Activity spaces in place and health research: Novel exposure measures, data collection tools, and designs

Camille Perchoux, Basile Chaix, Yan Kestens

Title: Activity spaces in place and health research: Novel exposure measures, data collection tools, and designs

Authors: Camille Perchoux[1], Basile Chaix[2], Yan Kestens[3]

[1] Luxembourg Institute of Socio-Economic Research, Esch/Alzette (LISER), Luxembourg ; camille.perchoux@liser.lu

[2] INSERM, Sorbonne Université, Institut Pierre Louis d'épidémiologie et de Santé Publique, IPLESP UMR-S1136, F75012 Paris, France ; basile.chaix@iplesp.upmc.fr

[3] Centre de Recherche de l'université de Montréal (CRCHUM), Université de Montréal, Canada, QC ; yan.kestens@umontreal.ca

Acknowledgements: None

Declaration of Interest statement: None

Corresponding author: Dr. Camille Perchoux, Luxembourg Institute of Socio-Economic Research, 11 porte des Sciences, L-4366 Esch/Alzette, Luxembourg, Telephone number : +352 58 58 55 998, Email: camille.perchoux@liser.lu

Abstract

Activity space research provides a framework to consider mobility while linking environments to behaviors in the study of neighborhood effects on health. Increased use of wearable location sensors provides new opportunities to observe and analyze fine-grained spatial and temporal information on individuals' mobility patterns, environmental exposures and behaviors; however, these analysis does not easily translate into causal inference. Additional dimensions underlying behavioral decision-making likely influence or even modify environmental effects on behaviors. This commentary discusses how further progresses in exposure measurement, integration of data collection tools, and development of study designs could support future interventions to optimize how environments shape health profiles and inequities.

Keywords

Activity space; Selective daily mobility bias; Neighborhood effects; Causal inference

Highlights

Activity space research accounts for mobility when linking environments to behaviors

Spatio-temporal data on behaviors do not automatically translate in causal inference

Behavioral decision-making information beyond exposure could improve causal inference

Novel data collection tools and designs will further inform health interventions

The article by Smith, Foley, and Panter provides a timely and informative review of activity space studies in environment and physical activity research (Smith et al., 2019). We welcome this paper that posits key challenges and opportunities linked to our ability to observe and analyze human-environment interactions at increasingly refined spatial and temporal scales. Activity space research not only provides a framework for considering mobility when linking environments to behavior such as physical activity, it also offers venues to more fully consider the complex interactions between people's structure of opportunities, behavior and health. The authors thoroughly review various representations of activity space, corresponding environmental exposure measures, and thoughtfully discuss the implications for causal inference when analyzing physical activity.

Activity space research provides a useful paradigm in the study of neighborhood effects on health, shifting from a residence-focused assessment of exposure to a more comprehensive analysis accounting for various locations visited over time and corresponding contrasted exposures (Perchoux et al., 2013). The difficulty for causal inference is linked to the fact that mobility - and corresponding multiple exposures - is itself a result of environmental conditions. Consequently, even if wearable location sensors do provide fine-grained spatial and temporal data on behavior, its analysis does not easily translate into causal conclusions, partly because complementary information on the underlying decision-making process leading to mobility and the health behavior of interest is lacking. In this regard, we aim to discuss how current innovations in exposure measurement, data collection tools and study designs could contribute to support future developments to help us unravel the role our environments play in shaping health profiles and inequities.

New space-time measures of environmental exposure and challenges in causal inference

Precise geocoding of individuals' daily activities derived from GPS, map-based questionnaires, or detailed travel surveys provide useful information to generate spatial representations of individuals' activity spaces. Measures such as anchor points or daily path buffers, standard deviational ellipses, or convex hulls, represent different while complementary ways of accounting for individual mobility patterns, and condition how exposure measures are established (Perchoux et al., 2014). For instance, while daily path measures account for directly experienced spaces, a much broader standard deviational ellipse encompasses potential non-experienced, accessible and possibly non-accessible areas. In summary, the way activity spaces are operationalized impacts both exposure measures and the potential for causal inference. Specifically, confounding arises when spatial accessibility to resources measured from locations specifically visited to conduct the behavior of interest is used as predictor of said behavior. Similar to the issue of residential selection, it generates selective daily mobility bias (Chaix et al., 2013). This is a very common bias, as many GPS studies determine accessibility to resources using the entire observed GPS track over several days that includes the locations where the behavior of interest is observed. Proposed solutions include measuring spatial accessibility from majors anchor points (e.g., home, work, etc.). Restricting the evaluation of accessibility to such locations - more strongly fixed in space and time-, limits the potential confounding bias associated with accessibility measures derived from more spontaneous or variable visited places; however, this restriction to a subset of the available locations also represents an underuse of the available mobility data. Alternatively, one can exclude from the set of locations considered to measure accessibility those that were specifically visited to conduct the behavior of interest. Such a data-demanding approach would for example identify the fast-food restaurants that were effectively visited over the study follow-up and refrain from calculate the exposure to fast-foods from these locations. In studies of environmental effect on travel mode choice, it is suggested to consider, instead of the characteristics of the actual GPS-recorded itineraries, those of the shortest routes between visited locations. Actual itineraries are selected by participants on the basis of their chosen travel mode, thus considering environments along such GPS itineraries would introduce circularity (Chaix et al., 2016). Selective daily mobility bias is also intertwined with residential selection bias: self-selection of residential environment might spill over to selective daily mobility by influencing local travel and access to environmental resources close to the residence. Consequently, additional data is needed to improve causal inference. In GPS follow-up interviews, participants could report if any detour was made to arrive to a given destination and whether this destination was visited only to the extent that the previous or the next one was visited (conditional relationships among chained destinations) (Chaix, 2018). Such decision-making information will be useful to define which destination to include when assessing impact of exposure and addressing the selective daily mobility bias.

While spatial dimensions of activity space are increasingly used for exposure assessment, temporal aspects such as time spent at specific locations or travel times are only rarely considered. Promising developments include the "time-base objective measure of exposure" (Scully et al., 2019) which proposes to weight exposure based on duration spent at a given location or along a route. Other developments include adaptive activity space representations that account for the time spent at a given location while considering potential environmental barriers that prevent access (Wang et al., 2018). Time-weighting of exposure represents one further step in the individualization of exposure measurements, and assumes that the longer the exposure, the more susceptible to generate the behavior of interest. Yet such causal interpretation of an exposure duration dose-response relationship can be challenged by the complex mechanisms - including cognitive, psychological, or social - shaping health behaviors (Kestens et al., 2016), that point to the need for complementary information documenting people-place interactions and decision-making. New methods can help us both capture such complementary information, and improve our capacity to disaggregate exposures, confounders, and outcomes over space and time.

New data collection tools to document complementary dimensions on people-place interactions

Beyond the geographical location itself, the nature of the activity being conducted is important to consider. Map-based questionnaires gather types of activity location visited and complementary information such as the nature and flexibility of activities that are done at these locations, or social interactions. For a given environment, not all types of activity locations do equally influence the likelihood to engage in active behaviors (Perchoux et al., 2015). The nature of activities undertaken at a specific location can be seen as a proxy for unmeasured factors at play in behavioral decision-making. These include cognitive factors such as perceived barriers, spatial or temporal constraints including time budget limitations, or lack of flexibility in space and time or even physical or social constraints.

Adding localized information on social networks and social interactions can further help understand why and how people engage in a specific behavior. Social connections are intrinsically related to spatial behavior, either when performing an activity, traveling with peers, or visiting families or friends. The social dimension of individuals tends to influence in turn the structure of their activity space by shaping major activity locations, frequency of visits, nature of activities undertaken or place attachment. Socio-spatial questionnaires such as the Social VERITAS (Kestens et al., 2017) can help document the socio-spatial ties, e.g. the where, the with whom, and what for. “Geotag” of activities with peers from social networks such as Twitter or Facebook might offer interesting avenues to study the role of social networks in spatialized behavioral decision-making, although social media users may have quite specific profiles (Pew Research Center, 2019). Other strategies include GPS-based mobility surveys, that provide self-reported complementary information on travel models, types of location visited, social network members present with the participant, stresses experienced during trips, among other aspects (Chaix, 2018).

Further momentary conditions can further be useful to understand behavior. Moment-to-moment variations of feelings and emotions are a strong driver of behavioral decision-making, while conditioned by environmental surroundings (Kirchner and Shiffman, 2016). Ecological momentary assessment (EMA) coupled with GPS have been used to document real-time subjective experience over space (Epstein et al., 2014; Mitchell et al., 2014). In addition to EMA providing highly relevant mental health or behavioral outcomes (e.g., places and times for consuming cigarettes or alcohol), time-stamped covariates derived from EMA (i.e. intent, motivation, affect) can further be used to mitigate the selective daily mobility bias, to evaluate how much "intent" or "affect" played a role in behavioral decision-making at a specific place and time (Kestens et al., 2017).

When precise information on the space-time budgets (types of travel modes and visited places) is available from a travel diary or a GPS-based mobility survey, it is then particularly relevant to collect additional data from other passive sensors, i.e., in a multisensor perspective. Such sensors can include air pollution or sound pressure monitors, recorders of images or audio sounds (e.g., to measure social interactions (Roecke et al., 2018)), smartphone and screen usage behavior, heart and respiratory rate, etc.

Toward new study designs for a continuous monitoring of environmental and health changes over time

In the same way that activity space research tends to continuously monitor individuals, purposefully continuous monitoring of environmental changes should be considered (Kestens et al., 2019). Changes in environments can be viewed as interventions modifying environmental barriers and opportunities, subjective experiences of space, and behaviors. Identification of causal pathways and quality of causal inference are strengthened when matching such continuous urban transformations with changes in behaviors. High-resolution monitoring also increases the power of detection of micro-scale or short-term environmental impact which can be relevant for future decision making on urban design and impact long-term outcomes. Examples may include effect of new urban furniture on local social participation and long-term social cohesion, or of micro-variations in greening on intra-day variations in hedonic well-being and long-term life satisfaction.

However, to be up to the task, traditional longitudinal study designs may need to be revisited. Large samples are needed, and participants' monitoring over longer periods implies more passive, low-burden protocols. Open cohorts could mean more flexible, temporary, and recurring participation phases. Passive smartphone sensing increasingly provides relevant data on specific health behavior (physical activity and travel behavior), mobility, and social interactions. At the same time, various sensors including street-level imagery or high-resolution satellites capture changes in urban environments. Such methods allowing the capture of massive people-place interaction data are key for unlocking future population health citizen science (Den Broeder et al., 2016). A number of challenges remain. Such a participatory approach of knowledge production could mean communities' involvement and inclusion. Yet, the profile of citizens involved in data production and the vision and goals of economic and political actors who will collect and process these data will impact the nature of future environmental interventions. Inclusion of marginalized populations and deprived neighborhoods are key when designing such participatory projects (Pandya, 2012).

Conclusion

In conclusion, the population health research community is increasingly taking advantage of the high-precision monitoring tools to track people and environments. As presented by Smith, Foley, and Panter when looking at the specific example of physical activity, if not handled carefully, more data does not always easily translate in better inference (Smith et al., 2019). While continuous efforts should be put in the development of new analytic methods to handle such new massive data troves, the ubiquity of multiple sensors also represents a unique opportunity for scaling up. With appropriate infrastructure, tools and methods, tomorrow's very large cohorts (Lyles et al., 2018) will provide unique high-resolution multi-level data to unravel the complex system of our continuously changing environments and societies. Hopefully, these data will generate high-accuracy and high-impact evidence to target health determinants at micro, meso, and macro scales - be it through just-in-time adaptive smartphone interventions, local urban planning changes, or policy regulations - for a better and more equal future.

References

Chaix, B., 2018. Mobile Sensing in Environmental Health and Neighborhood Research. Annu. Rev. Public Heal. Annu. Rev. Public Heal. 39, 369–84. https://doi.org/10.1146/annurev-publhealth

Chaix, B., Kestens, Y., Duncan, D.T., Brondeel, R., Méline, J., El Aarbaoui, T., Pannier, B., Merlo, J., 2016. A GPS-Based Methodology to Analyze Environment-Health Associations at the Trip Level: Case-Crossover Analyses of Built Environments and Walking. Am. J. Epidemiol. 184, 579–589. https://doi.org/10.1093/aje/kww071

Chaix, B., Méline, J., Duncan, S., Merrien, C., Karusisi, N., Perchoux, C., Lewin, A., Labadi, K., Kestens, Y., 2013. GPS tracking in neighborhood and health studies: A step forward for environmental exposure assessment, A step backward for causal inference? Heal. Place 21, 46–51. https://doi.org/10.1016/j.healthplace.2013.01.003

Den Broeder, L., Devilee, J., Van Oers, H., Schuit, A.J., Wagemakers, A., 2016. Citizen Science for public health. Health Promot. Int. daw086. https://doi.org/10.1093/heapro/daw086

Epstein, D.H., Tyburski, M., Craig, I.M., Phillips, K.A., Jobes, M.L., Vahabzadeh, M., Mezghanni, M., Lin, J.L., Furr-Holden, C.D.M., Preston, K.L., 2014. Real-time tracking of neighborhood surroundings and mood in urban drug misusers: Application of a new method to study behavior in its geographical context. Drug Alcohol Depend. 134, 22–29. https://doi.org/10.1016/j.drugalcdep.2013.09.007

Kestens, Y., Chaix, B., Shareck, M., Vallée, J., 2016. Comments on Melis et al. The Effects of the Urban Built Environment on Mental Health: A Cohort Study in a Large Northern Italian City. Int. J. Environ. Res. Public Health, 2015, 12, 14898–14915. Int. J. Environ. Res. Public Health 13, 250. https://doi.org/10.3390/ijerph13030251

Kestens, Y., Wasfi, R., Naud, A., Chaix, B., 2017. “Contextualizing Context”: Reconciling Environmental Exposures, Social Networks, and Location Preferences in Health Research. Curr. Environ. Heal. Reports 4, 51–60. https://doi.org/10.1007/s40572-017-0121-8

Kestens, Y., Winters, M., Fuller, D., Bell, S., Berscheid, J., Brondeel, R., Cantinotti, M., Datta, G., Gauvin, L., Gough, M., Laberee, K., Lewis, P., Lord, S., Luan, H., McKay, H., Morency, C., Muhajarine, N., Nelson, T., Ottoni, C., Stephens, Z.P., Pugh, C., Rancourt, G., Shareck, M., Sims-Gould, J., Sones, M., Stanley, K., Thierry, B., Thigpen, C., Wasfi, R., 2019. INTERACT: A comprehensive approach to assess urban form interventions through natural experiments. BMC Public Health 19. https://doi.org/10.1186/s12889-018-6339-z

Kirchner, T.R., Shiffman, S., 2016. Spatio-temporal determinants of mental health and well-being: advances in geographically-explicit ecological momentary assessment (GEMA). Soc. Psychiatry Psychiatr. Epidemiol. 51, 1211–1223. https://doi.org/10.1007/s00127-016-1277-5

Lyles, C.R., Lunn, M.R., Obedin-Maliver, J., Bibbins-Domingo, K., 2018. The new era of precision population health: Insights for the All of Us Research Program and beyond. J. Transl. Med. https://doi.org/10.1186/s12967-018-1585-5

Mitchell, J.T., Schick, R.S., Hallyburton, M., Dennis, M.F., Kollins, S.H., Beckham, J.C., McClernon, F.J., 2014. Combined ecological momentary assessment and global positioning system tracking to assess smoking behavior: A proof of concept study. J. Dual Diagn. 10, 19–29. https://doi.org/10.1080/15504263.2013.866841

Pandya, R.E., 2012. A framework for engaging diverse communities in Citizen science in the US. Front. Ecol. Environ. https://doi.org/10.1890/120007

Perchoux, C., Chaix, B., Cummins, S., Kestens, Y., 2013. Conceptualization and measurement of environmental exposure in epidemiology: Accounting for activity space related to daily mobility. Heal. Place 21, 86–93. https://doi.org/10.1016/j.healthplace.2013.01.005

Perchoux, C., Kestens, Y., Brondeel, R., Chaix, B., 2015. Accounting for the daily locations visited in the study of the built environment correlates of recreational walking (the RECORD Cohort Study). Prev. Med. (Baltim). 81, 142–149. https://doi.org/10.1016/j.ypmed.2015.08.010

Perchoux, C., Kestens, Y., Thomas, F., Hulst, A. Van, Thierry, B., Chaix, B., 2014. Assessing patterns of spatial behavior in health studies: Their socio-demographic determinants and associations with transportation modes (the RECORD Cohort Study). Soc. Sci. Med. 119, 64–73. https://doi.org/10.1016/j.socscimed.2014.07.026

Pew Research Center, 2019. Sizing Up Twitter Users.

Roecke, C., Katana, M., Fillekes, M., Martin, M., Weibel, R., 2018. MOBILITY, PHYSICAL ACTIVITY AND SOCIAL INTERACTIONS IN THE DAILY LIVES OF HEALTHY OLDER ADULTS: THE MOASIS PROJECT.

Innov. Aging 2, 274–274. https://doi.org/10.1093/geroni/igy023.1014

Scully, J., Moudon, A., Hurvitz, P., Aggarwal, A., Drewnowski, A., 2019. A Time-Based Objective Measure of Exposure to the Food Environment. Int. J. Environ. Res. Public Health 16, 1180. https://doi.org/10.3390/ijerph16071180

Smith, L., Foley, L., Panter, J., 2019. Activity spaces in studies of the environment and physical activity: a review and synthesis of implications for causality. Heal. Place.

Wang, J., Kwan, M.P., Chai, Y., 2018. An innovative context-based crystal-growth activity space method for environmental exposure assessment: A study using GIS and GPS trajectory data collected in Chicago. Int. J. Environ. Res. Public Health 15. https://doi.org/10.3390/ijerph15040703