A Generalized Model of Activity Space

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This article introduces the concept of a generalized activity space to bridge area-based and activity-based representations of geographic context. We argue that microscale space–time paths fail to account for contextual determinants of behavior, because they emphasize "contacts" over "contexts," a problem that could be solved, in part, by using a broader "generalized" representation of geographic context. This article develops the idea of a generalized activity space and empirically tests the viability of the concept. Support for the viability of the idea is identified through analysis of 34,500 trips by 7,550 individuals in Atlanta. We find that demographic characteristics and residential location jointly shape a person's geographic context. Through a series of hypothesis tests, we find evidence that these location–demographic groupings are generalizable; that is, people with similar socioeconomic backgrounds and residential locations exhibit similar generalized activity spaces. Residential location, by itself, however, is not an effective descriptor of the configuration of a person's context. We argue that generalized activity spaces have potential to inform study of how the environment influences behavior by allowing a more robust consideration of interplay between socioeconomic characteristics and the use of space. *Key Words: activity space, context, environment-behavior, neighborhood effects.*

In a 1969 address to regional scientists Torsten Hagerstrand outlined the principles of time geography. Time geography is a representational system that recognizes that human activities are embedded in space and time and thus are constrained by them. Hagerstrand motivated this idea by reference to a "twilight zone" between biographical analysis (of the kind conducted by historians) and the analysis of areal data (as is done by regional scientists). Time geography was envisioned as a system to establish "coherence between the two ends of the scale" (Hagerstrand 1970, 9). Since Hagerstrand's initial formulation, enormous progress has been made extending and operationalizing its concepts (Miller 1991, 2003; Kwan 2000, 2010; Mennis, Mason, and Cao 2013; Patterson and Farber 2015). The widespread availability of Global Positioning Systems (GPS) and mobile devices has increased the contemporary relevance of Hagerstrand's ideas. Fifty years later, though, researchers still bemoan the fundamental problem Hagerstrand identified. Schläpfer et al. (2021) in *Nature* noted, "the link between this microscopic behaviour and the temporal spectrum of recurrent mobility fluxes arising from an entire population is missing" (522). Although the literature that directly engages with time-geographic concepts has remained largely contained to the discipline of geography, the basic idea of looking at movement in space and time has spread well beyond the discipline.

The broad body of work on human movement contains within it fundamental tensions. Some of these tensions relate to epistemic differences between disciplines, for example, the orientation of physicists toward generalization based on statistical properties of phenomena compared to social scientists' orientation toward theory built on the observed particulars of place (O'Sullivan and Manson 2015). Many of these tensions, however, are genuine problems in which well-grounded theories, observational studies, or both disagree. For example, decades of work in transportation research find that the characteristics of individuals (location, wealth, stage in the life course) are fundamental drivers of human spatial behavior, but recent work in physics finds that "high degree of temporal and spatial regularity" regardless of these demographic characteristics (González, Hidalgo, and Barabási 2008, 779). Furthermore, within the social sciences there is disagreement between those who believe sociospatial context is individually constructed through spatiotemporal activity versus those who see it as collectively constructed through networks, institutions, and structural forces (we refer to these, respectively, as the individualist and collectivist perspective).

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In this article we introduce the concept of a generalized activity space in an attempt to reconcile these tensions. Generalized activity spaces apply a geodemographic lens to the problem of context by arguing that similar types of people might have similar types of generalized activity spaces. That is, by knowing about a person's socioeconomic and demographic characteristics one might be able to make inferences about their activity space based on the activity spaces of other similar individuals. Generalized activity spaces provide a way to refine the parameters of the movement models identified in physics and in so doing link them with the social scientific literature. Generalized activity spaces also provide a way to reconcile the tension between the individualist and collectivist views of social context. This article describes these tensions in more detail, introduces the concept of a generalized activity space, and then attempts to develop empirical evidence for its viability as a concept. This work is by no means a proof of generalized activity spaces: Our goal is to introduce the idea and begin a conversation on how to reconcile tensions in the study of human environmental and social contexts. We believe such a reconciliation is necessary to advance our understanding of how human behavior shapes and is shaped by the environment.

Sociospatial Context

Decades of work in public health, sociology, and other social sciences finds that area of residence, often delimited by some type of census geography, can have important impact on well-being and human development. The term *neighborhood effects* is a catch-all for this interdisciplinary body of work. The neighborhood effects literature asks, "To what extent are geographic patterns in health and/or other social outcomes due to neighborhood-level characteristics as opposed to individual or family-level characteristics?" This question can be difficult to answer because people are often clustered (or segregated) geographically by race, ethnicity, or socioeconomic status. The close linkage between demographic factors and area of residence makes it difficult to statistically separate "compositional effects" (e.g., age, racism, or poverty) from the "contextual effects" of neighborhoods or other types of places. Kwan (2012) and others have noted that the identification of neighborhood effects is complicated by uncertainty in the appropriate geographic definition of social context. Work by Spielman and Yoo (2009) has shown that changing the geographic definition of a person's neighborhood can have a profound effect on statistical inference.

Richardson et al. (2013) argued that the solution to this problem lies in analysis of high-resolution activity data: "Life paths of individuals collected with GPS/GIS methods can provide more accurate assessment of exposures to environmental or social risk factors" (1391). The Richardson et al. (2013) argument that space–time paths provide a "more accurate" assessment of individual environmental contexts is what we refer to as the individualist perspective on social context. This stands in contrast to the collectivist view of social context that focuses on exogenous institutional and social forces that structure and shape life. The collectivist view is not divorced from space, as it argues that space matters because it structures access to opportunities and supports but that not all socially meaningful forces are transmitted via proximity.

The literature on space–time paths highlights the individualist–collectivist divide. Hagerstrand's conception of time geography was deeply connected to thinking about how space and time structure interpersonal interactions. Giddens (1985) criticized the time geographic framework, though, because it stresses the physical location of a person and hence neglects to account for broader social forces on behavior. Giddens (1985) noted that Hagerstrand's time geography emphasizes "the corporeality of the human being, in structured space-time contexts," and treats individuals "independently of the social settings they confront in their day-to-day lives" (270). Giddens's point is that location matters not only because of the direct physical exposures it provides; location structures interactions with institutions, policies, and cultures that are key social determinants of health and behavior (Diez-Roux 1998; Macintyre, Ellaway, and Cummins 2002; Browning and Cagney 2003). The collectivist perspective is that critical elements of sociospatial context are place specific but not transmitted through geographic mechanisms such as exposure via proximity.

The application of a time geographic perspective to the measurement of sociospatial contexts does not jibe with the collectivist conceptualization of spatial contexts in the social sciences. Historically, in the social sciences, context has been seen as important because it is collectively constructed and not "personal." Abbott (1997), in describing the influential Chicago School of Sociology, emphasized the collective nature of space: "no social fact makes any sense abstracted from its context in social (and often geographic) space and social time. … Every social fact is situated, surrounded by other contextual facts and brought into being by a process relating it to past contexts" (1152). Contemporary theoretical concepts, like social capital and collective efficacy, are properties of collective contexts that can have positive spatial externalities; for example, the willingness of people to intervene on behalf of others can have broad impacts (Sampson, Morenoff, and Gannon-Rowley 2002; Sampson 2012). Browning et al. (2006) found that unequal distributions of community resources produced conditions that made residents of some areas more vulnerable than others to the 2003 Chicago heat wave. Traditional place-based social scientific analysis, for all of its shortcomings, uses area of residence (place) as a proxy for a complex set of forces, including cultural, economic, and political. Schulz and Northridge (2004) saw physical exposures as one element in a complex multiscale ecosocial system that connects place to health outcomes. Radil, Flint, and Tita (2010) argued that "The ability of spatial analysis to incorporate the relative location of social actors, and the linkages between them, can, paradoxically, atomize actors being studied through a 'spatial fetishism' that ignores or is unable to address the social relations that construct the spaces within which actors operate" (308). An exclusive focus on an individual's location in space fails to capture broader social context.

Stated simply, Giddens and others suggest that microscale time geographic analysis of individual behavior is vulnerable to the conflation of location and context. Location structures social and environmental context but does not fully reveal it. This critique of time geography can seem counterintuitive. Time geography is inherently concerned with social relations and how they constrain activity spaces. Time geography emphasizes "contacts" (direct social interactions such as coupling constraints) over "contexts" (neighborhoods, place-based norms, culture, social supports), which might operate through sociospatial mechanisms other than colocation. Space–time paths emphasize the corporeality of human experience and neglect the fact that locations that people do not enter can influence behavior. A child who lives near an open-air drug market might actively avoid it. Even though she never enters the space where the danger exists, it could influence her behavior, activity space, and well-being. Mennis, Mason, and Cao (2013) went a long way toward addressing this concern through the incorporation of affective information about locations within a person's activity space. Nonetheless, Giddens's critique challenges Richardson et al.'s (2013) assertion that GPS provides "a more accurate assessment" of exposure to social risk factors than traditional place-based approaches. We believe that both location-based and place-based study of social systems have value and develop the concept of *generalized activity spaces* in an attempt to bridge these two analytic paradigms.

Generalized Activity Spaces

A generalized activity space expands on the individual-centric notion of an observed path to consider how groups of similar people behave spatially. It is "generalized" in that the concept attempts to abstract away some of the physical geographic and individual specific constraints that might shape movement at a microscale to look for patterns or similarities at the mesoscale. The concept is also generalized in the sense that it tries to integrate individual (activity) and communal (place) based definitions of sociospatial context.

Generalization of activity spaces involves developing broad group-specific statements about spatial behavior from the observation of individual behaviors. The concept looks beyond generalizations based purely on the geometry of movement to consider both demographic characteristics and spatial behavior simultaneously. That is, a generalized activity space reasons over observations of spatial behavior and the demographic characteristics of the moving person. In some sense the concept feels problematic: Why develop generalized representations if the raw individual-level information is available?

We believe that the concept of a generalized activity space, an empirically derived area that delineates a person's context based on both individual attributes and the space–time paths of other similar individuals, might provide a unit of analysis that overcomes the trap of spatial fetishism described by Giddens (1985) and Radil, Flint, and Tita (2010). Generalized activity spaces are aggregations of space–time paths into mesoscale areal units of

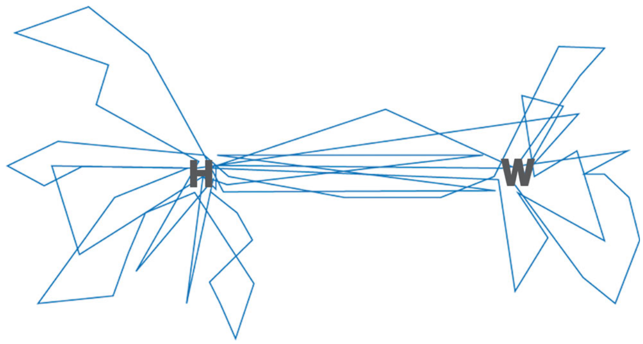

Figure 1. An example prototype activity space: "Dog bone." *Note:* H = home location; W = work location).

analysis that are rooted in observed behaviors of groups of people. They are in a sense a geodemographic approach to activity spaces in that they group people with similar characteristics. They are inspired, to some extent, by Hagerstrand (1970), who noted that, "over a lifetime he steers his path through a string of daily prisms, growing in radius during early years of his life and shrinking at an advanced age" (14). The concept of a generalized activity space accommodates changes in the sphere of spatial activity over the life course, as Hagerstrand suggested, but does so in way that attempts to overcome the shortcomings of focusing only on an individual's location in space and time.

For example, one type of generalized activity space might be the "dog bone" in Figure 1. This type of space might be associated with professionals, with no children, who have a single stationary place of employment and residence. For those with a single home and job, activity over time might take a particular form, with activity geographically distributed around home and work. These expansive areas form the ends of the bone, and a person's commuting path forms the shank of the bone. The dog bone is just a conceptual prototype; it does not refer to a specific individual or a particular place.

There is already substantial evidence of the existence of generalized activity spaces. Gonzalez et al. (2008) found regular patterns of activity in a data set describing 100,000 mobile phone users over six months. Song et al. (2010) similarly found that human movement patterns were regular and predictable using 50,000 anonymized call records. Because these data are anonymized, however, this work neglects decades of research on travel behavior that tell us that individual characteristics such as age, gender, employment, vehicle ownership, and family structure are all important drivers of travel behavior (Hanson and Hanson 1981; Pas 1982; Goodchild and Janelle 1984; Janelle, Goodchild, and Klinkenberg 1988; Pisarski 2006). Work by Sila-Nowicka et al. (2016) found that gender and age conditioned activity spaces using a small sample of nonanonymized GPS traces covering multiple locations in Scotland.

For all of its methodological sophistication most recent work in computational movement dynamics is limited in its ability to account for known demographic, social, and economic drivers of mobility. For example, a comprehensive review titled "Human Mobility: Models and Applications," Barbosa et al. (2018) provided little insight on how to marry trajectories and the demographic characteristics of moving people. We believe that such models can (and should) accommodate demographic information. The concept of generalized activity spaces could be easily integrated into work on movement from physics and other disciplines. For example, Schläpfer et al. (2021) developed an argument that that the probability of visiting a particular location—in this case a location is a grid cell on a map—can be predicted by

$$p_i(\mathrm{r},\mathrm{f}) = {}^{\mu_i}/_{(rf)^\eta}$$

where r is the distance of a person's home from that location, f is the number of previously observed visits, and μ_i is a parameter describing the attractiveness of a place. From a social scientific perspective, this formulation is challenging because of its total disregard of the characteristics of a person. It implies that the attractiveness of a place is universal and race or socioeconomic status does not affect the attractiveness of a place. Generalized activity spaces provide a way to better account for social, demographic, and economic attributes within these and other equations; for example, by making $p(\mathrm{r},\mathrm{f})$ or μ conditional on g, where g is an observed type of generalized activity space.

Despite the arguments in favor a "generalized" approach to activity, it is not at all clear how these generalized representations of spatial behavior might be identified empirically, scaled-up from individual characteristics and trajectories. One approach could be to group people based on the neighborhood (or census zone) in which they live and to use such groupings to identify a sphere of activity for the residents of a particular area. Miller (2007) and Wellman, Boase, and Chen (2002), however, argued that the nature of place is changing; new technologies and the subsequent intermingling of real and virtual spaces have altered the meaning of residential location such that people living near each other can have very different daily experiences. By this argument, residential location is of declining importance. Forrest and Kearns (2001) noted, "it would seem that as a source of social identity the neighborhood is being progressively eroded with the emergence of a more fluid, individualized way of life. Social networks are city-wide, national, international and increasingly virtual" (2129). Such effects have been exacerbated because of the COVID-19 pandemic, although with heterogeneity between those who have worked or could work from home (Bick, Blandin, and Mertens 2021; Trasberg and Cheshire 2021). Miller (2007) argued that the declining influence of place on human experience due to space adjusting technologies will increasingly lead to the potential for a place-based fallacy. The place-based fallacy occurs when one incorrectly infers the attributes, activities, or experiences of people based on the places they live. Although it is possible to group space–time paths based on residential location, the place-based fallacy suggests that this could lead to spurious conclusions about activity spaces because it would mix heterogenous groups.

Another type of approach might be to focus on characteristics of the movement itself via the techniques emerging from computational movement analysis. For example, McArdle et al. (2014), Laube, Imfeld, and Weibel (2005), and Dodge, Weibel, and Lautenschütz (2008) developed ways to create taxonomies or clusters of movement patterns based on geometric characteristics; Buchin, Dodge, and Speckmann (2014) extended this idea by developing ways to measure the similarity of trajectories accounting for the context in which the movement takes place. Similarly, Jaegal and Miller (2020) developed wats to measure the similarity of space–time prisms. Shoval and Isaacson (2007) used sequences of visiting locations to identify types of trips. Demšar et al. (2018) used aggregated data to show urban circulation patterns via the density of paths in a place-time. These approaches, however, neglect the characteristics of the moving entities, in part because human movement databases tend to be attribute poor.

Demographic characteristics and movement are intertwined. The COVID-19 pandemic clearly highlighted this. Using mobile phone trajectory data, Weill et al. (2020) showed how area-level socioeconomic status is clearly related to movement patterns before and during the pandemic, suggesting that wealth creates a kind of elasticity of movement: Wealthier areas were more able to reduce movement during the pandemic than lower income areas. This work is unfortunately limited by data availability. Demographic and economic information for the national extent is only available at the area level, so although the individual movements of phones are tracked, the characteristics of those people transporting them are unknown. The socioeconomic trends in Weill et al. (2020) are established by ascribing the ecological characteristics of the area where the phone spends the night to the person.

Social and Economic Drivers of Generalized Activity Spaces

The concept of a generalized activity space links movement to demographic and economic characteristics. It is rooted in the idea that similar kinds of people use space in similar ways. We use the concept of lifestyle to define groups of similar individuals. Lifestyle can be considered both an independent and dependent variable (Kipnis 2004). Marketers typically take the latter position, viewing lifestyle as a product of consumption. In the transportation literature, though, lifestyle is traditionally viewed as an independent variable, a shaper of active spaces, not a consequence of them (Hanson and Hanson 1981; Salomon and Ben-Akiva 1983; Dieleman, Dijst, and Burghouwt 2002; Kressner and Garrow 2012; Dong, Allan, and Cui 2015).

Dog bones describe one lifestyle, where a person has a single home and a single job and commutes regularly between them; the illustration links a lifestyle to an activity space. The idea of lifestyles starts

> with the assumption that tastes are neither completely determined by economic status, as was implied by Marx, nor totally individualized. Tastes are determined in part by relative position in the markets for wealth and prestige, in part by individual choice informed by education and experience, and in part by voluntarily chosen, collectively held standards that determine lifestyles. Lifestyle differentiation takes place both inside and outside the markets for wealth and prestige and hence crosscuts them. (Zablocki and Kanter 1976, 269)

Salomon and Ben-Akiva (1982) defined lifestyle relative to an individual's choice in three domains: (1) formation of a household, (2) participation in the labor force, and (3) orientation toward leisure. Lifestyles are determined by a person's behavior in family, work, consumption, and leisure. Therefore, by observing these variables it should be possible to gain insight into a person's lifestyle. Thus, lifestyles exist in the middle space between microscale individual decisions and macroscale social and economic forces that constrain choice.

Generalized activity spaces, as a concept, are closely linked to the concept of lifestyle, the idea being that economic, demographic, and activity data in combination might be used to identify general types of activity spaces. The aspatial concept of lifestyle could have a generalized spatial projection. Lifestyle and location are not independent, however, and, to varying degrees, might be endogenous. This raises questions about how to best approach the generalization of activity spaces. Area-based units of analysis could be problematic because of the place-based fallacy identified by Miller (2007). On the other hand, geographic units of analysis might describe shared social, cultural, and political experiences that translate into shared drivers of behavior. One alternative to area-based units of analysis is to focus exclusively on lifestyle as an alternative to place. Grouping people with similar lifestyles might provide a basis for the generalization of activity spaces. Lifestyle is constrained by location, though, so ignoring location completely seems suboptimal. An analytical point of entry is necessary to create generalized activity spaces, such as the dog bone, but does lifestyle or location provide a better basis for aggregation?

Data

There are few data sources that integrate rich individual-level demographics and human movement. GPS traces of mobile phone users are locationally rich but demographically poor: They provide high spatial and temporal resolution data about location but almost always lack meaningful demographic and economic data about the user. The only data set that we were able to obtain that contained rich descriptions of spatial behavior coupled with demographic and economic data about respondents was a 2001 travel survey in Atlanta, Georgia, which consisted of three survey instruments. Although these are dated, the purpose of this analysis is to explore the viability of a concept, rather than provide an empirical understanding of these specific sets of collective behaviors. As such, for this example, we are not interested in the urban geography of Atlanta per se; rather, this offers a conveniently workable data set with limited access constraint. The sample is large and balanced by socioeconomic status and county of residence (the Atlanta Metro has thirteen counties), and it includes 7,552 heads of household. Household heads completed a travel diary describing their travel patterns (origin, destination, time, purpose, and mode of travel). All trip origins and destinations were geocoded. The database includes 34,582 trips. Each household's trips were recorded by phone interview and were reported over a two-day period. The data are suited to the problem at hand because they include both detailed individual-level demographic characteristics and detailed records of spatial behavior. The data were downloaded from the University of Minnesota Travel Survey Data Archive.

Methods

To assess the viability of generalized representation of activity we ask the following questions: Do people who live in similar locations have similar activity traces? Independent of location, do similarities in lifestyle translate into similarities in the use of space? As such, a key contribution of this article is to look for evidence of group-specific patterns across two-dimensional projections of activity traces. These methods are exploratory, aimed at suggesting further directions for the identification of generalized activity spaces. Three different ways of grouping paths are explored: First, location-based aggregations of space–time paths are created, then nonspatial aggregates based on the notion of lifestyles are constructed, and finally we explore the joint combination of location and lifestyle. This article does not explicitly consider the temporal component of space–time path, but this might be an important differentiator of generalized activity spaces in future extensions to this work.

Activity Space Standardization

The principal challenge to the identification of generalizable patterns of paths across space and time is that these detailed geolocation data tend to encode a great deal of information about the configuration of the built environment that might obscure generalizable trends. Space–time paths are very sensitive to local constraints such that two semantically identical paths in different places would appear different because they are shaped by one's position in the urban field. For example, a delivery driver who works in the central business district and lives in a middle-class suburb on the northern edge of the city would have a different activity space than a delivery driver who lives on the western edge of the city by virtue of both configurational differences in the built environment in different parts of the city and the simple fact that one has a south–north commute and the other has an east–west commute. These two delivery drivers, although they have different activity spaces because they live in different places, are otherwise very similar. At one level of abstraction the delivery drivers lead very different spatial lives, yet at another they are quite similar.

To directly compare the activity spaces of the two delivery drivers, the paths must be expressed in a standardized form that abstracts them from their locational constraints. A common way in which a variable can be standardized is by expressing it in terms of deviations from the mean; a corollary is that activity spaces can be standardized by expressing them as deviations from a common reference point. Thus, as the standardization of numbers makes them unitless, the standardization of activity spaces makes them "placeless." Calkins and Marble (1980) developed polar transformations for geographic data and Saxena and Mokhtarian (1997) first used this technique to standardize travel patterns using a home–work axis. Kwan (1999, 2000) also used this technique to produce geographic information system (GIS) style overlays of spatiotemporal activity patterns. Standardization to the home–work axis potentially allows one to statistically compare activity spaces, but it only works for people who are employed in a single job. For those who do not work or who have multiple jobs, standardization of paths to a home–work axis is problematic. One of the persistent challenges to the idea of generalized activity spaces is therefore the difficulty of standardizing space–time paths.

We standardize activity spaces using a polar coordinate system that was constructed for each of the 7,552 households in the analysis. Polar coordinate systems look like a dartboard and the bullseye is the origin of the projection. Degrees are measured as departures from some arbitrary azimuth, conventionally due east or due north. If the azimuth is due east, zero degrees is due east, 90 degrees is south, and so on. Distance from the origin, when combined with the angular departure from the azimuth, provides a unique location on a polar coordinate system. On planar coordinate systems locations are described by an x, y pair where the x and y coordinates represent distance from some arbitrary reference line, and polar coordinates are given by their angle of displacement from an arbitrary reference and distance from the origin (ρ and θ, respectively). We defined the origin of each person's coordinate system as their residential address, and the reference axis (i.e., 0 degrees) as a line drawn between the address and the Atlanta City Hall (Figure 2). Although Atlanta is a large polycentric area, employment density Downtown is almost twice (55.21 people/acre) that of the next nearest center (Emory 29.39 people/acre), and the residential–workplace flows that one might expect because of such geography are borne out in our sample. For each person, trips were projected onto their unique, personal polar coordinate system. Figure 2 graphically illustrates the outcome of the projection procedure. There are people living within two houses, i and j, the city hall (indicated by the building with a flag on top), and a supermarket (indicated by the shopping cart). For each person, a unique polar coordinate system is defined from their household location. The supermarket can be described by a single coordinate vector in a Euclidean coordinate system. After the projection, the coordinates of the supermarket are defined relative to each house's unique coordinate system. Projecting paths to an individual-specific polar coordinate system allows the generalization and standardization of paths.

We fully recognize that our method of standardization is imperfect. Atlanta is a polycentric city, making a choice of a reference direction somewhat problematic. In spite of this shortcoming, we believe it to be effective for expository purposes, and we empirically test the standardization in later sections. We hope that others will innovate and develop new ways of standardizing activity. One interesting potential approach to standardization lies in the work of Pappalardo et al. (2015), who used semantic information about activity, the kinds of places people go, as captured in a travel diary, to generatively

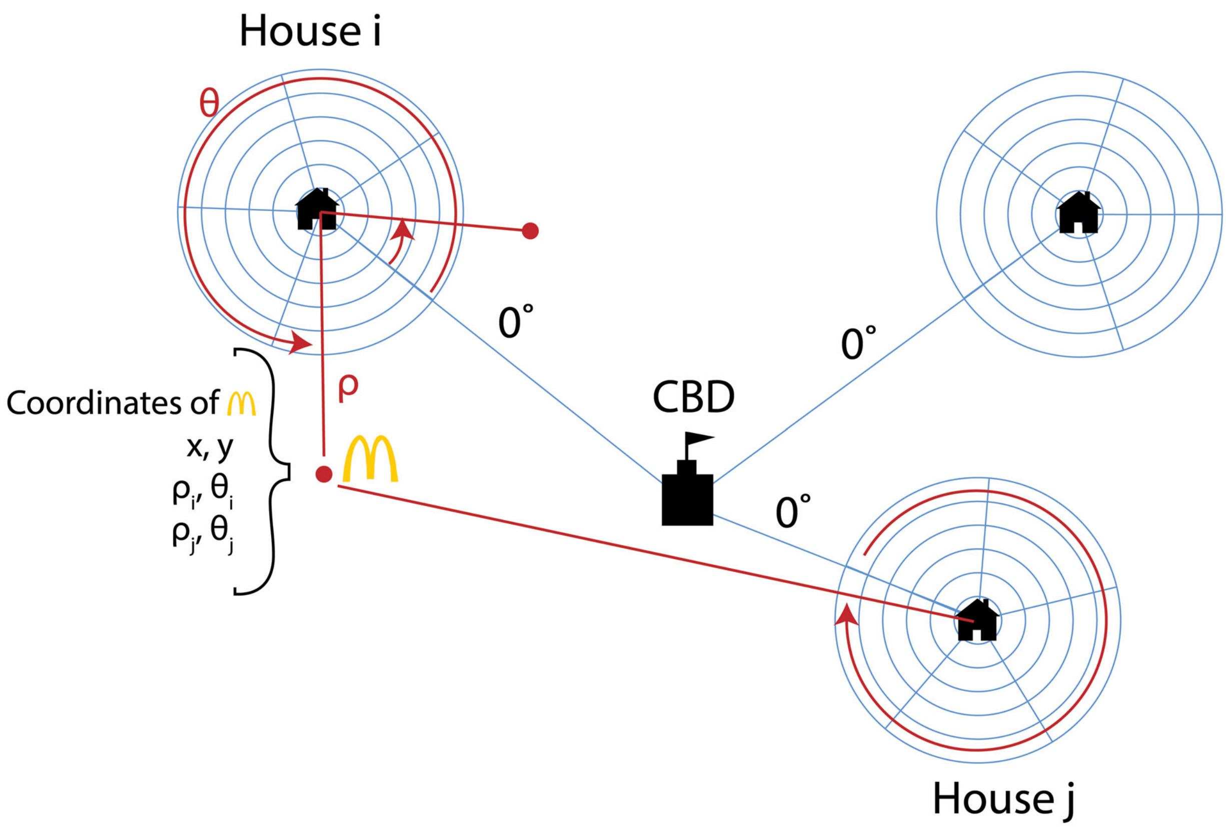

Figure 2. A simplified example of polar reprojection. *Note:* CBD = central business district.

simulate travel patterns. The idea is that generalized activity sequences might have some potential basis for synthetically creating generalized activity spaces.

Identifying Lifestyles

Lifestyle segmentation systems divide populations into discrete groups based on similarities in behavioral or demographic characteristics. Segmentation is widely used in the commercial sector because of its ability to profile consumption patterns (Webber and Burrows 2018). These systems are also useful for profiling general travel behavior (Hincks et al. 2018; Martin et al. 2018; Birkin 2019). Constructing lifestyle groups is a technical exercise and there are a variety of different options available to analysts, including cluster analysis via K-means or other clustering algorithms (Singleton and Spielman 2014), data reduction techniques such as self-organizing maps (SOM; Spielman and Thill 2008; Y. Liu, Singleton, and Arribas-Bel 2019), or latent class analysis, which is commonly prescribed to individual-level data (Swait 1994). A latent class represents a variable that is not directly observable (in this case, "lifestyle"), with the probability that people belong to a group given their observed characteristics. In this instance, latent class analysis has some important advantages over *k*-means type cluster analysis. First, it accepts a variety of input measurement types; although initially the technique was conceived for categorical data, in its modern implementation it allows for input of mixed data including nominal, ordinal, count, and continuous data. Because classifications are model-based one can evaluate how well a given classification scheme fits the data using likelihood ratio chi-square statistics and other information criteria such as the Bayesian information criterion (BIC) or Akaike information criterion (AIC).

Directional Statistics

Directional statistics are used to analyze angular observations and are particularly useful when working with polar coordinate systems. The angular component of a set of points in a polar coordinate system can be described in terms of their directional mean and degree of dispersion, dispersion measures how evenly distributed observations are around the mean (Mardia 1972; Rohde and Corcoran 2015). With directional data conventional statistical procedures are not appropriate, for example, taking the arithmetic mean of trajectories in the 1- and 359-degree direction would be incorrect. There are a limited number of hypothesis tests for directional distributions, these examine: (1) the uniformity of a distribution (Rayleigh test), which measures the extent to which the vectors are distributed evenly in all directions around the circle; (2) the equality of a set of directional distributions (circular analysis of variance); and (3) the equality of a pair of distributions (Watson two-sample test; Lund and Agostinelli 2007). We employ these tests to compare standardized trajectories for geographic and lifestyle-based groups of people.

Research Design

We argue that the standardization of space–time paths makes it possible to compare travel patterns without regard for the effects of location. We explore this empirically in a series of hypothesis tests implemented using directional (or circular) statistics. These tests allow us to determine if lifestyle or location-based groups have statistically significant differences in directional means or degrees of dispersions. Activity spaces with different directional means and amounts of dispersion, if standardized and superimposed, will show a different use of space. Directional statistics are a simple, parsimonious mechanism for finding differences in complex spatial patterns. The use of direction statistics is also limiting, however. It allows the identification of group-level differences but it does not permit identification of shapes, or areas, that might constitute a generalized activity space.

We evaluate a series of simple null hypotheses to test the efficacy of the standardization and identify both lifestyle and place-based geographic regularities in activity spaces. The null hypotheses are:

1. The mean direction of travel is equal in all residential locations.
2. The amount of variability in trip direction (trip dispersion) is equal in all residential locations.
3. The mean direction of travel is equal for all lifestyle groups.
4. The amount of variability in trip direction is equal in all lifestyle groups.
5. The mean direction of travel is the same for all groups defined by the interaction of lifestyle and location.
6. The amount of variability in trip direction is the same for all groups defined by the interaction of lifestyle and location.
7. The mean distance traveled is the same for all lifestyle groups.
8. The mean distance traveled is the same for all locations.

Hypothesis tests 1, 2, and 5 examine the efficacy of the standardization, and if effective, these null hypotheses will be rejected with the direction and dispersion of space–time paths not being geographically differentiated. Hypotheses 3, 4, and 6 examine the impact of lifestyle on space–time paths, and these hypotheses will be rejected if lifestyle is not associated with the direction or variability in travel patterns. Hypotheses 4 and 5 examine the interaction of lifestyle and location, and instead of defining groups geographically or based on their lifestyle, for these tests' groups, cases are defined through the cross-product of lifestyle and location. A person with lifestyle *A* in location *B* is in a different group from a person with lifestyle *A* in location *C*. Hypotheses 7 and 8 examine the distance traveled.

Results

Lifestyle Analysis

The data include a total of 7,552 people collectively making 34,582 trips during the survey period. The analysis was restricted only to adults (over the age of eighteen) who were the primary survey respondents. Individuals with missing data were omitted from the classification. We used all available demographic and economic variables. The groups are primarily differentiated by employment, household size, and home ownership (see Table 1 and Figure 3).

The latent class analysis was implemented, and a four-class model (Table 2) selected that optimized AIC and BIC, and accounted for 76 percent of the variance in the data set, meaning that the negative log likelihood from a one-class model decreased 76 percent with the addition of three classes to the model. The results are shown in Figure 3 where the *x* axis shows each of the variables included in the analysis standardized to 0 to 1 range, with the lines representing the mean value of each variable for each class.

Table 1. Latent class analysis input variables

Variable	Description
Age	Ordinal variable with five age ranges
Home ownership	Indicator variable for home ownership
Vehicle ownership	Number of vehicles per household
Ethnicity	Ethnicity (White, Black, Hispanic, Asian/other)
Employment	Indicator variable for full-time employment (35 hours/week at one job)
Professional	Indicator variable for those who identify as "professionals" or "managers"

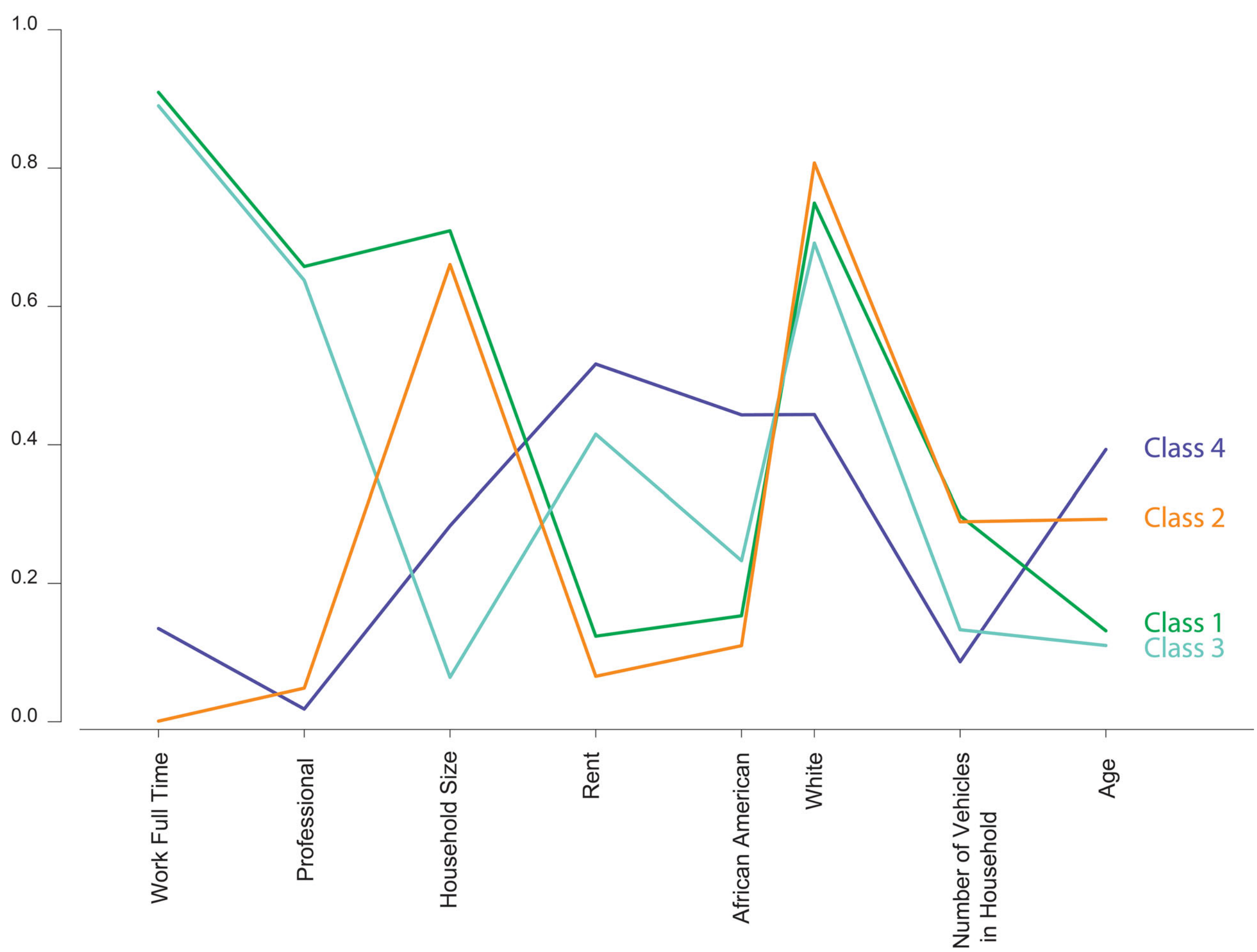

Figure 3. Lifestyle class profiles.

Two groups (Classes 1 and 3) consist of people who work full time, forty hours per week, a large proportion of whom call themselves professional or managerial workers. Two groups (Classes 2 and 4) include people who either work part time or do not work (i.e., are unemployed, disabled, retired). Almost half of the people (44 percent) are in groups with a high proportion of full-time workers, who self-identified as professionals or managers, owned their own home, lived in multiperson households, and owned multiple cars. The second group of full-time workers (Class 3) represented 19 percent of the people. By contrast they lived in small households, had a much higher tendency to rent their home, were younger, owned fewer cars per household, and although largely White had higher probability of being African American, Hispanic, or Asian than members of the first group. The two groups where part-time workers or unemployed were dominant represented 35 percent of the data set and on

Table 2. Lifestyle groups

Class	Description
Class 1: Professional families	Young professional families who own their home and multiple cars; predominantly White
Class 2: Part-time, nonprofessional families	Older families; own multiple cars; nonprofessional, do not work full time
Class 3: Professional singles	Young professional singles who are equally likely to own or rent their home; usually own one car; Predominantly White
Class 4: Older non-full-time workers	Older racially diverse renters who are unemployed, retired, or work part time; lowest vehicle ownership

average were older than members of the group containing full-time workers. The first group (Class 2), representing 22 percent of the people, lived in large households, tended to own their home, owned multiple cars, and had a very high probability of being White. The second group (Class 4), representing 13 percent of the data, was the most racially diverse group, and had the highest probability of renting their home. They also owned the lowest number of vehicles per household.

Figure 4 shows the aggregation of all activity traces for members of each lifestyle group. Paths are displayed using the polar coordinates from each person's coordinate system. The origin of the projection is each person's home, and the zero degrees is at the top of each panel.

If members of a particular lifestyle group are geographically clustered, the effect of location and lifestyle on spatial behavior might be confounded. That is, it becomes impossible to separate lifestyle and location effects. The difference of Ripley's K-functions comparing each of the lifestyle groups to the entire sample indicate that two of the lifestyle groups are significantly geographically clustered when compared to the geographic distribution of the entire sample. Statistical evaluation of the difference between two K-functions is difficult (see Diggle and Chetwynd 1991 for a discussion), a difference near zero is seen as evidence that the two K-functions describe similar patterns, a positive value can be interpreted as evidence of clustering. At all scales, Classes 3 and 4 (professional singles and older part-timers) appear to be geographically clustered. To reduce the impact of geographic clustering, locations were described using quadrants. The city was divided using north–south and east–west axes with City Hall at the center. Each person was associated with one of four quadrants; location thus became a categorical variable in the analysis. The objective was to minimize the effect that particular locations are strongly correlated with particular lifestyles. Moreover, the number and size of zones was constrained by sample size; the cross-tabulation of geographic and lifestyle groups would dilute the sample if too many geographic groups were used. The data we have available are imperfect, but we believe they are sufficiently robust for our purposes.

Distance and Directional Patterns

Generally, the number of trips in each lifestyle group was proportional to the number of individuals in the group. Figure 5 shows directional kernel density plots of trip direction for each lifestyle group. The number of trips in each direction determines the height of the kernel. When looking at the directional patterns interesting trends emerge, particularly when the groups representing full-time workers are compared to groups representing unemployed or part-time workers. In the groups representing full-time workers, there are many trips in the 180-degree range. These appear as bumps in the kernel density plots of trip frequency by direction for each group. This bump occurs because people tend to run errands on their way home. The morning commute (in the zero-degree direction) represents a single trip, but the trip home, if it includes multiple stops, appears as multiple trips, yielding a spike in the distribution.

The profiles in Figure 5 represent only the directional component of trips; short trips and long trips are not differentiated. If lifestyle groups have different directional profiles it seems, as a matter of course, that they will have different activity spaces. Without regard for distance, if groups tend to travel in different directions within the standardized space, they are using the space around their home in a different way. It is possible, however, that many short distance trips, with varied directions, could yield a

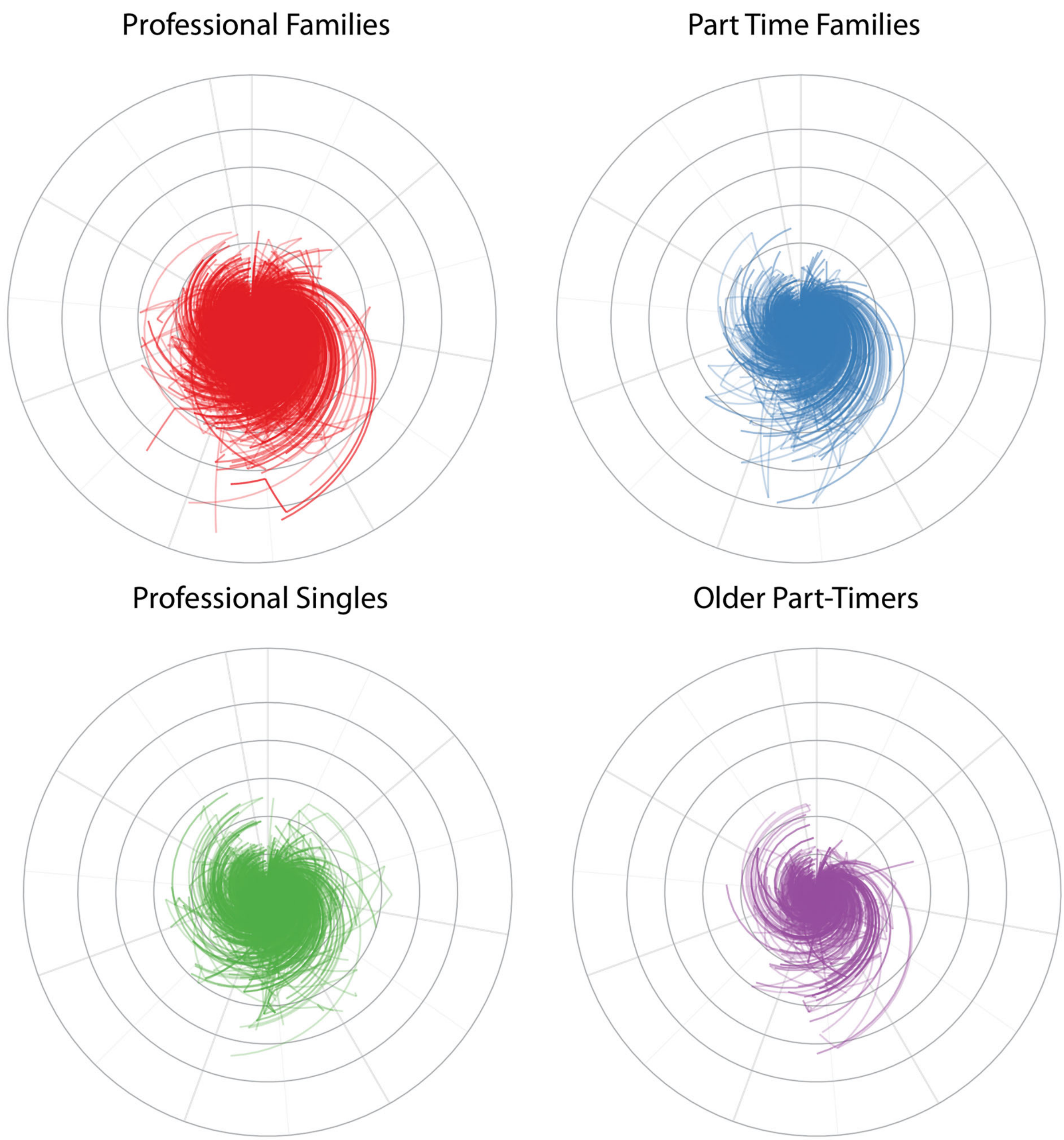

Figure 4. Spatiotemporal activity traces aggregated by lifestyle.

generalized activity space like one with fewer long trips even though it would have a different direction distribution.

The analysis found that lifestyle, location, and the interaction of lifestyle and location were not significant predictors of the mean travel direction for the standardized data (Table 3). Location was not associated with the variability of directional patterns, but lifestyle was associated with variability. This finding also held for an interaction of lifestyle and location; that is, people of the same lifestyle in different locations had different amounts of variance in the directions they traveled. This provides some support for the efficacy of the standardization; it shows that the standardization washes out the directional effects of location. Lifestyle, regardless of where a person lives, is associated with the directional variability of travel (but not the actual direction).

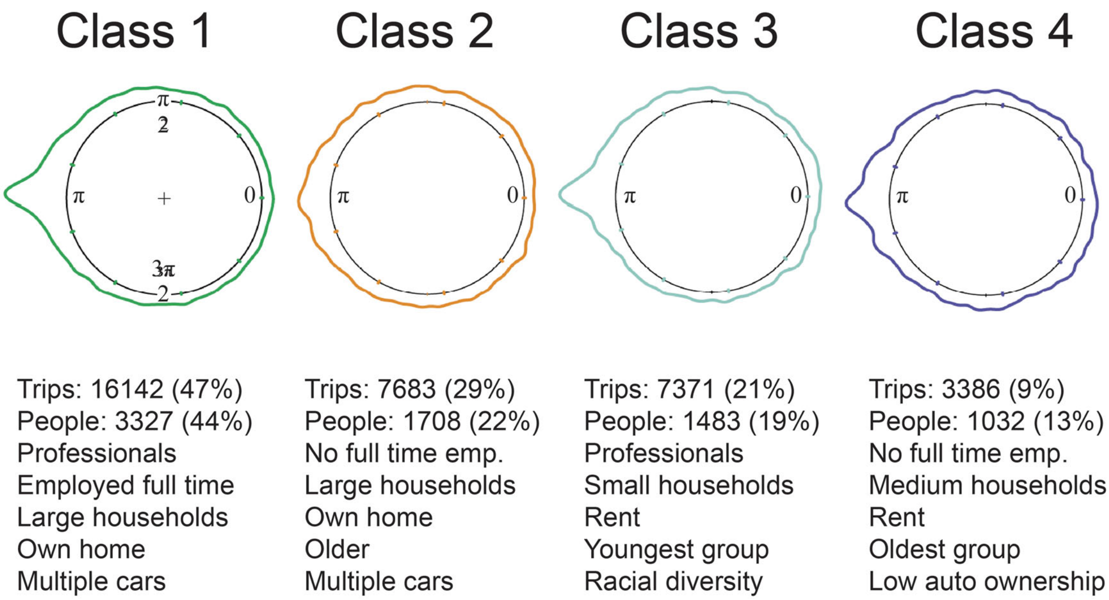

Figure 5. Lifestyle group directional profiles.

Table 3. Summary of hypothesis tests

	Location	Lifestyle	Location*Lifestyle
Mean direction	Hypothesis 1: Not significant ($p = 0.1185$)	Hypothesis 3: Not significant ($p = 0.6576$)	Hypothesis 5: Not significant ($p = 0.4311$)
Dispersion	Hypothesis 2: Not significant ($p = 0.6167$)	Hypothesis 4: Significant ($p = 0.00599$)	Hypothesis 6: Significant ($p = 0.00544$)

Table 4. Distributional hypothesis tests

Null hypothesis	Test	Result	Significance
The lifestyles have the same directional pattern	Watson two-sample test	Reject (for all pairwise comparisons)	$p < 0.001$
Randomly selected subsets of the data have the same directional pattern	Watson two-sample test	Accept (for all pairwise comparisons)	$p > .10$
Travel isotropic (entire sample)	Rayleigh test for uniformity	Reject	$p < 0.001$
Travel isotropic (latent classes)	Rayleigh test for uniformity	Reject (for all groups)	$p < 0.001$

To further explore the differences and similarities among groups, a series of pairwise comparisons were conducted. A Watson two-sample test of homogeneity was used to test the null hypothesis that a pair of lifestyle groups have the same directional travel patterns. The same null hypothesis was examined for four randomly generated groups. For all pairwise comparisons of lifestyle groups there were significant differences in directional distributions (Table 4). These results agree with previous studies and find statistically significant differences in travel between analytically derived population groups (Pas 1982; Salomon and Ben-Akiva 1982; Goulias et al. 2007) and are also supported by the tests in Table 3. For randomly generated groups there was no difference in directional distribution (Table 4); this test was done to verify the utility of the method. We recognize the potential multiple testing problems here but are unaware of an alternative for directional distributions.

Hypotheses 7 and 8 examine the distance traveled and were tested using a standard analysis of variance and Tukey's honestly significant difference (HSD) test. For all pairs of lifestyles and quadrants, the difference in mean trip length is significant ($p < .0001$, except for the comparison between grayer part-timers and part-time families, which had $p = 0.003$).

Finally, the null hypothesis that travel has a uniform directional distribution was examined; that is, do travel patterns tend to be isotropic relative to a person's home? This is particularly pertinent given that lags in spatial analysis often assume isotropy. These results challenge this assertion, however. The Rayleigh test of uniformity rejected the null hypothesis that travel is isotropic both for the entire sample and for each lifestyle group (Table 4; Figures 4 and 5).

Discussion

This article examines the feasibility of identifying generalized activity spaces to link individual and area-based definitions of sociospatial context and to provide a framework for incorporating socioeconomic data into large-scale studies of human movement. Lifestyle, residential location, and the combination of lifestyle and location are examined as a basis for defining generalized activity spaces. The goal was to test the tenability of the concept of generalized activity spaces and to identify avenues for further development of the concept.

Our analysis finds that lifestyle seems to be associated with the amount of variability in the direction that a person travels but not the actual direction: People with similar lifestyles exhibit similar variance in travel direction. This is not true of geography, as location is not associated with the variability or the mean direction of travel, and this finding supports Miller's (2007) place-based fallacy. People with similar lifestyles but residing in different locations seem to have different amounts of variability in travel. The separation of lifestyle and location was not as neat as one would have liked, as some lifestyles are geographically clustered. The similarities and differences identified are based on an analysis at a rather coarse granularity, but this level of abstraction was necessary to prevent the confounding of lifestyle and location, as using finer units of analysis would have caused particular locations to be dominated by particular lifestyles. Furthermore, Stopher et al. (2007) noted that twelve days of tracking information might be necessary to gain a full understanding of an individual's activity patterns, as beyond twelve days the patterns tend to get repetitive. This analysis used a large sample of short-duration activity paths, but a more robust and freely available data set with longer duration travel and deeper demographic richness would not only advance interrogation of the concept of generalized activity spaces, but would substantially advance the field.

Standardized space–time paths are not isotropic (as indicated by the Rayleigh tests in Table 4), a finding confirmed by Gonzalez et al. (2008). This has some implications for the spatial social sciences. First, anisotropy in spatial behavior raises questions about the use of radial buffers or simple contiguity-based weights matrices in spatial analysis of behavior. Radial buffers, commonly constructed "as the crow flies" or using the street network, are not supported by this analysis. Even when location is standardized, travel patterns are not uniformly distributed in all directions. Second, this raises some interesting questions about how to best characterize the shape of human activity spaces. For example, Sebastian, Klein, and Kimia (2002) developed a shape similarity metric that can be used to query databases of shapes to identify objects with a similar morphology. An interesting area of future work might be incorporating such metrics into movement databases or identifying the extent to which similarity in the morphology of movement patterns relates to individual characteristics and residential location. One might hypothesize that within location-demographic groups, shapes are more similar than across groups; that is, living in the same census tract and having similar demographic characteristics leads to similarly shaped activity spaces. Our preliminary work here suggests that both who you are and where you live may interact to shape the morphology of activity spaces. Doi, Mizuno, and Fujiwara (2020) take an interesting approach by inverting the problem, trying to estimate individual characteristics from semantically enriched GPS traces. By using GPS traces to understand the nature of the places that people stopped, they estimated gender and age with mixed success.

Generative approaches seem an extremely promising alternative to focusing on the geometric characteristics of observed movement. Pappalardo and Simini (2017) developed ways to generate synthetic activity patterns based on travel diaries. Extending this idea, if one created a lifestyle-specific sequence of activities, one could synthetically generate a potential activity space for a specific type of person in a specific location. This would sidestep the need to empirically estimate the shape of a generalized activity space by allowing a researcher to generate one (or many) based on the characteristics of a person.

With a robust data set describing human activity, that covered many types of places, one might be able to determine if there are generalizable shapes—informed by demographics and locational characteristics. Successfully identifying generalized activity spaces would allow more detailed understanding of social and environmental exposures without requiring invasive GPS-based tracking of people. The COVID-19 pandemic highlights the need to understand how spatial behavior is conditioned by socioeconomic characteristics. Although studies such as Weill et al. (2020) made it clear that area-level characteristics are associated with spatial behavior, generalized activity spaces add precision to this idea by providing a generic framework for understanding how location and lifestyle shape potential behavior. If developed to fruition, generalized activity spaces would allow one to proactively estimate exposure risk for types of people in types of places without a reliance on ex post facto analysis.

Conclusions

Taken together, these hypothesis tests suggest potential for the concept of a generalized activity space. There is more work to be done to develop the concept and a need for better understanding of how lifestyle conditions the relationship between the environment and behavior. Here preliminary evidence in support of the idea that different types of people have different prototypical activity patterns is presented. We argue that generalized representations of activity spaces overcome the spatial and locational fetishism inherent in time geography and the neglect of individual spatial behavior in most research on neighborhood effects. We find that people who live near each other do not have similar space–time paths but nearby people with similar lifestyles do. Statistically significant differences were found for sixteen discrete lifestyle–location categories, suggesting that activity spaces are simultaneously conditioned by both who you are and where you live.

We present the concept of a generalized activity space while recognizing significant room for theoretical and empirical improvements. In the future, we hope that the fusion of individual characteristics (or lifestyles) and movement patterns can be more elegantly executed if and when better data become available. The tractability of the concept of generalized activity spaces was explored, and it seems to have promise as way to bridge multiple perspectives and reconcile tensions in the literature.

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