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ORIGINAL ARTICLE

A place-based model of local activity spaces: individual place exposure and characteristics

Kamyar Hasanzadeh[1] · Tiina Laatikainen[1] · Marketta Kyttä[1]

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Abstract Researchers for long have hypothesized relationships between mobility, urban context, and health. Despite the ample amount of discussions, the empirical findings corroborating such associations remain to be marginal in the literature. It is growingly believed that the weakness of the observed associations can be largely explained by the common misspecification of the geographical context. Researchers coming from different fields have developed a wide range of methods for estimating the extents of these geographical contexts. In this article, we argue that no single approach yet has sufficiently been capable of capturing the complexity of human mobility patterns. Subsequently, we discuss that reaching a better understanding of individual activity spaces can be possible through a spatially sensitive estimation of place exposure. Following this discussion, we take an integrative person and place-based approach to create an individualized residential exposure model (IREM) to estimate the local activity spaces (LAS) of the individuals. This model is created using data collected through public participation GIS. Following a brief comparison of IREM with other commonly used LAS models, the article continues by presenting an empirical study of aging citizens in Helsinki area to demonstrate the usability of the proposed framework. In this study, we identify the main dimensions of LASs and seek their associations with socio-demographic characteristics of individuals and their location in the region. The promising results from comparisons and the interesting findings from the empirical part suggest both a methodological and conceptual improvement in capturing the complexity of local activity spaces.

✉ Kamyar Hasanzadeh
kamyar.hasanzadeh@aalto.fi

Tiina Laatikainen
tiina.laatikainen@aalto.fi

Marketta Kyttä
marketta.kytta@aalto.fi

[1] Department of Built Environment, Aalto University, PO Box 14100, 00076 Aalto, Finland

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1 Introduction

Researchers from various fields have long been interested in analyzing and describing human mobility patterns. Increase in interest in human spatial behavior is also reflected in a "mobility turn" in social sciences which is marked by a focus on person-based and dynamic analysis of mobility patterns and a departure from static and "sedentarist" approaches (Sheller and Urry 2006; Faist 2013). These approaches have been specifically important in social sciences, as well as in health geography, and environmental health promotion research. Accordingly, a considerable amount of research has focused on assessing the human exposure to specific environmental characteristics to find empirical evidence of their associations with health and wellbeing (van Kamp et al. 2004; Mitchell and Popham 2008; Zenk et al. 2011; Perchoux et al. 2013; Kyttä and Broberg 2014). Additionally, researchers studying human activities and mobility have been identifying relationships between urban form, socio-demographic characteristics, and mobility behavior among various social groups (e.g., Ewing and Cervero 2010; Naess 2012; Kwan 2012a; Patterson and Farber 2015).

Although some studies have been able to verify the importance of urban environment on inhabitants' lived experiences (Dalgard and Tambs 1997; Frank and Engelke 2001; Dye 2008), the results from prior research on environment–health relationship have generally revealed marginal influence of contextual factors (Pickett and Pearl 2001; Diez Roux 2004; Subramanian 2004; Adams et al. 2009; Kyttä et al. 2015). A growing number of researchers attribute the weakness of observed associations to the misspecification of contextual boundaries (Spielman and Yoo 2009; Kwan 2012b; Perchoux et al. 2013; Vallée et al. 2014). In these studies, it is crucial to have a precise understanding of not only the extents of the geographical context, but also place exposures (Matthews 2011; Vallée et al. 2011). However, our understanding of exposure in social sciences and environmental health research appears to lag behind researchers from exposure sciences (Matthews 2011). Particularly, yet to this point, the environment–health research has not fully integrated the space–time behavior of individuals to draw a relevant way of assessing environmental exposure that can account for hypothesized contextual effects.

The growing literature from different fields of research such as public health, transportation, urban planning, health geography, epidemiology, and environmental psychology has brought along various terms for referring to the arguably similar concepts related to human activities and mobility in space and time. These terms include, but are not limited to, activity space (Schönfelder and

Axhausen 2004b), home range (Botte 2015; Hasanzadeh et al. 2017), territorial range (Broberg et al. 2013), action space (Dijst 1999a), home zone (Hamilton-Baillie 2000), and neighborhood (Vallée et al. 2011; Alidoust et al. 2017). These terms do not precisely represent the same concept. However, a considerable level of similarity is often present in how they are defined and treated by researchers. Although an explicit classification of these methods does not yet appear in current body of the literature, we believe their applications can be categorized under two major groups. First, activity space (AS), as an unrestrained part of the environment, which individuals use for their daily activities (e.g., Dijst 1999a, b; Schönfelder and Axhausen 2004a; Wong and Shaw 2011). Second, local activity space (LAS), a subarea of the same space that is exclusively concentrated around the individual's domicile or located in its immediate surrounding (e.g., Kyttä et al. 2012; Hasanzadeh et al. 2017). In this paper, to avoid confusions, we use these two terms.

While having their own pros and cons, both can be valid approaches depending on the context, geographical scale, and goal of the study. While AS approach is less restraining and broader in its geographical extents, the local approach can facilitate contextual analysis by presenting a more functional, bounded, definition of such spaces. Although the latter approach can be criticized for overlooking what is going on beyond its strictly defined boundaries, it may also be praised for enabling scrutiny; an opportunity for taking a closer look at the space containing the majority of the most frequent activity places (Flamm and Kaufmann 2006; Perchoux et al. 2013). Despite these differences, we should note that the geographical scope and focus are what mostly distinguishes the two approaches. Therefore, most theories and methods discussed under the broader term AS can also apply to LAS as its subarea.

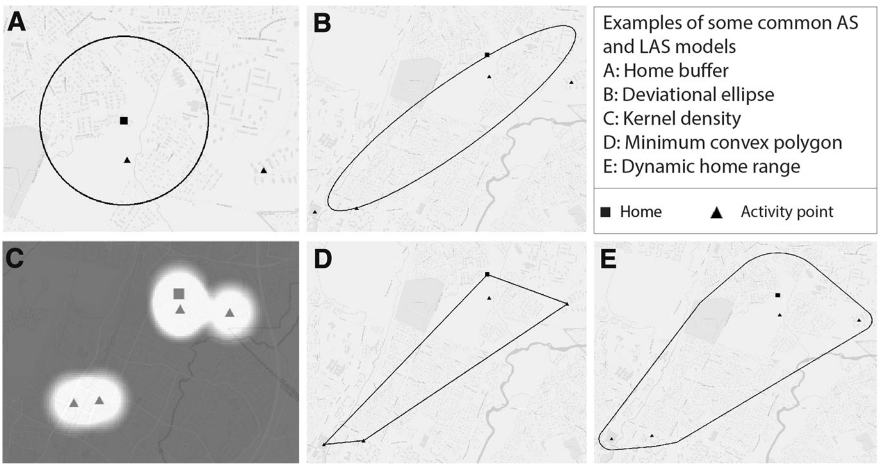

Fig. 1 Examples of various approaches used in previous research. More elaborate reviews of existing methods are presented in a number of studies (e.g., Golledge et al. 1997; Patterson and Farber 2015)

Reviewing the literature on AS and LAS reveals that the lack of consensus in this field is not limited only to the use of terminology as the spatial delimitation of these spaces is still a matter of ongoing discussion (Perchoux et al. 2013, 2016). Figure 1 presents examples from some of the most used methods. Until recently, research on the residential environment and health was mostly relying on administrative boundaries and census tracts to model LASs (Diez Roux 2001). In spite of their readily availability, administrative units are often ill-fitting solutions which typically do not represent the true individual area of exposure (Lee et al. 2008; Perchoux et al. 2013).

To tackle this limitation, research has more recently focused on ego-centered spatial models through circular (e.g., Seliske et al. 2009; Kyttä et al. 2016), or street network (e.g., Karusisi et al. 2013; Lee et al. 2015) buffers of different sizes typically centered around individual's residence. Although individual buffering is an important step forward in modeling LASs, the approach is not yet sensitive enough to the context and it does not account for individual differences in exposure areas (Perchoux et al. 2016). As a response to these limitations, person-based modeling has been discussed as a rallying theme for new research (Kwan 2009; Farber et al. 2012). Minimum convex polygon (MCP), dynamic home range (Hasanzadeh et al. 2017), standard deviational ellipse (Sherman et al. 2005; Arcury et al. 2005), and the shortest path area connecting the visited locations (Schönfelder and Axhausen 2003, 2004a) are some examples of such approaches.

All methods discussed to this point fall into the category of the so-called *container* approaches. A common limitation of these approaches is that they are based on the inaccurate assumption that people are equally exposed to all areas within the defined boundaries. In other words, in these approaches the geographical extent of environmental exposure is estimated while its magnitude and spatial variations are overlooked. This is a critical limitation as it can introduce biases as a result of overestimating exposure to certain contextual factors which appear to be abundant within the defined boundaries. For example, a high percentage of land covered by green areas in one's LAS does not necessarily imply a high exposure to this type of land. Depending on the person's mobility patterns, this exposure can be anything from very low to very high.

Despite the necessity for a more spatially sensitive LAS modeling, this has rarely been addressed in research. The few attempts on this often concern use of kernel density surfaces (Kestens et al. 2010; Schönfelder and Axhausen 2004a, b). This approach produces a heat map indicating the density of activity points throughout an individual AS. Although this is a step forward, we argue that this is not yet a comprehensive solution to the problem. These studies are not context-sensitive enough and can potentially be biased by the wrong assumption of equal accessibility throughout the modeled space (Weiss et al. 2007; Laatikainen et al. 2015). Furthermore, the accuracy of these models may be negatively influenced by their exclusive dependence on spatial density of visited points, while overlooking other potentially important factors such as frequency of visit, travel path, and transportation mode.

While Kwan (2009) discusses the importance of moving from place-based to people-based exposure measures, we believe that an integrative approach addressing both of these concurrently can result in a more comprehensive understanding. Further, we believe that ASs, and thus LAS as their subareas, are not only variable in their boundary (Hasanzadeh et al. 2017), but also throughout their surface. In other words, the place exposure not only varies from one person to another in its geographical extents, but also from place to place in its magnitude. The individualized residential exposure model (IREM) introduced in this paper is based on this understanding. IREM builds on existing literature and tries to provide a more refined picture of LASs through a better assessment of place exposure. This is accomplished by merging and integrating positive features of different methods such as kernel density surfaces, dynamic home range, and the shortest path area.

However, the complexity of LASs does not end with modeling them. In fact, understanding and interpreting these spaces following their modeling are far from easy and require a comprehensive and multidimensional approach. Accordingly, several studies have developed and used different measures to explore and evaluate various characteristics of AS and LASs. The majority of measures to this point focus on geometric characteristics, and perhaps the most common among them are those that describe the size of these spaces (Jarv et al. 2015; Kwan et al. 2016). The size of AS is meant to capture the degree of person's mobility and can be measured in a variety of ways. A common measure of AS size is the area of the MCP containing all locations visited by a person (Buliung and Kanaroglou 2006; Kwan et al. 2016). Standard deviational ellipses (SDE) are another widely used measure of AS size, dispersion, and other geometrical characteristics (Schönfelder and Axhausen 2003; Buliung and Kanaroglou 2006; Jarv et al. 2015). Besides size and dispersion, SDEs may be used to describe elongation and direction of ASs. Further measures aim to address the non-geometrical aspects of ASs, such as the types of visited destinations, or their intensity, which captures the number and frequency of unique visited locations over specific time frame (Perchoux et al. 2014). Although most of the studies have used single measures of ASs to describe their characteristics, a few studies have used multiple measures, compared them, and discussed the differences in their interpretation (Patterson and Farber 2015). In an isolated effort, Perchoux et al. (2014) looked at the interrelationships between various measures and identified five dimensions of AS measurement. The dimensions included (in order of importance) "centering of the AS on the residential neighborhood," "size of the AS," "volume of activities," "specialization of the AS," and "elongation of the AS."

Following this line of inquiry, and motivated to understand the model outputs better, we continue this paper by applying IREM empirically and trying to identify its main descriptive dimensions. Subsequently we explore the existence of associations between LAS, socio-demographic, and regional characteristics. This empirical part is based on a dataset collected through an online map survey, from aging citizens of Helsinki metropolitan area (55–75 years).

In short, this study pursues a threefold gold: First, to implement an improved model of LASs to enhance our understanding of these spaces. Second, to compare different LAS models and discuss their strengths and limitations as a reference for future empirical research. Third, to demonstrate the use of proposed model in an empirical case and exhibit a multidimensional approach for understanding and analyzing it. Consequently, we will conclude this paper by discussing our findings and reflecting on our method by identifying its limitations and potential significance for future research.

2 Materials and methods

Figure 2 illustrates a conceptual overview of the present study. As the first step, we create an individualized residential exposure model (IREM) of local activity spaces using information collected through a public participation GIS (PPGIS) method. The information used for creating this model include home location, daily errand points, frequency of activities, transportation mode, and potential travel routes. The model is subsequently compared with several other LAS models using the criteria adopted from Hasanzadeh et al. (2017). Eventually, the usability of the model is empirically demonstrated through a case study. In this empirical part, we identify the main dimensions of individualized LASs and seek whether they are meaningfully associated with individuals' socio-demographic characteristics as well as their location of residence in the region.

2.1 Data

The data used for modeling and the empirical case study were collected using softGIS methodology, a public participation GIS (PPGIS) method that combines Internet maps with traditional questionnaires (Brown and Kyttä 2014). The data collection was conducted in Helsinki metropolitan area (HMA), Finland. A random sample of 5000 residents of HMA aged between 55 and 75 was obtained from Finnish Population Register Center, and an invitation to participate in an Internet-based PPGIS survey was sent to participants' home addresses in October 2015.

In the survey (Fig. 3), respondents used an online interface to mark their daily errand points (DEP) on a map. The DEP categories included: leisure and recreational activity places, shopping, services, and sport facilities. For each category, examples were provided in the survey to help respondents. In addition, the

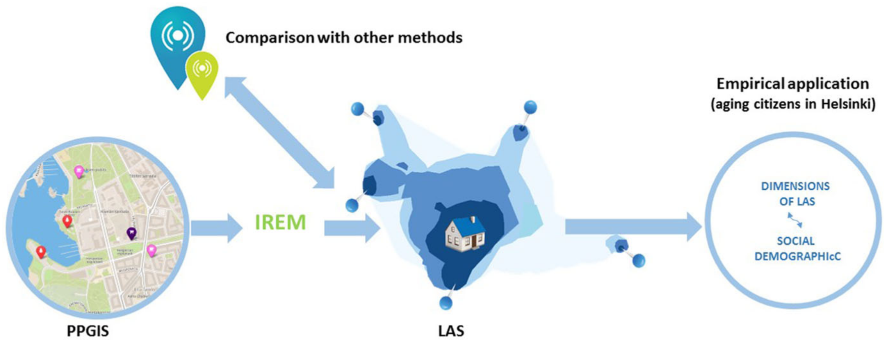

Fig. 2 A conceptual overview of the present study. *LAS* is short for local activity space

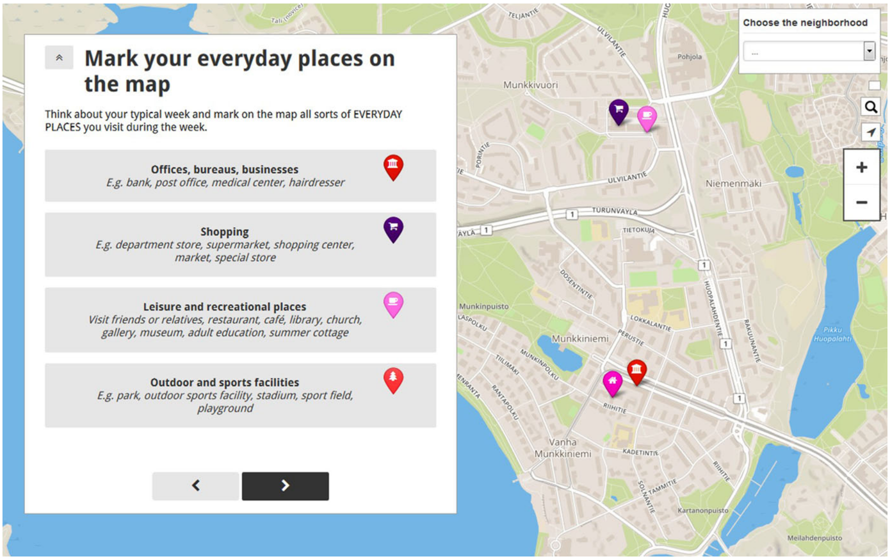

Fig. 3 Locating daily errand points in the 'Me and my everyday environment' PPGIS survey (accessible at: www.maptionnaire.com/825)

respondents indicated by which transportation mode and how frequently they accessed these places. The respondents were also asked to mark on a map their home and places of their everyday environment where they feel happy and answer a series of questions about their personal life goals, background, and health. There were 1139 full or partial responses, and after removing incomplete responses, 844 were taken for further analysis in the empirical part. The data showed general consistency with Statistics Finland on most socio-demographic variables ("Appendix").

To study the relationships between location in the region and LASs in the empirical part, we used the urban zone classification provided by Finnish Environment Institute (YKR). It is a GIS-based (250 × 250 m grid of cells) classification that divides urban regions into zones according to their location in the urban form (e.g., in relation to the city center), and travel-relevant variables, population characteristics, public transport supply, building stock, and jobs (Söderström et al. 2015). For this article, we used an aggregation into four zones starting from the most central areas identified as *urban*, through outer rings classified as, respectively, *semiurban* and *suburban,* to peripheral areas with more *rural* settings.

2.2 Individualized residential exposure model (IREM)

The present study takes an integrative approach to create an individualized residential exposure model (IREM) to estimate the LASs of the individuals. The modeling process described here was implemented using Python programing language and ESRI Arcpy package and was applied for each individual through automated iterations.

In the first step, the spatial delimitation of LAS was defined using a convex polygon by following the home range identification process introduced by Hasanzadeh et al. (2017). Accordingly, we listed all daily errand points (DEP) based on their distance from the participant's home location. The Jenk's optimization method revealed 4 km as the suitable home range distance for the dataset (Jenks 1967; Hasanzadeh et al. 2017). This distance is based on the first natural break value including at least 80% of DEPs marked by the participants (Hasanzadeh et al. 2017). The remaining DEPs which were further than 4 km from the individuals' homes were left out of the study (Fig. 4). To avoid the crisp boundary pitfall (Hasanzadeh et al. 2017), and to take the fuzzy characteristic of activity spaces into consideration (Perchoux et al. 2013), buffers with distances 500 and 140 m were applied to the home locations and DEPs, respectively. The buffer distances were adopted from an earlier study conducted in the same geographical area (Hasanzadeh et al. 2017). According to Hasanzadeh et al. (2017), 500 m is the most frequently used distance for defining immediate neighborhoods in the literature. In the same study, 140-m distance is identified as a suitable estimation of activity cluster sizes in a dataset collected from Helsinki area. This distance is calculated as the average diameter of the spatial clusters formed by the aggregate of DEP markings (Hasanzadeh et al. 2017). Following the application of buffers, a convex hull was applied to enclose all polygon features for each individual (Fig. 4).

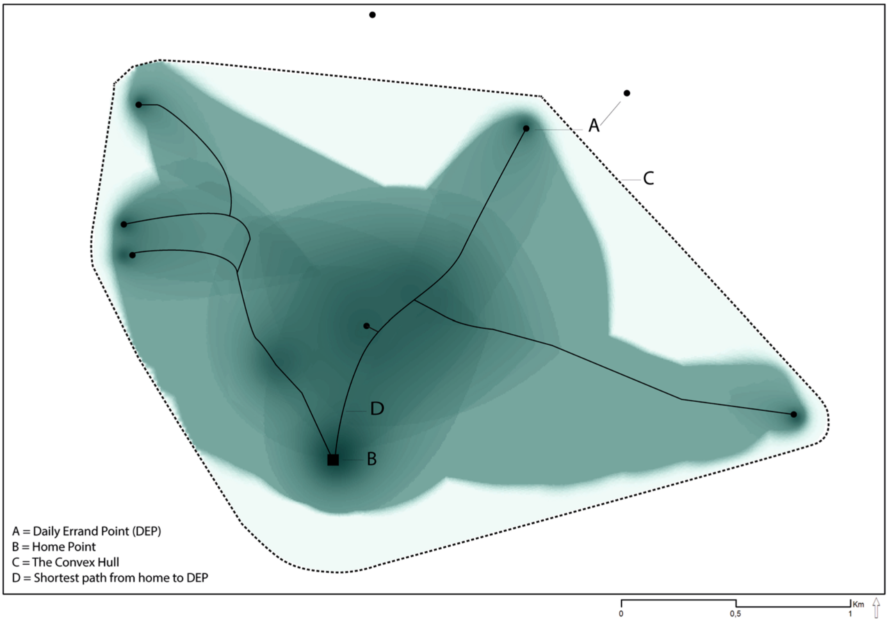

Fig. 4 Exemplary local activity space model of an individual study participant

In the second step, the shortest path between each participant's home location and their DEPs was found using Network Analyst toolbox of ArcGIS (Fig. 4). The transportation mode indicated by the participant for visiting each specific DEP was taken into consideration while choosing the shortest path.

In the third step, the place exposures were estimated. To quantify the level of exposure, weights were assigned to each feature (A = DEPs, B = home and D = shortest path). Following how frequency questions were asked in the survey, the weights for point features were calculated in terms of frequency of visit per month. Accordingly, the highest weight, 30, was allocated to home points as the location people typically frequent on a daily basis. Depending on the frequency of visit indicated by the participant for each DEP, weights were allocated to each point. A weight for each path was determined by its frequency of use and the used travel mode (walking, biking, or motorized). This was operationalized as the geometric mean of destination and origin weights divided by the ratio of transportation mode's speed to walking speed (μ). The average speed for each transportation mode was obtained from Helsinki Region Transport office (HSL). It should be noted that the transit timetables were not considered in calculation of transportation mode speeds.

Following calculation of weights for all geographical features, a sigmoid function was applied to normalize the values. Consequently, all the values were interpolated using inverse distance as the distance decay function to produce a uniform surface represented as a raster with an estimation of exposure value for each cell (Fig. 4). The output raster is made of square-shaped cells each with an area of 25 m^2. Mathematically speaking, the exposure value E at a given raster cell x based on the calculated exposure weights, E_i, of all features $i = 1, 2,\ldots, N$, is calculated as follows:

$$E(x) = \begin{cases} \dfrac{1}{1 + e^{-\left(\frac{\sum_{i=1}^{N} w_i(x) E_i}{\sum_{i=1}^{N} w_i(x)}\right)}} & \text{, if } d(x, x_i) \neq 0 \text{ for all } i \\ \dfrac{1}{1 + e^{-(E_i)}} & \text{, if } d(x, x_i) = 0 \text{ for all } i \end{cases}$$

where d is Euclidean distance,

$$w_i(x) = \frac{1}{d(x, x_i)^1},$$

and

$$E_i = \begin{cases} 30, & \text{if feature } i \text{ is home} \\ f_p/30, & \text{if feature } i \text{ is a visited point} \\ \sqrt{f_{p_{\text{origin}}} \times f_{p_{\text{destination}}}}/30 \times \mu, & \text{if feature } i \text{ is a route between two points} \end{cases}$$

f is the frequency of visit as times per month and μ is the ratio of transportation mode's speed to walking speed $\left(\mu_{\text{walking}} = \frac{5}{5}, \mu_{\text{biking}} = \frac{17}{5}, \mu_{\text{motorized}} = \frac{50}{5}\right)$.

2.3 Comparing IREM with other methods

IREM is an integrative model inspired by good features of several LAS and AS modeling approaches. Therefore, it is useful to evaluate how it performs in comparison with these existing methods. In this study, we compare IREM to three other LAS modeling methods: 500-m circular buffer, shortest path area (SPA), and kernel density. The first method is chosen as one of the most commonly used container approaches in the literature. The SPA and kernel density are also common approaches from the literature that have specially been inspirational for the design of IREM. The comparisons made in this study are based on the evaluation criteria proposed by Hasanzadeh et al. (2017), which assesses the effectiveness of the spatial delimitation models based on their *accordance with reality, support by empirical evidences,* and *usability*. A detailed list of the criteria and their descriptions can be found in Table 2.

The first group of criteria, *accordance with reality,* is based on the most common limitations of LAS models in capturing an acceptable degree of accordance with the actual LASs as perceived by the individuals. The second group of criteria, *support by empirical evidences,* test the capability of the models in capturing well-established evidences from earlier research concerning the characteristics of LAS models. In order to evaluate how different models conform to empirical evidences from earlier studies, we used Pearson correlation and one-way ANOVA tests. Finally, the third group of criteria, *usability,* assesses the usability of the models, both in terms of creation and analysis, for empirical research. Given the applied nature of LAS models, these criteria are especially important to provide guidelines as how demanding or practical each model is for use in research.

2.4 IREM in practice: empirical case of Helsinki metropolitan area

Following the modeling phase and comparisons, the proposed model is applied empirically to a dataset of 844 individuals aged 55–75, from HMA. The empirical part is primarily intended as a demonstration of how IREM can be applied in empirical research. In this empirical case, we demonstrate a framework that can be used to measure and understand IREM through identifying its main descriptive dimensions. Additionally, we use these measurements to examine the interplay of LASs, socio-demographic characteristics, and respondents' location in the region. In the following sections, we will present the study framework and discuss the used methods more elaborately.

2.4.1 Measures

2.4.1.1 Activity space measures Using the spatial information collected through the survey and GIS calculations done on the model, we defined three categories of the total of 13 indicators to quantify LAS characteristics and activity measures: (a) physical indicators related to the geometrical characteristics of the LAS, (b) structural characteristics, primarily related to the greenness of the LAS, and (c) activity characteristics, which describe the types, frequency, and whereabouts of

Table 1 LAS and activity measures

Indicator category	Indicator	Measurement method	References
(a) Physical characteristics	Surface	GIS calculation: area of convex hull	Sherman et al. (2005), Buliung et al. (2008) and Perchoux et al. (2014)
	Perimeter	GIS calculation: perimeter of convex hull	Perchoux et al. (2014)
	Total exposure	GIS calculation: total pixel values of exposure surface (Python script)	
	Average exposure	GIS calculation: average pixel values of exposure surface (Python script)	
	Major to minor axis ratio	GIS calculation: length to width ratio of the smallest rectangle enclosing the neighborhood convex hull	Lord et al., (2009), Newsome et al. (1998), Perchoux et al. (2014) and Schönfelder and Axhausen (2004a, b)
(b) Structural characteristics	Green area percentage	GIS calculation	Broberg et al. (2013)
	Green exposure ratio	GIS calculation: total exposure values in green areas divided by total exposure (Python script)	
	Average green exposure	GIS calculation: average exposure values in green areas	
(c) Activity characteristics	Average distance to DEP	GIS calculation (Python script)	Perchoux et al. (2014)
	Maximum distance to DEP	GIS calculation (Python script)	Perchoux et al. (2014)
	Number of visits to DEPs per month	Number of DEP markings multiplied by their frequency of visit	Schönfelder and Axhausen (2004b), Buliung et al. (2008) and Perchoux et al. (2014)
	Number of DEPs	Number of unique DEPs marked	Schönfelder and Axhausen (2004b), Rai et al. (2007), Buliung et al. (2008) and Perchoux et al. (2014)
	Percentage of DEPs inside neighborhood boundary	GIS calculation (Python script)	Perchoux et al. (2014)

DEPs. Table 1 presents a summary of these measurements followed by a brief description of how they were calculated. In case the measurement was previously used in other studies, references are provided in the last column.

It should be noted that the use of green area coverage for identifying structural characteristics was inspired by the fact that in the literature, greenness has frequently been referred to as one of the most important urban structural variables contributing to health (Mitchell and Popham 2008; Thompson et al. 2012).

2.4.1.2 Personal variables Using the information acquired from the survey, the following individual characteristics were considered as explanatory variables: sex, age, retirement status, education (4 categories: basic, upper secondary, bachelors, masters or higher), income, marital status (3 categories: separated or widowed, single, married), family type (4 categories: alone no children, alone have children, married no children, married have children), number of happy places, regular exercise (yes or no), having hobbies (yes or no), having pets (yes or no), having grandchildren whom one regularly visits (yes or no), home type (3 categories: house, apartment, terrace house), home ownership (owned or rental). Home location in the region (4 categories: 1-urban 2-semiurban 3-suburban 4-rural) was assessed for each individual based on the classification by the Finnish Environment Institute.

2.4.2 Statistical analyses

As presented earlier in Table 2, a wide range of measures was used to describe LASs. Although each measure is calculated differently and is intended to capture certain characteristics of the LAS, some of the measures, such as perimeter and area, are highly correlated with each other. Furthermore, the high dimensionality of the LAS makes any further analyses more difficult. Therefore, as a common statistical practice, we performed a principal component analysis (PCA) on the 13 LAS indicators to identify the main dimensions of spatial behavior and structural characteristics (Perchoux et al. 2014). A varimax rotation was used and a five-component solution was selected based on the Eigen values greater than 0.90. Scores were created using Anderson–Rubin method.

Subsequently, the association between these components and individual characteristic variables was estimated using hierarchical linear model (HLM) with random effects at neighborhood level which were identified by postal codes. Only the outcomes significant at 0.05 level were reported in the results. We report the log-likelihood ratio and the Akaike information criterion (AIC) for the null models and the final models. All statistical analyses in this study were conducted with IBM SPSS 23.

3 Results

Running IREM, we created 844 raster files, each representing the LAS of a participating individual. In the following sections, we will present comparison results as well as the findings from the empirical case.

Table 2 Comparison results of IREM, and three other LAS/AS models

Group	Criteria/method	Description	IREM	500-m circular buffer	Shortest path area (SPA)	Kernel density
Accordance with reality	Inclusiveness	What percent of DEPs does the model cover?	*64%*	16%	*100* %*	*100* %*
	Individually and spatially sensitive?	Does the model provide an individualized and spatially refined understanding of potential exposure variations?	*The model is individual-specific and provides place-based estimations based on travel behavior (mode and route), and intensity of activities*	The model is individual-centered but not individual-specific. This is a container approach and no understanding of spatial variation of exposure is provided	The model is individual-specific. However, it is a container approach and does not provide a spatially sensitive picture of exposure variations	The model is individual-specific and provides place-based estimations based on density and intensity of activity points
	Accessibility	Does the model consider accessibility?	*The model is travel route-informed; therefore, it is less biased by equal accessibility assumption*	The model is based on equal accessibility assumption	The model is travel route-informed. However, the output may still be biased by equal accessibility assumption	The model is based on equal accessibility assumption
Support by empirical evidences	Urban structure (Based on population density and LAS size)	In denser areas due to higher availability of nearby services, the home range is smaller (Van Vliet 1983; Krizek 2003).	$r(844) = -0.08$, $p < 0.05$	*NA*-geometric characteristics of LAS are constant for all individuals	$r(844) = -0.01$, $p = 0.66$ (statistically not significant)	*NA*-model does not define a working spatial delimitation. Thus, geometric characteristics cannot be measured
	District effect (Based on LAS size)	People living within the same district (census tract) have relatively similar ASs compared to people from other districts (Vallée et al. 2014)	$F(149{,}688) = 1.40$, $p = 0.003$	*NA*-geometric characteristics of LAS are constant for all individuals	$F(149{,}688) = 0.56$, $p = 1.000$ (statistically not significant)	*NA*-model does not define a working spatial delamination. Thus, geometric characteristics cannot be measured

Table 2 continued

Group	Criteria/method	Description	IREM	500-m circular buffer	Shortest path area (SPA)	Kernel density
Usability	Easiness of use	How easy is the model to create and work with?	The model requires several layers of data and multiple GIS analyses. The boundaries are easy to work with but the raster output demands advanced GIS skills for further analysis	*The model only needs home location as data. The model can be readily created and used with basic GIS skills*	The model requires multiple layers of data. However, it can be readily created and used with basic GIS skills	The model requires multiple layers of data. It can be readily created with basic GIS skills. However, the raster output demands advanced GIS skills for further analysis
	Sensitivity to errors	How significantly do errors affect the outputs?	*Big spatial blunders are systematically left out when model parameters are applied. Smaller individual errors may bias the extents of model but have little effect on exposure estimations*	The model is highly sensitive to the spatial accuracy of home location	Big spatial blunders can significantly bias the geometrical characteristics of the model	*Single errors have little effect on the output of the model*

*Assuming that points have not been manually left out based on any distance-based criteria

3.1 IREM, in comparison with other models

Table 2 presents a description of the used comparison criteria, as well as the models' performances for each of them. For each criterion, the cell from the method yielding the most favorable outcome is highlighted in italics.

According to the comparison results, IREM has the best performance in terms of its accordance with reality with its considerably high coverage of DEPs, individual and spatial sensitivity, and consideration of accessibility. IREM also appears to have the highest performance in meeting the second group of criteria. The statistically significant negative correlation between the LAS size—as modeled by IREM—and population density conforms to the earlier evidences from empirical research predicting a generally more compact LAS in central urban areas. The result yielded from SPA is statistically insignificant, thus do not meet the criterion. Similarly, IREM meets the criterion related to district effect, while SPA yields insignificant results. The other two models do not provide the possibility of performing any of the two analyses, as they are incapable of capturing the physical characteristics of LASs.

The comparison results related to the usability of the model are not as definitive as the previous criteria as they can be subjective to the required level of complexity, availability of data, and the GIS skills of the users. Although, IREM poses a challenge to the users in both modeling and analytical stages, other methods can be more readily used in research. However, when it comes to sensitivity toward errors, IREM and Kernel approach offer better reliability compared to the other two methods.

3.2 IREM in practice: empirical case of Helsinki metropolitan area

3.2.1 Main dimensions of local activity spaces

PCA is conducted on measures present in Table 1, to identify the main components describing the LAS characteristics of the individuals. Table 3 shows the results of the PCA. The five components explained 91% of the variance.

Component 1 explained 30% of the variation. Indicators with the highest factor loadings were the surface of LAS, total exposure, and perimeter of the LAS. This component, therefore, captures the LAS's size. Accordingly, we labeled this component as "Size of LAS." Component 2 explained 22% of the variation. Indicators with the highest factor loadings were the green area percentage, average green exposure, and green exposure ratio. This component was labeled as "Greenness of LAS." Component 3 explained 21% of the total variance. Indicators with the highest factor loadings were average distance to DEP, maximum distance to DEP, and percentage of points outside LAS. This component captures the proportion of activities, which take place outside LAS boundaries. Therefore, we labeled this component as "Exteriority of AS." Component 4 explained 11% of variation. Variables with the highest factor loadings were the number of visits to DEPs per month, average exposure, and number of activity types. This component captures the intensity of activities and thus was identified as "Intensity of LAS."

Table 3 Principal component analysis results

% of variance explained	*C*1 Size of LAS 30%	*C*2 Greenness of LAS 22%	*C*3 Exteriority of AS 21%	*C*4 Intensity of LAS 11%	*C*5 Elongation of LAS 7%
Surface	0.981*	–	–	–	–
Perimeter	0.914*	–	–	–	0.342
Total exposure	0.956*	–	–	–	–
Average exposure	–	–	–	0.853*	–
Major to minor axis ratio	–	–	–		0.964*
Green area percentage	–	0.910*	–	–	–
Green exposure ratio	–	0.972*	–	–	–
Average green exposure	–	0.959*	–	–	–
Average distance to DEP	–	–	0.955*	–	–
Maximum distance to DEP	–	–	0.931*	–	–
Number of visits to DEPs per month	–	–	–	0.899*	–
Number of DEPs	0.377	–	–	0.818*	–
Percentage of DEPs inside neighborhood boundary	–	–	– 0.857*	–	–

Loadings bigger than 0.8 are marked with *

Loadings smaller than 0.3 are not reported in the table

C is short for component

Finally, component 5 explained 7% of the total variance. The only variable with the high factor loading was the major to minor axis ratio. This component, therefore, was labeled as "Elongation of LAS."

3.2.2 Socio-demographic variables and characteristics of local activity spaces

To study the associations between socio-demographic variables and LAS characteristics, multilinear regression analysis was performed. Table 4 presents the results of the five hierarchical linear models. Component 1, size of LAS, was associated with income, number of happy places, and home type. Individuals who have higher income tend to have bigger LASs than those with lower incomes. Participants who have marked more happy places in the survey have bigger LASs in general. People who live in apartments tend to have smaller LASs than those who live in houses. Component 2, the greenness of LAS, was associated with family status and pet ownership. Couples with children and pet owners tend to have greener LASs in comparison with those who do not have children or pets. There are associations between component 3, the exteriority of AS, and the number of happy places, pet ownership, and home location in the region. AS of the participants who have marked more happy places tend to be more centered outside their home vicinity. Furthermore, individuals who do not have pets seem to do more activities outside

Table 4 Association between individual socio-demographic characteristics, location in the region, and different components of spatial behavior (n = 840)

	Size of LAS β (95% CI)	Greenness of LAS β (95% CI)	Exteriority of AS β (95% CI)	Intensity of LAS β (95% CI)	Elongation of LAS β (95% CI)
Location in the region (*1: Most urban to 4: rural*)	–	–	**0.49** (0.25, 0.72)	**− 0.46** (− 0.67, − 0.24)	0.23 (0.00, 0.47)
Male (vs. female)	–	–	–	–	–
Age	–	–	–	–	–
Retired (vs. not retired)	–	–	–	–	–
Education	–	–	–	–	**0.13** (0.04, 0.22)
Income	**0.02** (0.00, 0.05)	–	–	–	–
Marital status (*vs. separated or widowed*)					
Single	–	–	–	–	–
Married	–	–	–	–	–
Family type (*vs. couple with children*)					
Single, no children	–	–	–	–	–
Single, with children	–	–	–	–	–
Couple, no children	–	− 0.29 (− 0.48, − 0.10)	–	–	–
I don't have grandchildren (*vs. I do*)	–	–	–	–	–
I don't have pet(s) (*vs. I do*)	–	− 0.18 (− 0.37, 0.01)	− 0.25 (− 0.50, 0.00)	**− 0.32** (− 0.55, − 0.10)	–
Home type (*vs. house*)					
Apartment	**− 0.28** (− 0.51, − 0.05)	–	–	–	
Terraced house	–	–	–	–	**0.39** (0.11, 0.67)
Owned home (*vs. rental*)	–	–	–	–	–
No. of happy places	**0.04** (0.1, 0.7)	–	**0.02** (0.00, 0.04)	**0.04** (0.01, 0.06)	–
I don't exercise (*vs. I do*)	–	–	–	**− 0.34** (− 0.56, − 0.12)	–
I don't have hobbies (*vs. I do*)	–	–	–	–	–
Null model − 2ll	1254.658	1365.112	1405.368	1327.808	1369.939

Table 4 continued

	Size of LAS β (95% CI)	Greenness of LAS β (95% CI)	Exteriority of AS β (95% CI)	Intensity of LAS β (95% CI)	Elongation of LAS β (95% CI)
Null model AIC	1269.658	1407.112	1447.368	1369.808	1411.939
Full model − 2ll	1220.320	1218.582	1405.368	1323.417	1362.699
Full model AIC	1264.320	1266.582	1447.368	1367.417	1466.696

AIC akaike information criterion; *CI* confidence interval;− *2ll* maximum log-likelihood

Only statistically significant values are shown ($p < 0.05$). Values significant at $p < 0.01$ are bolded

their LAS boundaries. Moreover, people who live in outer suburbs are more likely to do activities outside their LAS than those who live closer to the central areas.

Regarding the fourth component, the number of happy place markings appears to have a positive relationship with the intensity of activities. Moreover, a higher intensity of activity can be observed for the participants who reported doing exercises regularly. It can also be seen in the results that people who have pets tend to have a higher intensity of activities in general. Finally, people who live in more central areas seem to have a higher intensity of activities and hence tend to be more active than individuals who live in outer suburban areas.

Education, home type, and home location in the region were associated with the fifth component, the elongation of the LAS. People with higher levels of education tend to have more elongated LASs. Moreover, people living in terraced houses are more likely to have elongated LASs than people in houses. Finally, people who live in outer suburban areas tend to have more elongated LASs than those living in central locations.

The maximum log-likelihood (-2ll) was significantly lower in most models after accounting for individual and contextual variables. This can be largely attributable to the difference in mobility behavior in different regions and by people who have marked different numbers of happy places.

4 Discussion

As the primary objective, this study focused on the local activity spaces (LAS) and developed a new versatile modeling approach based on an individualized, place-based estimation of environmental exposure. The individualized residential exposure model (IREM) is built on the existing literature and adopts some of the best features of the current LAS and AS models. IREM follows the idea that there is more to a LAS than a boundary. While a person-based approach enables capturing individual differences in LASs, a place-based exposure assessment approach provides a more spatially refined understanding of these differences. Hence, reaching a comprehensive understanding of LAS may be more feasible through an integrative person-based and place-based approach, rather than exclusively focusing on either of them. The model was created based on data collected through an online map survey in which participants were asked to mark their homes, DEPs, and provide additional information about their regular trips such as their frequency and common mode of transportation. Using the provided information, each individual's LAS was modeled as a raster file with varying values for pixels, each representing the estimated magnitude of exposure in that location.

IREM suggests a considerable improvement, both conceptually and operationally. The comparison results indicate a potentially improved congruence with reality, compared to other models commonly used in the literature. This is realized through an acceptable coverage of activity places, a person and place-based modeling approach, and consideration of accessibility in modeling. Furthermore, among the models included in the comparison, IREM was the only one, which matched the empirical findings from earlier research. Given the widely empirical application of LAS models, this is an especially important feature. Moreover, compared to boundary approaches, IREM is less sensitive to biases and errors mainly for two reasons. First, the used distance parameters can identify blunders and therefore prevent extreme biases to the estimated spatial extents. Second, the used sigmoid and inverse distance functions moderate the effects of single extreme values on overall estimated exposures.

Despite these improvements, IREM is not free from limitations. Developing and using IREM pose technical challenges, which require considerable amount of computing resources and GIS skills. The model is created based on several layers of data and it can be computationally expensive for large datasets. Further, working with raster files as the representation LASs brings additional complexity to the empirical analyses compared to simpler polygon representations. Further, there are other limitations regarding the definition of the model, which can be improved in future research. The current model takes a simplistic approach in predicting travel routes assuming that all trips originate from place of residence and are made through the shortest path. Having additional information about participants' trips, such as about taken routes and origin, can help ameliorate this limitation in future studies using this model. Another potential limitation of this model is its exclusive focus on what is happening inside local boundaries of ASs. Although this limitation is potentially ameliorated by the versatile and personalized approach used for defining model parameters, as well as use of exteriority as a dimension, future research should more precisely address the polycentric characteristic of ASs (Flamm and Kaufmann 2006; Vallée and Chauvin 2012).

It is known to all that complexity is inherent to human behavior. Therefore, any advanced model of it turns out as complex as well. Accordingly, as a secondary objective of this article we applied IREM empirically to demonstrate how it can be used and measured in empirical research. In the first step, we adopted a multidimensional procedure (Perchoux et al. 2014), to identify the main descriptive dimensions of the modeled LASs. These five components, namely *size*, *greenness, exteriority, intensity*, and *elongation of LAS,* were identified by performing PCA on a number of geometrical, structural, and activity-related measurements. Implementation of this multidimensional approach for studying LASs helps us understand their different characteristics. It also facilitates performing other analyses by lowering the dimensionality and, therefore, the complexity of the model.

The current study highlights the importance of such multidimensional approaches and extends the list of components reported by Perchoux et al. (2014), by adding a new dimension based on structural characteristics of the LAS. Greenness was the only structural variable included in this study. However, we believe, where relevant to the theme of a future study, other structural variables can be measured and included in the analysis. Furthermore, we extend the list of our measurements in identifying LAS dimensions by introducing new measures using estimated exposures. This can be particularly important to future research as it can moderate the effects of overestimated exposure resulting from abundance of a certain land type in one's LAS.

Although not at the center of focus of this paper, the empirical findings from the case study are interesting for further discussion and investigation. A big part of our findings related to the association of socio-demographic variables, location in region, and characteristics of LASs matches findings reported in earlier research. As in numerous studies, location of domicile in region appeared as a strong predictor of LAS characteristics. Living in the suburbs was more associated with a higher number of activity destinations outside home vicinity. With increasing distance from dense urban areas, individuals had more extended LASs and lower intensity of activities. Comparable suburbia effects were previously reported in two German cities (Schönfelder and Axhausen 2002), as well as in Paris (Perchoux et al. 2014). These observations can be explained by the urban morphology of suburbs—with lower street connectivity and lower density of services—that forces suburbanites to travel longer distances to visit their destinations (Perchoux et al. 2014; Holliday et al. 2017). This could also serve as a factor discouraging higher intensity of activities. However, the observed associations are not limited to location in region. Factors such as income, housing type, education, pet ownership, and family type seem to be associated with different LAS characteristics. Although some of these findings, such as positive association between income and LAS size (Mitchell and Popham 2008; Perchoux et al. 2014), or pet ownership and greenness (Schipperijn et al. 2010), match results from earlier studies, some other findings need further investigation.

The promising comparison results, together with findings from the empirical case, highlight the relevance of IREM for future research seeking the contextual effects of residential areas on individuals. Particularly, the empirical findings suggesting associations between physical activity and different characteristics of LAS demonstrate the potential significance of the proposed framework for environmental health promotion studies. Although IREM is designed based on data from Helsinki area, thanks to its flexibility and parametric design, we believe it can equally perform in other urban contexts. However, regarding the empirical part it should be noted that some of the variables are context-dependent. For example, while a measurement such as the size of LAS can be applicable to any empirical study, use of green areas as a descriptive characteristic of LAS may not be relevant for all geographical areas.

Further, it should be noted that this empirical study has other limitations that need to be addressed in a future design. The present study is conducted on a dataset collected through a PPGIS method. Online mapping surveys such as softGIS may result in some increased spatial and thematic biases in relation to other methods of measurement such as mobile phone data and GPS tracking. Some of the measures we employed rely on number of locations marked on map. These measures may be confounded by the level of respondents' engagement in mapping activity and their level of mapping skills (Brown 2016). However, the errors pertain to individual participants, and there is no known reasons for errors to be systematically related to the variables of interest of the study. Therefore, we can safely assume that the individual errors do not introduce strong biases to the aggregate analysis presented in the article. Furthermore, future research can benefit from wider and potentially more accurate measures of LAS and environmental exposure. A more comprehensive approach would provide better evidence for public health policies and interventions promoting healthy behavior including active living.

5 Conclusion

With the extensive amount of the literature on the characteristics of residential environments and their influence on different aspects of residents' lives, there is little doubt on the significance of this line of research. The empirical evidence remains, however, scarce concerning the associations between physical environment characteristics and health. We argued in this paper that this can largely be attributed to the inability to define the actual geographical context of influence. Here, there is an evident lack of both conceptual and methodological consensus in the field that already starts in the use of terminology, and becomes most evident in specification and assessment of the geographical models.

This study took a novel step toward tackling these limitations by proposing an integrative approach for modeling individual local activity spaces (LAS) based on data collected through a PPGIS survey. This individualized residential exposure model (IREM) is based on a person-based assessment of place exposure in the home range encapsulating most frequent activities of individuals. Using place exposure in definition of LAS can result in a more refined and spatially sensitive model that can in turn improve our understanding of contextual effects. Compared to other commonly used methods, IREM is closer to reality and provides better support for empirical evidences. The robustness of IREM toward different types of errors is another improvement in this approach.

Further, the empirical part of this study shows how IREM can be examined and analyzed along with other datasets. The interesting results showing associations between LAS characteristics and various socio-demographic and regional characteristics display how the proposed method can be used in future studies investigating the interrelationship of residential environments and individuals. The implemented model together with the empirical case of this study demonstrates a research framework, which can serve as a guideline for future research. In this line, it will be interesting to see future studies addressing the remaining methodological and conceptual limitations discussed in this paper. Future research can also benefit from a comparative study, assessing and comparing the effectiveness of various modeling approaches in different geographical contexts. The empirical findings reported in this study require further investigation and can serve as a starting point for future research in the field.

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Appendix: Socio-demographic characteristics of respondents (N = 1139)

	Sample (%)	Statistics Finland (%)*
Gender		
Male	41	45
Female	59	55
Age		
55–64	51	55
65–74	48	45
Retired	60	59
Education[a]		
Basic education	13	40
Upper secondary education	42	33
Lower university degree	16	11
Higher university degree	29	17
Marital status		
Married	64	55
Unmarried	12	17
Divorced	17	23
Widow	7	6
Living arrangement		
Couple	68	60
Living alone	28	35
Other	4	5
Housing		
Apartment	59	70
Row house apartment	21	10
Detached house	20	19
Mother tongue		
Finnish	89	87
Swedish	9	7
Other	3	6

	Sample (%)	Statistics Finland (%)*
Income (median)[b]		
Ages 55–64	3501–4000	4001–4500
Ages 65–74	3001–3500	3001–3500

*The sample consists of Finnish people living in the capital area, aged 55–75 in year 2015 (a and b exceptions)

[a]The reference sample consists of Finnish people living in the capital area, aged 55+ in year 2014

[b]The reference sample consists of all the Finnish people aged 55–75 in year 2014

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