The Quantified Self-in-Place: Opportunities and Challenges for Place-Based N-of-1 Datasets

Benjamin W. Chrisinger*

Department of Social Policy and Intervention, University of Oxford, Oxford, United Kingdom

Causal mechanisms connecting place and health have long vexed public health researchers and epidemiologists. While some relationships occur along readily measurable pathways, many linkages are less clear. This is especially true of non-communicable or "lifestyle" diseases, which often exist in a conceptual "black box"—wherein multiple, possibly interacting and interconnected, mechanisms complicate population-level generalizations about exactly how places affect health (Macintyre et al., 2002). Without observations over a variety of potential pathways, time periods, and individual-level characteristics and behaviors, researchers are limited to relatively high-level observations of associations between the characteristics of people and the places where they live, work, and play.

When paired with geocoordinates, data from self-tracking technologies can offer new opportunities for researchers and participants to explore these causal pathways. This paper describes how geolocated N-of-1 datasets could contribute to inquiries about place and health, and improve upon common limitations of place-based research. It also identifies several significant logistical, methodological, and ethical issues that could present barriers to these kinds of projects. Overall, the paper offers a vision for situating the quantified self *in place*, where researchers could support and amplify the creativity of self-tracking communities, and build testable hypotheses from rich, multidimensional datasets. With appropriate attention to the inherent challenges and limitations, researchers and self-trackers can meaningfully expand our knowledge of place effects on human health.

TECHNOLOGICAL OPPORTUNITIES IN SELF-TRACKING

A new era of place-based study has been ushered in by the development of relatively low-cost, portable geographic positioning system (GPS) technologies (Pendyala and Bhat, 2012). Researchers can now more precisely describe daily exposures within *activity spaces*, rather rely on static, administrative, and often residentially-focused representations of place, which suffer from a variety of validity issues (Cummins et al., 2007; Juarez et al., 2014). "Modifiable unit" problems can arise out of the relative arbitrariness of certain cut-offs and levels of aggregation (e.g., time points or "spatial boundaries") (Dark and Bram, 2007; Cheng and Adepeju, 2014). For instance, estimates of an individual's exposure to tobacco retailers could vary substantially if outlets are summarized as counts within streets, blocks, or counties. Kwan famously extended these challenges by describing the *uncertain geographic context problem* (UGCoP), which highlighted the potentially significant influence of spatial boundary definitions on constructs of exposure and behavior (Kwan, 2012a). High-resolution GPS data can alleviate some of these concerns (Kwan, 2012b), and the development of wearable, environmental sensing technologies, such as portable air pollution monitors (Koehler and Peters, 2015; Seto et al.), has also enabled new kinds of individual-level

datasets to be generated. Thus, individual-level, geolocated datasets could allow researchers to improve upon common limitations of GIS approaches, including issues with spatiotemporal joining of layers and datasets.

Opportunities for Place-Based N-OF-1

The proliferation of GPS and GIS technologies present particular opportunities to those interested in single-subject or N-of-1 investigations (De Groot et al., 2017). As identified by a recent systematic review of GPS measures in built environment-physical activity studies by Yi and colleagues, individual-level, geolocated datasets might also help address selection bias in place-based research by helping account for potentially influential individual characteristics, and enabling improved experimental or quasi-experimental research designs (Yi et al., 2019). Analytical frameworks, such as those proposed by Jankowska, Schipperijn, and Kerr for physical activity research (Jankowska et al., 2015), also provide guidance for integrating participant-level GPS and behavior data with existing GIS layers, and conceptualizing the different temporal, spatial, and behavioral exposures.

By placing N-of-1 investigations in environmental contexts, researchers might better understand how treatments and interventions work, for whom, and under which conditions. In patient-provider settings, the place-health nexus often presents a challenge to prescribing appropriate behavioral solutions to health problems, even in situations supported by self-tracking. For example, a physician might recommend that a patient increase their daily minutes of physical activity and use a smartphone app to track their progress. Absent contextual information, these activity data say little about how and where the provider's suggestions were put into practice. If the patient achieves the prescribed targets, important insights could be gained from learning exactly how they did it, and where. Did the patient pursue physical activity in their neighborhood? At a gym or at work? Using community parks or sidewalks? Contextual, and especially environmental information, present new dimensions of considering health behavior change, and, with appropriate supports for data collection and interpretation, could offer providers clues about the generalizability of their recommendations.

Place-based N-of-1 datasets might also help patients and providers retest significant observations to understand if and how findings depend on contextual factors. Many smartphone owners have already collected baseline datasets that, if paired with location data, could be used prospectively or retrospectively to investigate changes and relationships between environment, behavior, and health. These might include actively recorded information (e.g., meal records logged in a diet app), as well as those collected passively, such as daily step counts. For instance, a patient might observe a correlation between their daily step counts and the average walkability of the environments where they spent time. However, if they base their observation on data from warm summer months, and fail to adjust for average outside temperature, they could wrongly conclude that the place effect is not generalizable to colder times or environments. The outside temperature is likely to moderate the place effect of walkable street networks, but not wholly determine it. With observations across multiple spatial and temporal settings, place-based N-of-1 datasets open new avenues for considering the relative influence of different contextual factors.

Everyday "Natural Experiments"

Together, researchers and long-term self-tracking participants could also conceptualize possible areas for inquiry in advance of changes to the built environment or policy, or in retrospective studies that leverage geolocated tracking data across numerous dimensions (Fox and Duggan, 2013). These investigations could include "natural experiments" that emulate the methodological rigor of randomized controlled trials (RCTs), while also providing feedback to stakeholders about the effectiveness of a program or policy (Sampson, 2010). Natural experiments can pose challenges for researchers, including how to conceptualize and adequately measure treatment (e.g., the dose, duration, or intensity of the intervention), and develop rigorous baseline datasets with appropriate counterfactuals. These issues can sometimes prove to be prohibitive, especially in terms of time and resources required to prospectively collect baseline data, or in cases where the intervention could not have been anticipated (e.g., disruptions to a transport network, or shelter-in-place orders related to COVID-19).

Natural experiment designs can also face logistical or ethical challenges when applied in community settings (Sampson, 2010). For example, while random assignment to a treatment or control group is a cornerstone of RCTs that helps guard against selection bias, such assignments can be impossible or impractical. Quasi-experimental evaluation of how a new neighborhood park influences residents' physical activity demands that a reasonable control group be identified (i.e., a neighborhood that could have received the treatment, but did not). However, the determination of where and when a new park is built is, in reality, far from random, and subject to influence from unobserved or unmeasured political and community factors. As Sampson observes in his critique of the "experimental turn" in evaluation research, "the hard truth is that we have little choice but to adapt in creative ways to the limitations that confront all social science inquiry" (Sampson, 2010). The place-based N-of-1 dataset offers one such creative adaptation to the random assignment problem by making available potential counterfactuals from within-subject baseline data. This could strengthen both the validity of the treatment or exposure variable, as well as our confidence in the comparability of the control units.

Quantified Self-in-Place

The opportunities for place-based N-of-1 studies are complemented by a broadening public use of wearable and self-tracking technologies, including a growing "quantified self" movement of individuals who use self-measurement to improve or optimize aspects of their lives, like health, happiness, or productivity (Fox and Duggan, 2013; Lupton, 2016; De Moya and Pallud, 2020). These avid self-trackers might be willing to volunteer long-term "baseline" data and may also be tracking across multiple devices or applications. Additionally, those in the quantified self-community could be interested in developing and testing new self-tracking technologies in

collaboration with researchers. Thus, by working with quantified self-participants, researchers not only gain access to unique and potentially geolocated datasets, but also draw upon the community's ingenuity and curiosity to develop new tools or hypotheses.

Thinking of place-based N-of-1 research in a community-engaged or participatory research frameworks also has epistemological and ontological benefits. Citizen science approaches, which might include the quantified self-movement, can help integrate participants' environmental perceptions into otherwise "objective" data collection methodologies (Pykett et al., 2020). While more controlled research settings use standardized ecological momentary assessments (EMA), citizen science approaches may instead follow more participant-driven protocols, though they might still employ standardized tools (e.g., photo-taking, neighborhood audits). This allows researchers to further engage participants in formulating hypotheses and interpreting outcomes, which could be especially relevant in exploratory settings without clear expectations of cause-and-effect relationships.

These engagement-focused approaches respond to calls for self-tracking researchers to leverage both quantitative and qualitative methods (Gilmore, 2016), such as the "citizen social science" described by Pykett and colleagues, whereby individual-level data are measured via wearables and also elicited through surveys and interviews (Pykett et al., 2020). Communities of self-trackers might also share insights to help one another optimize a behavioral intervention, or collectively assess the impact of an environmental change. Examples of quantified self-communities organizing for mutual support, learning, and advocacy are also evocative of the empowerment and engagement potential identified by De Groot et al. (2017), King et al. (2019), and De Moya and Pallud (2020). Thus, a complete vision for "quantified self-in-place" projects should include possible hypotheses of place-health relationships, and also make room for participants to suggest new directions, tools, or variables.

CHALLENGES

These opportunities are not without logistical, methodological, and ethical challenges. While some of these may be addressed with future technological improvements, it is important to recognize both the current limits to our capabilities and methods, as well as the potential risks that the imagined high-resolution, individual-level datasets might introduce.

Logistical Issues

Collecting and interpreting place-based N-of-1 datasets is no small task. Geospatial researchers have increased the internal validity of exposure measures with high-frequency GPS tracking, though conceptual (e.g., how do we operationalize exposure to a neighborhood park?) and logistical (e.g., how often should location be recorded to capture exposure?) questions remain. Furthermore, broad heterogeneity rooted in device-specific particularities and individual motivations for participation are likely to complicate or preclude between-participant comparisons from crowdsourced data. Crowdsourcing also

requires that participants know how to collect and extract high-resolution, geolocated data from mobile applications or wearable devices. Even among tech-savvy quantified self-communities, self-trackers are sometimes limited in their ability to extract and analyze data from tracking devices.

When GPS, GIS, and biometric data are collected with the express purpose of integration, analysts can anticipate some of these challenges by setting data formatting standards, conducting sensitivity analyses, or making adjustments to statistical models. Examples of web-based dashboards that integrate specific kinds of geodata, such as Patrick and Kerr's Personal Activity Location Measurement System (PALMS), may provide inspiration for future open-source platforms that could guide users through the various steps and stages of collecting, curating, and interpreting their own multidimensional datasets (Kerr et al., 2011). Additionally, advanced computing technologies like machine learning could provide future opportunities for automating data cleaning and harmonization, as well as uncovering relationships between spatial, temporal, and biometric variables.

Representation and Inclusion

Social determinants of health exert strong influences on both health behaviors and outcomes, but these constructs may not be well-represented in place-based N-of-1 datasets (Gabriels and Moerenhout, 2018). The degree to which these variables are integrated from self-tracking sources depends both on whether they are valued and collected by researchers or data collection/integration platforms, and whether participant populations are distributed across these socioeconomic gradients. As others have noted, disadvantaged populations face barriers in accessing tracking technologies and responding to insights gleaned from self-tracking data (Lupton, 2016; Gabriels and Moerenhout, 2018; Lupton). Well-documented mistrust of academic, medical, and research communities among many marginalized and exploited groups, stemming from decades of real and perceived harms perpetrated against them, could also limit the applicability and acceptability of place-based N-of-1 projects in certain settings (George et al., 2013; Bonevski et al., 2014). Furthermore, participation through geolocated personal data could elevate concerns about the independence of researchers from other potentially mistrusted and surveillance-interested parties, such as financial institutions, police, immigration officials, or case workers. Clear delineation of data protection, processing, and sharing protocols are necessary to make N-of-1 studies accessible to all communities, including legally-informed procedures regarding data requests from outside parties.

Without addressing these concerns about inclusion, place-based N-of-1 studies may thus be limited to a subset of "worried well," relatively healthy and high-income individuals with time and resources to devote to self-study (Gabriels and Moerenhout, 2018; Lupton). While researchers might still leverage learnings from pilot testing among this specific community for broader applications, more inclusive thinking is needed to avoid replicating inequality in N-of-1 research. Novel participatory approaches which aim to reduce power imbalances

between researchers and participants potentially enable new collaborations that would not be possible in conventional patient research paradigms (English et al., 2018; King et al., 2019).

Construct Validity

Researchers may seek to operationalize relatively ambiguous constructs in place-based N-of-1 studies. In some domains, validated measurement standards provide a strong start, so that, for instance, a daily step count is derived from an assemblage of high-resolution accelerometer data. Environment may complicate this relationship; as in the step count example, local terrain or topography could be markedly different than the validated standard (Huang et al., 2016). Other constructs are the result of more complex physiological measurements (e.g., accelerometer data to gauge movement and intensity), and still others aim to represent psychological or social constructs (e.g., excitement, fear, stress) (Pykett et al., 2020). While these measures may have a biological basis derived from laboratory settings, important questions emerge about the validity of these measures when used in the field, especially measures that indicate response to external stimuli (Chrisinger and King, 2018; Pykett et al., 2020). These questions become even more complex when comparisons between individual datasets are desired, but data have been collected with different kinds of applications or devices, and/or individuals' motivations for contributing their data are unclear.

Additionally, researchers must be aware of the contested nature of place terminologies themselves, including UGCoP and other challenges (Kwan, 2012a). Still, recent projects recognizing the "personal and subjective" nature of spatial perception (e.g., two neighbors may define their neighborhood quite differently) provide examples for how these uncertainties might be conceptualized and addressed (Pykett et al., 2020; Meier and Glinka). Furthermore, the moderating influences of environmental perceptions are also important to consider and could be measured with complementary methods, such as EMA (Yi et al., 2019). Ultimately, N-of-1 researchers should be cognizant of the uncertainties that surround the different constructs invoked by their analyses, and how interpretation of these constructs might vary between places and people.

Participant Privacy

Finally, as it becomes easier to volunteer and merge discrete streams of personal information into geolocated datasets, we must bear in mind the risks to participant privacy. For example, the "digital fingerprints" corporations assemble for individual consumers using multiple sources of online activity data illuminates just one of the risks posed by the "exploited" self-tracking described by Lupton (2016), and emerging "surveillance capitalism" identified by Zuboff (2015). Potential ethical

concerns about the intrusiveness of continuous GPS monitoring are possibly ameliorated in a quantified self-paradigm, where researchers and participants often agree to collect far more data than might otherwise be deemed necessary.

De Moya and Pallud describe possible benefits to self-tracking as "self-surveillance," observing how empowerment can come through visibility and accountability in data-sharing communities, and the ability to integrate data across multiple platforms and types (De Moya and Pallud, 2020). Still, the "consented self-surveillance" they describe relies on transparency of data integration and sharing, providing users opportunities to (dis)allow personal data from different sources to be integrated across platforms (De Moya and Pallud, 2020). Quantified self-participants might be more willing to accept more radical transparency in terms of data-sharing, though the exact privacy risks of geolocated datasets may not be entirely clear until they are created. Given the size and scale of place-based N-of-1 datasets, it may be difficult to ask participants to fully review and understand their contributions before volunteering them.

CONCLUSION

As new technologies expand our conceptualization of human and environmental variables, and the instruments used to measure them become more accessible to the general public in terms of cost, size, and skills required, the datasets available to health and built environment researchers will become increasingly large and multi-dimensional. For each the hundreds of potentially observable data points available to researchers, still greater numbers of linkages could be made to existing or simultaneously collected environmental data, enabling innovative observational and mechanistic studies that describe and predict the effects of place on human health. These place-based N-of-1 datasets also create new opportunities for engagement and collaboration outside of traditional researcher-participant paradigms, and may draw inspiration from flourishing quantified self and citizen science communities. While encouraging patients and citizen scientists to collect, analyze, and share their own data, researchers can also help educate participants about the challenges and opportunities inherent in place-based research. By developing a higher-resolution understanding of how place and health are connected for different individuals, the contours of etiological black boxes will become more legible, including the contextual and conditional dynamics that so often exist within them.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

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