete spatial choice model of the 2011 London riots. *Criminology* 51(2):251–85

Bengtsson L, Lu X, Thorson A, Garfield R, Schreeb JV. 2011. Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: a post-earthquake geospatial study in Haiti. *PLOS Med*. 8(8):e1001083

Bernasco W. 2010. A sentimental journey to crime: effects of residential history on crime location choice. *Criminology* 48(2):389–416

Bichler G, Christie-Merrall J, Sechrest D. 2011. Examining juvenile delinquency within activity space: building a context for offender travel patterns. *J. Res. Crime Delinq*. 48(3):472–506

Boivin R, D'Elia M. 2017. A network of neighborhoods: predicting crime trips in a large Canadian city. *J. Res. Crime Delinq*. 54(6):824–46

Brantingham PJ, Brantingham PL. 1981. *Environmental Criminology*. Beverly Hills, CA: Sage

Brantingham PJ, Brantingham PL. 2008. Crime pattern theory. In *Environmental Criminology and Crime Analysis*, ed. R Wortley, L Mazerolle, pp. 78–93. Abingdon, UK: Willan

Brockmann D, Hufnagel L, Geisel T. 2006. The scaling laws of human travel. *Nature* 439(7075):462–65

Browning CR, Calder CA, Boettner BB, Smith A. 2017a. Ecological networks and urban crime: the structure of shared routine activity locations and neighborhood-level informal control capacity. *Criminology* 55(4):754–78

Browning CR, Calder CA, Soller B, Jackson AL, Dirlam J. 2017b. Ecological networks and neighborhood social organization. *Am. J. Sociol.* 122(6):1939–88

Browning CR, Soller B. 2014. Moving beyond neighborhood: activity spaces and ecological networks as contexts for youth development. *Cityscape* 16(1):165–96

Browning CR, Soller B, Jackson AL. 2015. Neighborhoods and adolescent health-risk behavior: an ecological network approach. *Soc. Sci. Med.* 125:163–72

Burgess EW. 1925. The growth of the city: an introduction to a research project. In *The City*, ed. RE Park, EW Burgess, pp. 47–62. Chicago: Univ. Chicago Press

Cagney KA. 2016. *Activity space, social interaction and health trajectories in later life*. Grant R01AG050605, Natl. Inst. Aging, Washington, DC, awarded Aug. 25

Cagney KA, Browning CR, Jackson AL, Soller B. 2013. Networks, neighborhoods, and institutions: an integrated 'activity space' approach to research on aging. In *New Directions in the Sociology of Aging*, ed. LJ Waite, TL Plewes, pp. 60–80. Washington, DC: Natl. Acad.

Cagney KA, York Cornwell E. 2018. Place, aging, and health. In *Future Directions for the Demography of Aging: Proceedings of a Workshop*, pp. 131–55. Washington, DC: Natl. Acad.

Cairncross F. 2001. *The Death of Distance: How the Communications Revolution Is Changing Our Lives*. Cambridge, MA: Harv. Bus. Press

Catlett CE, Beckman PH, Sankaran R, Galvin KK. 2017. Array of things: a scientific research instrument in the public way. In *Proceedings of the 2nd International Workshop on Science of Smart City Opererations and Platforms Engineering* (*SCOPE '17*), pp. 26–33. New York: ACM

Catlett CE, Cesario E, Talia D, Vinci A. 2018. A data-driven approach for spatio-temporal crime predictions in smart cities. In *Proceedings of the 2018 IEEE International Conference on Smart Computing* (*SMARTCOMP 2018*), pp. 17–24. Piscataway, NJ: IEEE

Chaix B. 2009. Geographic life environments and coronary heart disease: a literature review, theoretical contributions, methodological updates, and a research agenda. *Annu. Rev. Public Health* 30:81–105

Chaix B, Kestens Y, Bean K, Leal C, Karusisi N, et al. 2012. Cohort profile: residential and non-residential environments, individual activity spaces and cardiovascular risk factors and diseases—the RECORD Cohort Study. *Int. J. Epidemiol.* 41(5):1283–92

Chaix B, Méline J, Duncan S, Merrien C, Karusisi N, et al. 2013. GPS tracking in neighborhood and health studies: a step forward for environmental exposure assessment, a step backward for causal inference? *Health Place* 21:46–51

Choudhury T, Pentland AS. 2002. The sociometer: a wearable device for understanding human networks. In *Proceedings of Computer Supported Cooperative Work—Workshop on Ad Hoc Communications and Collaboration in Ubiquitous Computing Environments*. **http://www.lifewear.gatech.edu/resources/Choudhury,_Pentland_-_The_Sociometer_-_A_Wearable_Device_for_Understanding_Human_Networks.pdf**

Choudhury T, Pentland AS. 2003. Sensing and modeling human networks using the sociometer. In *Proceedings of the 7th International Symposium on Wearable Computers*, pp. 216–22. Piscataway, NJ: IEEE

Choudhury T, Pentland AS. 2004. Characterizing social networks using the sociometer. In *Proceedings of the North American Association of Computational Social and Organizational Science* (*NAACSOS*). **http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.61.8296&rep=rep1&type=pdf**

Colabianchi N, Coulton CJ, Hibbert JG, McClure SM, Ievers-Landis CE, Davis EM. 2014. Adolescent self-defined neighborhoods and activity spaces: spatial overlap and relations to physical activity and obesity. *Health Place* 27:22–29

Colombo GB, Chorley MJ, Williams MJ, Allen SM, Whitaker RM. 2012. You are where you eat: Foursquare checkins as indicators of human mobility and behaviour. In *Proceedings of the 2012 IEEE International Conference on Pervasive Computing and Communications Workshops* (*PERCOM*), pp. 217–22. Piscataway, NJ: IEEE

Cornwell B. 2015. *Social Sequence Analysis: Methods and Applications*. Cambridge, UK: Cambridge Univ. Press

Costa J, Guimbretière F, Jung M, Choudhury T. 2019. BoostMeUp: improving cognitive performance in the moment by unobtrusively regulating emotions with a smartwatch. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3(2):40

Cranshaw J, Schwartz R, Hong J, Sadeh N. 2012. The livehoods project: utilizing social media to understand the dynamics of a city. In *Proceedings of the 6th International AAAI Conference on Weblogs and Social Media*, pp. 58–65. Palo Alto, CA: AAAI

D'Silva K, Noulas A, Mascolo C, Misra A. 2018. The role of urban mobility in retail business survival. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2(3):1–22

Daggitt ML, Noulas A, Shaw B, Mascolo C. 2016. Tracking urban activity growth globally with big location data. *R. Soc. Open Sci.* 3(4):150688

de Montjoye YA, Hidalgo CA, Verleysen M, Blondel VD. 2013. Unique in the crowd: the privacy bounds of human mobility. *Sci. Rep.* 3(1):1376

de Montjoye YA, Radaelli L, Singh VK. 2015. Unique in the shopping mall: on the reidentifiability of credit card metadata. *Science* 347(6221):536–39

Diez Roux AV, Mair C. 2010. Neighborhoods and health. *Ann. N. Y. Acad. Sci.* 1186(1):125–45

Dong G, Ma J, Kwan MP, Wang Y, Chai Y. 2018. Multi-level temporal autoregressive modelling of daily activity satisfaction using GPS-integrated activity diary data. *Int. J. Geogr. Inf. Sci.* 32(11):2189–208

Dong X, Morales AJ, Jahani E, Moro E, Lepri B, et al. 2019. Segregated interactions in urban and online spaces. arXiv:1911.04027 [cs]

Eagle N, Pentland AS. 2006. Reality mining: sensing complex social systems. *Pers. Ubiquitous Comput.* 10(4):255–68

Ellis M, Wright R, Parks V. 2004. Work together, live apart? Geographies of racial and ethnic segregation at home and at work. *Ann. Assoc. Am. Geogr.* 94(3):620–37

Ferrari L, Mamei M. 2011. Discovering daily routines from Google Latitude with topic models. In *Proceedings of the 2011 IEEE International Conference on Pervasive Computing and Communications Workshops* (*PERCOM*), pp. 432–37. Piscataway, NJ: IEEE

Fischer CS. 1982. *To Dwell Among Friends: Personal Networks in Town and City*. Chicago: Univ. Chicago Press

Gabrielli L, Rinzivillo S, Ronzano F, Villatoro D. 2014. From tweets to semantic trajectories: Mining anomalous urban mobility patterns. In *Citizen in Sensor Networks*, ed. J Nin, D Villatoro, pp. 26–35. Cham, Switz.: Springer

Gan M, Nie YM, Liu X, Zhu D. 2019. Whereabouts of truckers: an empirical study of predictability. *Transp. Res. C* 104:184–95

Gerdes G, Greene C, Liu XM. 2018. *The Federal Reserve Payments Study: 2018 Annual Supplement*. Washington, DC: US Fed. Reserve Syst.

Gibson C, Perley L, Bailey J, Barbour R, Kershaw T. 2015. Social network and census tract-level influences on substance use among emerging adult males: an activity spaces approach. *Health Place* 35:28–36

Golledge RG, Stimson RJ. 1997. *Spatial Behavior: A Geographic Perspective*. New York: Guilford

González MC, Hidalgo CA, Barabási AL. 2008. Understanding individual human mobility patterns. *Nature* 453(7196):779–82

Graif C, Freelin BN, Kuo YH, Wang H, Li Z, Kifer D. 2019. Network spillovers and neighborhood crime: a computational statistics analysis of employment-based networks of neighborhoods. *Justice Q*. **https://doi.org/10.1080/07418825.2019.1602160**

Griffiths G, Johnson SD, Chetty K. 2017. UK-based terrorists' antecedent behavior: a spatial and temporal analysis. *Appl. Geogr.* 86:274–82

Hamermesh DS, Frazis H, Stewart J. 2005. Data watch: the American time use survey. *J. Econ. Perspect.* 19(1):221–32

Hasan S, Schneider CM, Ukkusuri SV, González MC. 2013. Spatiotemporal patterns of urban human mobility. *J. Stat. Phys.* 151(1/2):304–18

Hawelka B, Sitko I, Beinat E, Sobolevsky S, Kazakopoulos P, Ratti C. 2014. Geo-located Twitter as proxy for global mobility patterns. *Cartogr. Geogr. Inf. Sci.* 41(3):260–71

Hill PW, Goldstein H. 1998. Multilevel modeling of educational data with cross-classification and missing identification for units. *J. Educ. Behav. Stat.* 23(2):117–28

Hoeben E, Weerman F. 2014. Situational conditions and adolescent offending: Does the impact of unstructured socializing depend on its location? *Eur. J. Criminol.* 11(4):481–99

Hurvitz PM, Moudon AV. 2012. Home versus nonhome neighborhood: quantifying differences in exposure to the built environment. *Am. J. Prev. Med.* 42(4):411–17

Inagami S, Cohen DA, Finch BK. 2007. Non-residential neighborhood exposures suppress neighborhood effects on self-rated health. *Soc. Sci. Med.* 65(8):1779–91

Ivory VC, Russell M, Witten K, Hooper CM, Pearce J, Blakely Y. 2015. What shape is your neighbourhood? Investigating the micro geographies of physical activity. *Soc. Sci. Med.* 133:313–21

Jiang S, Ferreira J, González MC. 2012. Clustering daily patterns of human activities in the city. *Data Min. Knowl. Discov.* 25(3):478–510

Jones M, Pebley AR. 2014. Redefining neighborhoods using common destinations: social characteristics of activity spaces and home census tracts compared. *Demography* 51(3):727–52

Kestens Y, Lebel A, Daniel M, Thériault M, Pampalon R. 2010. Using experienced activity spaces to measure foodscape exposure. *Health Place* 16(6):1094–103

Krivo L, Washington JHM, Peterson RD, Browning CR, Calder CA, Kwan MP. 2013. Social isolation of disadvantage and advantage: the reproduction of inequality in urban space. *Soc. Forces* 92(1):141–64

Krysan M, Crowder K. 2017. *Cycle of Segregation: Social Processes and Residential Stratification*. New York: Russell Sage Found.

Kwan M-P, Wang J, Tyburski M, Epstein DH, Kowalczyk WJ, Preston KL. 2019. Uncertainties in the geographic context of health behaviors: a study of substance users' exposure to psychosocial stress using GPS data. *Int. J. Geogr. Inf. Sci.* 33(6):1176–95

Lammers M, Menting B, Ruiter S, Bernasco W. 2015. Biting once, twice: the influence of prior on subsequent crime location choice. *Criminology* 53(3):309–29

Le Menach A, Tatem AJ, Cohen JM, Hay SI, Randell H, et al. 2011. Travel risk, malaria importation and malaria transmission in Zanzibar. *Sci. Rep.* 1(1):93

Lenormand M, Louail T, Cantú-Ros OG, Picornell M, Herranz R, et al. 2015. Influence of sociodemographic characteristics on human mobility. *Sci. Rep.* 5(1):10075

Leverentz A. 2019. Beyond neighborhoods: activity spaces of returning prisoners. *Soc. Probl.* 67(1):150–70

Li X, Pan G, Wu Z, Qi G, Li S, et al. 2012. Prediction of urban human mobility using large-scale taxi traces and its applications. *Front. Comput. Sci.* 6:111–21

Lima A, Stanojevic R, Papagiannaki D, Rodriguez P, González MC. 2016. Understanding individual routing behaviour. *J. R. Soc. Interface* 13(116):20160021

Lipperman-Kreda S, Morrison C, Grube JW, Gaidus A. 2015. Youth activity spaces and daily exposure to tobacco outlets. *Health Place* 34:30–33

Loebach JE, Gilliland A. 2016. Neighbourhood play on the endangered list: examining patterns in children's local activity and mobility using GPS monitoring and qualitative GIS. *Child. Geogr.* 14(5):573–89

Luo F, Cao G, Mulligan K, Li X. 2016. Explore spatiotemporal and demographic characteristics of human mobility via Twitter: a case study of Chicago. *Appl. Geogr.* 70:11–25

Malleson N, Andresen MA. 2015. The impact of using social media data in crime rate calculations: shifting hot spots and changing spatial patterns. *Cartogr. Geogr. Inf. Sci.* 42(2):112–21

Mason MJ, Korpela K. 2009. Activity spaces and urban adolescent substance use and emotional health. *J. Adolesc.* 32(4):925–39

Mason MJ, Mennis J, Way T, Light J, Rusby J, et al. 2015. Young adolescents' perceived activity space risk, peer networks, and substance use. *Health Place* 34:143–49

Massey DS, Condran GA, Denton MA. 1987. The effect of residential segregation on black social and economic well-being. *Soc. Forces* 66(1):29–56

Matthews SA. 2012. Thinking about place, spatial behavior, and spatial processes in childhood obesity. *Am. J. Prev. Med.* 42(5):516–20

Matthews SA, Yang T-C. 2013. Spatial polygamy and contextual exposures (SPACEs). *Am. Behav. Sci.* 57(8):1057–81

Menting B, Lammers M, Ruiter S, Bernasco W. 2016. Family matters: effects of family members' residential areas on crime location choice. *Criminology* 54(3):413–33

Mok D, Wellman B, Carrasco J. 2010. Does distance matter in the age of the internet? *Urban Stud*. 47(13):2747–83

Mooney SJ, Bader MDM, Lovasi GS, Neckerman KM, Teitler JO, Rundle AG. 2014. Validity of an ecometric neighborhood physical disorder measure constructed by virtual street audit. *Am. J. Epidemiol.* 180:626–35

Murnane EL, Abdullah S, Matthews M, Kay M, Kientz JA, et al. 2016. Mobile manifestations of alertness: connecting biological rhythms with patterns of smartphone app use. In *Proceedings of the 18th International Conference on Human–Computer Interaction with Mobile Devices and Services*, pp. 465–77. New York: ACM

Noulas A, Scellato S, Mascolo C, Pontil M. 2011. An empirical study of geographic user activity patterns in Foursquare. In *Proceedings of the 5th International AAAI Conference on Weblogs and Social Media*, pp. 570–73. Palo Alto, CA: AAAI

Palmer JRB, Espenshade TJ, Bartumeus F, Chung CY, Ozgencil NE, Li K. 2013. New approaches to human mobility: using mobile phones for demographic research. *Demography* 50(3):1105–28

Park RE. 1915. The city: suggestions for the investigation of human behavior in the city. *Am. J. Sociol.* 20:577–612

Phillips NE, Levy BL, Sampson RJ, Small ML, Wang RQ. 2019. The social integration of American cities: network measures of connectedness based on everyday mobility across neighborhoods. *Sociol. Methods Res.* **https://doi.org/10.1177/0049124119852386**

Quan-Haase A, Mo GY, Wellman B. 2017. Connected seniors: how older adults in East York exchange social support online and offline. *Inf. Commun. Soc.* 20(7):967–83

Rainham DG, Bates CJ, Blanchard CM, Dummer TJ, Kirk SF, Shearer CL. 2012. Spatial classification of youth physical activity patterns. *Am. J. Prev. Med.* 42(5):e87–96

Raudenbush SW, Bryk AS. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*. Thousand Oaks, CA: Sage. 2nd ed.

Rinzivillo S, Mainardi S, Pezzoni F, Coscia M, Pedreschi D, Giannotti F. 2012. Discovering the geographical borders of human mobility. *Künstl. Intell.* 26(3):253–60

Robinson AI, Carnes F, Oreskovic NM. 2016. Spatial analysis of crime incidence and adolescent physical activity. *Prev. Med.* 85:74–77

Rossmo DK, Lu Y, Fang T. 2012. Spatial-temporal crime paths. In *Patterns, Prevention, and Geometry of Crime*, ed. MA Andresen, JB Kinney, pp. 38–64. New York: Routledge

Roth C, Kang SM, Batty M, Barthélemy M. 2011. Structure of urban movements: polycentric activity and entangled hierarchical flows *PLOS ONE* 6(1):e15923

Sampson RJ. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago: Univ. Chicago Press

Sampson RJ, Groves BW. 1989. Community structure and crime: testing social-disorganization theory. *Am. J. Sociol.* 94(4):744–802

Sampson RJ, Raudenbush SW, Earls F. 1997. Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science* 277(5328):918–24

Sapiezynski P, Stopczynski A, Gatej R, Lehmann S. 2015. Tracking human mobility using WiFi signals. *PLOS ONE* 10(7):e0130824

Shareck M, Kestens Y, Frohlich KL. 2014. Moving beyond the residential neighborhood to explore social inequalities in exposure to area-level disadvantage: results from the Interdisciplinary Study on Inequalities in Smoking. *Soc. Sci. Med.* 108:106–14

Sharp G, Denney JT, Kimbro RT. 2015. Multiple contexts of exposure: activity spaces, residential neighborhoods, and self-rated health. *Soc. Sci. Med.* 146:204–13

Shaw CR, McKay HD. 1942. *Juvenile Delinquency and Urban Areas*. Chicago: Univ. Chicago Press

Shelton T, Poorthuis A, Zook M. 2015. Social media and the city: rethinking urban socio-spatial inequality using user-generated geographic information. *Landsc. Urban Plan.* 142:198–211

Sherman JE, Spencer J, Preisser JS, Gesler WM, Arcury TA. 2005. A suite of methods for representing activity space in a healthcare accessibility study. *Int. J. Health Geogr.* 4(1):24

Silm S, Ahas R. 2014. The temporal variation of ethnic segregation in a city: evidence from a mobile phone use dataset. *Soc. Sci. Res.* 47:30–43

Simmel G. 1971 (1903). Metropolis and mental life. In *On Individuality and Social Forms*, ed. DN Levine, pp. 324–39. Chicago: Univ. Chicago Press

Simons RL, Burt CH, Barr AB, Lei M-K, Stewart E. 2014. Incorporating routine activities, activity spaces, and situational definitions into the social schematic theory of crime. *Criminology* 52(4):655–87

Small ML, Adler L. 2019. The role of space in the formation of social ties. *Annu. Rev. Sociol.* 45:111–32

Song C, Qu Z, Blumm N, Barabási AL. 2010. Limits of predictability in human mobility. *Science* 327(5968):1018–21

Song G, Bernasco W, Liu L, Xiao L, Zhou S, Liao W. 2019. Crime feeds on legal activities: Daily mobility flows help to explain thieves' target location choices. *J. Quant. Criminol.* 35(4):831–54

Subramanian SV, Kubzansky L, Berkman L, Fay M, Kawachi I. 2006. Neighborhood effects on the self-rated health of elders: uncovering the relative importance of structural and service-related neighborhood environments. *J. Gerontol. Soc. Sci.* 61(3):S153–60

Sugie NF, Lens MC. 2017. Daytime locations in spatial mismatch: job accessibility and employment at reentry from prison. *Demography* 54(2):775–800

Sun L, Axhausen KW, Lee DH, Huang X. 2013. Understanding metropolitan patterns of daily encounters. *PNAS* 110(34):13774–79

Tamura KB, Elbel B, Regan CSD, Al-Ajlouni YA, Athens JK, et al. 2017. Residential and GPS-defined activity space neighborhood noise complaints, body mass index and blood pressure among low-income housing residents in New York City. *J. Community Health* 42(5):974–82

Tita GE, Cohen J, Engberg J. 2005. An ecological study of the location of gang set space. *Soc. Probl.* 52(2):272–99

Toole JL, Herrera-Yaqüe C, Schneider CM, González MC. 2015. Coupling human mobility and social ties. *J. R. Soc. Interface* 12:105

Townley G, Kloos B, Wright PA. 2009. Understanding the experience of place: expanding methods to conceptualize and measure community integration of persons with serious mental illness. *Health Place* 15(2):520–31

Trull TJ, Ebner-Priemer UW. 2009. Using experience sampling methods/ecological momentary assessment (ESM/EMA) in clinical assessment and clinical research: introduction to the special section. *Psychol. Assess.* 21(4):457–62

Vallée J, Cadot E, Roustit C, Parizot I, Chauvin P. 2011. The role of daily mobility in mental health inequalities: the interactive influence of activity space and neighbourhood of residence on depression. *Soc. Sci. Med.* 73(8):1133–44

Wan N, Lin G. 2016. Classifying human activity patterns from smartphone collected GPS data: a fuzzy classification and aggregation approach. *Trans. GIS* 20(6):869–86

Wan N, Qu W, Whittington J, Witbrodt BC, Henderson MP, et al. 2013. Assessing smart phones for generating life-space indicators. *Environ. Plan. B* 40(2):350–61

Wang D, Pedreschi D, Song C, Giannotti F, Barabási AL. 2011. Human mobility, social ties, and link prediction. In *Proceedings of the 17th ACM SIGKDD International Conference*, pp. 1100–8. New York: ACM

Wang J, Kwan MP, Chai Y. 2018. An innovative context-based crystal-growth activity space method for environmental exposure assessment: a study using GIS and GPS trajectory data collected in Chicago. *Int. J. Environ. Res. Public Health* 15(4):e703

Wang Q, Phillips NE, Small ML, Sampson RJ. 2018. Urban mobility and neighborhood isolation in America's 50 largest cities. *PNAS* 115(30):7735–40

Wang Q, Taylor JE. 2014. Quantifying human mobility perturbation and resilience in Hurricane Sandy. *PLOS ONE* 9(11):e112608

Wang Y, Kang C, Bettencourt LMA, Liu Y, Andris C. 2015. Linked activity spaces: embedding social networks in urban space. In *Computational Approaches for Urban Environments*, ed. M Helbich, JJ Arsanjani, M Leitner, pp. 313–36. Berlin: Springer

Wesolowski A, Eagle N. 2010. Parameterizing the dynamics of slums. In *Proceedings of the AAAI Spring Symposium*, pp. 103–8. Palo Alto, CA: AAAI

Wesolowski A, Eagle N, Tatem AJ, Smith DL, Noor AM, et al. 2012. Quantifying the impact of human mobility on malaria. *Science* 338(6104):267–70

Widhalm P, Yang Y, Ulm M, Athavale S, González MC. 2015. Discovering urban activity patterns in cell phone data. *Transportation* 42(4):597–623

Wikström P-OH, Ceccato V, Hardie B, Treiber K. 2010. Activity fields and the dynamics of crime. *J. Quant. Criminol.* 26(1):55–87

Wikström P-OH, Oberwittler D, Treiber K, Hardie B. 2012. *Breaking Rules: The Social and Situational Dynamics of Young People's Urban Crime*. Oxford, UK: Oxford Univ. Press

Williams SA, Hipp JR. 2019. How great and how good? Third places, neighbor interaction, and cohesion in the neighborhood context. *Soc. Sci. Res.* 77:68–78

Wilson WJ. 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: Univ. Chicago Press

Wodtke GT, Harding DJ, Elwert F. 2011. Neighborhood effects in temporal perspective. *Am. Sociol. Rev.* 76(5):713–36

Wong DWS, Shaw S-L. 2011. Measuring segregation: an activity space approach. *J. Geogr. Syst.* 13(2):127–45

Yin J, Soliman A, Yin D, Wang S. 2017. Depicting urban boundaries from a mobility network of spatial interactions: a case study of Great Britain with geo-located Twitter data. *Int. J. Geogr. Inf. Sci.* 31(7):1293–313

York Cornwell E, Cagney KA. 2017. Aging in activity space: results from smartphone-based GPS tracking of urban seniors. *J. Gerontol. Ser. B* 72(5):864–75

Yuan Y, Raubal M, Liu Y. 2012. Correlating mobile phone usage and travel behavior—a case study of Harbin, China. *Comput. Environ. Urban Syst.* 36(2):118–30

Zagheni E, Weber I. 2012. You are where you e-mail: using e-mail data to estimate international migration rates. In *Proceedings of the 3rd Annual ACM Web Science Conference*, pp. 348–51. New York: ACM

Zenk SN, Schulz AJ, Matthews SA, Odoms-Young A, Wilbur J, et al. 2011. Activity space environment and dietary and physical activity behaviors: a pilot study. *Health Place* 17(5):1150–61

Zhang W, Derudder B, Jianghao Wang J, Shen W, Witlox F. 2016. Using location-based social media to chart the patterns of people moving between cities: the case of Weibo users in the Yangtze River Delta. *J. Urban Technol.* 23(3):91–111

Zhang X, Wang J, Kwan MP, Chai Y. 2019. Reside nearby, behave apart? Activity-space-based segregation among residents of various types of housing in Beijing, China. *Cities* 88:166–80

Zhong C, Arisona SM, Huang X, Batty M, Schmitt G. 2014. Detecting the dynamics of urban structure through spatial network analysis. *Int. J. Geogr. Inf. Sci.* 28(11):2178–99