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Technologies to Measure and Modify Physical Activity and Eating Environments

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Abstract

Context: The explosion of technologic advances in information capture and delivery offers unparalleled opportunities to assess and modify built and social environments in ways that can positively impact health behaviors. This paper highlights some potentially transformative current and emerging trends in the technology arena applicable to environmental context–based assessment and intervention relevant to physical activity and dietary behaviors.

Evidence acquisition: A team of experts convened in 2013 to discuss the main issues related to technology use in assessing and changing built environments for health behaviors particularly relevant to obesity prevention. Each expert was assigned a specific domain to describe, commensurate with their research and expertise in the field, along with examples of specific applications. This activity was accompanied by selective examination of published literature to cover the main issues and elucidate relevant applications of technologic tools and innovations in this field.

Evidence synthesis: Decisions concerning which technology examples to highlight were reached through discussion and consensus-building among the team of experts. Two levels of impact are highlighted: the "me" domain, which primarily targets measurement and intervention activities aimed at individual-level behaviors and their surrounding environments; and the "we" domain, which generally focuses on aggregated data aimed at groups and larger population segments and locales.

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Conclusions: The paper ends with a set of challenges and opportunities for significantly advancing the field. Key areas for progress include data collection and expansion, managing technologic considerations, and working across sectors to maximize the population potential of behavioral health technologies.

Introduction

The advent of the personal computer, mobile communication devices, and related electronic innovations has heralded previously unheard of opportunities for impacting personal and population health. Among such technologic advances are the assessment, integration, and interpretation of massive amounts of diverse information about individuals (e.g., capture of real-time physiologic responses across a range of biological systems), as well as the environment (e.g., geo-graphic information system [GIS] and global positioning system [GPS]). Complementing these advances have been innovations in communication media that have substantively changed the ways in which people live, work, and play.

Technologic innovation has left virtually no scientific domain untouched, including the health behavior arena. For more than a decade, technologic innovations have contributed to understanding and improving eating and activity behaviors and the social and built environmental determinants that shape them.[1]

The purpose of this paper is to highlight current and emerging trends in health behavior–relevant built environment assessment and intervention, with an emphasis on applications to active living and healthy eating. A team of experts was convened in 2013 for this purpose. Although this article is not exhaustive and is a selective examination of published literature, it covers a number of the major technologic developments that are being applied in studying and improving built and social environments related to eating and activity. In this context, *environment* is conceptualized broadly as "the circumstances, objects, or conditions by which one isbsurrounded … as well as the aggregate of social and cultural conditions that influence the life of an individual or community" (Merriam-Webster Dictionary, www.m-w.com).

Two general levels of impact are highlighted: the "me" domain, which targets measurement and intervention activities aimed primarily at individual-level behaviors and their surrounding environments; and the "we" domain, which incorporates aggregated data aimed at groups and larger population segments and locales.[2] These two domains, although not mutually exclusive, have grown out of different traditions and objectives. The article ends with challenges and opportunities concerning the most promising avenues for harnessing technology to promote potentially paradigm-shifting science in the obesity prevention and health behavior–environmental arenas.

Technology and Environmental Assessment

The "Me" Domain: Person-Level Contexts and Behaviors

The "me" domain, rooted in the "Quantified Self" movement and similar consumer- or patient-driven self-awareness practices,[3] captures individuals' personal contexts and perceptions of their behaviors, health, and environments, typically in what can approximate real time. The increasing availability of smartphones and other mobile and wearable health- and behavior-related devices provides many opportunities for assessing a broad range of behaviors, health statuses, social interactions, and the environments that influence them. Broadly characterized, these include the self-tracking behaviors that individuals engage in themselves that can be leveraged by researchers, and the increasingly sophisticated set of technologies developed by researchers to provide objective measures of physiologic, behavioral, social, and environmental influences on personal health and daily function.

The ubiquity of mobile devices is increasing as they become smaller, faster, and less expensive. Early work in this area used PDAs [personal digital assistants] that were portable and could provide immediate feedback, such as tracking progress toward dietary goals, even though they lacked wireless capability.[4–6] A recent Pew Foundation study[7] found that 21% of individuals in the U.S. already use some form of digital device to track some type of information related to their health. Such tracking can occur through user-based input of information or data into the electronic device, or via sensors that passively track user behavior and feed that information back to the user, often in "real time." A signal of the potential growth in the area of personal health data tracking is the Quantified Self movement. This movement sponsors activities where individuals can share their self-tracked data on everything from diet and physical activity to results of medical tests and genetic profiles. Although the focus of Quantified Self is to enable individuals to gain a deeper understanding of their health status or health goals,[8] these same data may hold promise for researchers who are interested in deeper insights into the daily lives of individuals and their environmental contexts (e.g., the Health Data Exploration Project[9]). For example, in addition to tracking health behaviors such as physical activity, applications (apps) such as MapMyFitness allow users to track their activities spatially through use of the phone-based GPS or other wireless trackers.[10] Many of these apps are also available for desktop computers.

Advances in mobile sensing of physiologic state and health behaviors have occurred in several areas. These include devices incorporating accelerometers, gyroscopes, GPS, physiologic sensors (e.g., electrocardiography), cameras, and light and sound sensors, all with the intent to improve understanding of factors important at the bio-behavioral level. Platforms that integrate multiple sensors have been developed to make inferences about complex phenomena that may involve two or more behaviors concurrently or that fuse data from more than one sensor (e.g., tracking both calorie intake and physical activity data).[11] The use of wireless scales to transmit weight data is now feasible both in health monitoring programs and research.[12] Another example is measurement of electrocardiography, skin conductance, or respiration to detect episodes of stress[13] and smoking.[14] Smartphones have been used to assess dietary exposure, physical activity, and other health behaviors in a growing number of populations.[7,15] A potentially powerful next step in this arena is to more fully integrate data from contextual sensors (e.g., GPS) with physiologic and behavioral sensors to provide a more comprehensive understanding of the relations between proximal contextual factors and person-level data. For example, GPS data continuously measured from mobile phones have been used to capture information about how craving tobacco is influenced by exposure to point-of-sale tobacco outlets.[16] GPS devices have also been used to track when and where people purchase food in relation to its availability[17,18] and local weather conditions.[19] In addition, the use of GPS-enabled smartphone apps can provide detailed contextual information on physical activity environments across a sizable geographic scale.[10] Novel forms of behavioral assessment that include contextual domains are now enabled through the use of wearable cameras, such as the SenseCam, developed by Microsoft.[20] SenseCam takes continuous pictures every 15–20 seconds and can improve classification of sedentary behavior in free-living humans,[21] which is difficult to measure using accelerometer-based methods.

Targeting the "We" Domain: Aggregated Data Across People and Larger-Scale Contexts

Coming primarily from environmental and population science perspectives, the "we" domain focuses on aggregated data aimed at larger population segments and locales, and, increasingly, can include interactions among physical and social environmental contexts.

Map layers corresponding to different components of the physical environment provide necessary data infrastructure for identifying the context in which many individual-level health behaviors take place. The U.S. Census Bureau and municipal governments have produced most of these files and distribute them publicly through the Internet. Although the map layers, such as streets and census tracts, are available for all parts of the U.S., there is great variability in the local GIS base files made available by municipalities. Cities like Washington DC, Philadelphia, New York, Chicago, and Los Angeles make a wide range of map layers available through repositories of parcels, zoning, and public transportation systems. Lydar models, Google SketchUp, and other three-dimensional models can display physical environment features in these large urban areas. By contrast, smaller towns and cities may have little or no GIS infrastructure. This uneven coverage makes analysis across cities challenging.

Because of uneven coverage of GIS layers, the lack of attribute information in municipal layers, and the expense involved in primary data collection, researchers are increasingly turning to comprehensive web-based tools that use photographs and administrative data to show or describe the physical environment. These include walk-score, Google Earth, and Google Streetview. Some of these tools are proprietary and others are open-source. There are an increasing number of studies evaluating the reliability and validity of these data for built environment audits, many with promising results.[22,23] However, the capabilities and limitations of these systems remain unclear.

Wearable technologies are increasingly capable of providing information about larger groups and the environmental factors that might collectively influence their health. This is particularly the case if they are built as systems that leverage the use of multiple types of sensors and analytic methods, such as machine learning, that are capable of handling the large amounts of data they produce across large numbers of people. The Personal Activity Location Measurement System (PALMS; ucsd-palms-project.wikispaces.com), developed with support from the NIH Gene Environment Initiative, is a promising approach in this area,[24] and has been shown to identify travel behaviors that are often misclassified with other approaches to measurement.[25] Though this type of measurement system can readily fit within the "me" domain, given its personal data-capture capabilities across multiple domains, it also is directly relevant to the "we" domain given its ability to integrate personal information across large numbers of people with higher-level contextual data. Similarly, a system of mobile phones with Bluetooth-connected air quality sensors has been shown to improve both real-time exposure information for its users as well as improved modeling of air quality across an entire region.[26] Such aggregated, de-identified data from cell phones of thousands of users have been used to describe travel behaviors,[27] and have begun to be applied to diet and physical activity behaviors.[28] Other areas such as exposure to infectious disease and psychologic states have been the subjects of automated recognition based upon software on mobile phones,[29,30] which can allow analysis of geographic and related contextual factors that may be involved. These forms of "mobile sensing" can quantify time spent in face-to-face proximity to others in the mobile network via Bluetooth in addition to location information to better capture health behaviors, resources, and outcomes across a defined group.[30] Such data, in combination with self-reported information that is "crowd sourced" across a population, can allow tracking of health behavior patterns and determinants on a large scale.[31,32] Frameworks to leverage these technologies have been proposed,[32] and barriers and opportunities related to their use in social and behavioral sciences research have been identified.[33]

A growing number of validated observational tools have been developed to capture how community residents use physical environment spaces in relation to physical activity, eating, and other behaviors. For example, the validated System for Observing Play and Recreation in Communities (SOPARC) is a tool for assessing park and recreation areas in relation to physical activity levels and types along with demographic characteristics (e.g., gender, age group).[34] The online materials for the tool include protocols, data coding forms, mapping strategies, and training materials (activelivingresearch. org/node/10654). Recently, the tool has been automated via mobile technology to enhance its ease of use (iSO-PARC), and the mobile app version has been shown to be reliable and efficient for gathering observational data examining park contexts and users across several countries.[35] Related tools for observational capture of built environment–health behavior relations include the System for Observing Physical and Leisure Activity in Youth (SOPLAY),[36] System for Observing Fitness Instruction Time (SOFIT),[37] and System for Observing Children's Activity and Relationships during Play (SOCARP).[38] Arguably, all such observational systems could be executed, similar to SOPARC, via mobile device platforms. In addition, the Rand Corporation has developed an online app and user guide for SOPARC (soparc.rand.org). In the eating arena, the Nutrition Environment Measurement Survey for Stores has also been adapted for mobile data collection in a large survey of corner stores.[39]

Although relatively little systematic work has been published to date in the physical activity and dietary behavior fields,[12,28,40,41] social network analysis has been applied in other health behavior fields, including tracking sexual risk behavior,[42] obesity levels,[43] and other conditions (e.g., happiness) over extended periods of time.[44] Such analytic approaches potentially allow for a greater understanding of how social and physical environments (e.g., worksites, neighborhoods) interact to promote or discourage health-related behaviors.

An example of an innovative electronic social net-work–based surveillance approach used in the physical activity field has been the exploration of methods for tracking contextual factors and use of mobile fitness apps via Twitter.[45] Social network–based surveillance approaches to gathering relevant information across large populations can be conducted with less personal intrusiveness or reactivity than paper-and-pencil or interview-based assessment methods.

Technology and Environmental Interventions

Targeting the "Me" Domain

Despite an explosion of mobile apps aimed at individual health promotion and disease management,[46] relatively few have been evaluated systematically for scientific accuracy, efficacy, and long-term behavioral maintenance and use (examples in "me" and "we" domains shown in Table 1). Reviews of apps aimed at physical activity and dietary change indicate that, although promising for their wide reach, customized messages, and continuity, rigorous evaluation of the sustained effectiveness of such programs remains is rare.[15,47,48] Some available tools focus mainly on educational content rather than behavioral and environmental management, and have not been well evaluated.[49] Of particular relevance to the environmental arena is the potential for such mobile applications to capture, in real time, environmental contexts that may help or hinder individuals' health behavior decisions. For example, in a mobile device intervention study in which participants tracked walking levels and personal and perceived environments throughout the day, perceived access to local supportive environmental factors (e.g., access to walking paths), although not perceived environmental barriers, was positively associated with daily walking.[50] Participants reported walking on average about 20 minutes more at those times during the week when they had direct access to a walking path.[50]

Additional applications in this area include the use of electronic games, such as "exergames" (e.g., physically active video games played on Wii and Kinect systems), that link active play to "gaming" aspects and motives. One experiment found, for example, that when college students were "primed" with contextual stimuli and messages concerning the physical activity-related benefits of an active video game (i.e., Dance Central for Xbox Kinect), they used the video game system significantly longer than those for whom the activity was framed as "gameplay."[51] The results suggest that, at least for some groups, "healthifying" exergames may be a more powerful motivator for extended active use than "gamifying" health behaviors.[51] Through connecting with other players via online gaming apps, such recreational programs can be extended to larger groups of people. A complement to this approach is the addition of video games to traditional gym equipment.

Some innovative research has begun to explore the possibilities of virtual environments as potential enablers of individual health behavior change outside of the virtual world. For example, early research in this area indicated that when young adults watched a "virtual self" running on a treadmill, they exercised >1 hour more in the next 24-hour period relative to individuals who had observed a "virtual other" (not themselves) running or their "virtual self" being sedentary.[52] Similarly, participants who watched their "virtual self" lose weight as they exercised and gain weight when they did not, exercised significantly more over the short-term relative to participants who watched a "virtual self" that did not change.[52] Similarly, a recent study investigating the potential appropriateness of avatar-based virtual reality technologies for weight loss found that such tools might be useful for modeling weight loss behaviors (i.e., changes in diet and physical activity) in at least some groups of women.[53]

The “We” Domain

The potential power of online social networks to influence or support change in health behaviors has been noted in several recent studies.[32,40,54] For example, in a brief weight loss study, the use of Facebook combined with personalized text messaging resulted in greater 8-week weight loss than either using Facebook alone or a waitlist control.[55] Although yet to be fully explored, social networks and media also may serve as potentially potent tools for diffusing policies supporting environmental contexts that promote healthy lifestyles.[56]

Information technologies, if appropriately developed with the user in mind, can potentially be used to shrink the health disparities gap and promote greater health equity across a population as well as across regions of the world. One example of this approach has been the development and testing of an electronic tablet that can be used by residents from all educational and economic backgrounds to document the barriers to active living and healthy eating in their neighborhoods in ways that compel action at the policy level.[57–59] This electronic “discovery tool” is currently being used in different portions of the U.S. and in other countries to inform low-cost, resident-driven environmental solutions for promoting healthy lifestyles.

A complementary approach to the aforementioned types of intervention is the use of technology and built environment contexts to ostensibly promote non–health-specific motives and goals (e.g., fun, social engagement, cognitive challenge), with greater physical activity or healthier food choices a “side effect” of such interventions. An example of this type of approach is Bingo-WALK, created by the Social Apps Lab at the Center for Information Technology Research in the Interest of Society (CITRIS), University of California, Berkeley in collaboration with researchers there.[60] BingoWALK is an interactive electronic tablet-based game aimed at older adults that combines walking outdoors and navigational wayfinding with the game, Bingo. Players walk a specific route shown on the electronic tablet and find specific locations geocoded en-route to obtain Bingo points. Initial field tests of the electronic game are promising. The explosion of electronic games developed for mobile devices offers vast potential for engaging individuals in ways that encourage positive health behaviors within different environmental contexts.

A growing question of interest concerns whether web-based virtual worlds and community-oriented social network games (e.g., Farmville, Second Life) can lead to real-life behavior change. It has been reported, for instance, that current research is underway evaluating the weight loss effects of “Club One Island”—a weight loss community within the web-based virtual world of Second Life. As part of this virtual community, participants attend virtual nutrition classes, watch themselves exercise, and discuss how they are doing.

Other Emerging Technologies in the Field

Given that the current article was not meant to be an exhaustive review, other emerging technology platforms with potential to significantly shape the health behavior and obesity prevention fields could not be discussed in detail. Among the types of potentially transformative technology platforms that await further development and testing are Google Glass, Apple's Healthbook, and Android Wear. These represent just a few of the innovative technologies that hold promise for changing the ways in which users receive and interact with mobile health (mHealth) information. All promise a more seamless interface between the user and the device or program, which in turn may promote further granularity in assessment as well as more potent, lasting interventions.

Challenges and Opportunities

The relative newness of the field coupled with its rapid growth has resulted in both challenges and opportunities for scientists that deserve increasing focus and discussion. Some of the more timely issues are summarized below.

Technologies that support continuous collection of behavioral, social, and environmental data from individuals or groups raise several important questions for researchers in the areas of both privacy and participant informed consent. There are also practical considerations in conducting this type of research—should participants be provided with dedicated devices for the study, or use their personal devices? Who should assume the cost of the devices and their usage for the research? Answers to these questions depend on the specific scientific questions being pursued and where on the scientific continuum the research questions fall. For instance, providing participants with a single type of dedicated device and assuming the costs of the device and its usage could increase consistency across subjects and remove potential barriers to study participation and adherence. By contrast, allowing participants to use their own smartphones and cover the costs themselves would provide a more contextually relevant evaluation of the intervention.

Maintaining privacy and confidentiality in an era when geocoded data can be easily linked with social and behavioral data can be challenging.[61] Moreover, the use of self-tracked and mobile technology–based data for health-related research is relatively new, thus there are few reports of how privacy is being addressed. A recent survey conducted on behalf of the Robert Wood Johnson Foundation Health Data Exploration project[9] revealed that about 70% of respondents would be willing to share their data with academic researchers, with the dominant condition (57%) for sharing being an assurance of privacy for those data. Importantly, the survey also found a considerable cohort of roughly 30% for whom privacy was not a consideration with regard to sharing.

A 2013 Pew Foundation survey[62] found substantial concerns about how the new digital world is compromising anonymity. More than 85% of respondents reported having taken some action to reduce identifying information from their online behavior. Despite these actions, there is growing research to suggest that re-identification of individuals who were anonymous in separate data bases can be accomplished through various mathematical strategies. For example, anonymous cell phone data for millions of users can be mined to identify 95% of individuals if as few as four spatial–temporal data points are available for each user.[63] Thus, the expectations of anonymity that researchers and research participants have become accustomed to in traditional medical and public health research may be more difficult to sustain in the new digital era. Among potential solutions to such challenges is the increased use of technologic safeguards (e.g., encryption, strong passwords, industry vigilance in combatting misuse of information), along with more thorough consumer education concerning threats to privacy and more realistic consumer expectations related to data security and protections. Some data security companies have suggested that many of the problems related to data theft and user identification could be mitigated if companies offering information technology services to the public would install basic data protections to reduce data access vulnerabilities. Policy or legislative action may be required to speed up this process, and consumer education about data security and potential breaches is a lower-cost option. Further qualitative research is needed to understand how new technologies influence privacy-related attitudes and practices, and ideally the results of this research can inform policy.

In addition to difficulties with respect to assuring privacy and anonymity, health-related research using self-tracking, mobile, and other new technologies raises new issues about how to address informed consent. Two of these issues are the value of collecting these data over an extended period of time, and the re-use of data in successive experiments. Current practices of informed consent are generally based on time-limited studies where measurements occurred infrequently. Thus, it has been possible to fully inform participants about all the uses of their data and provide assurance that, upon completion of a study, the data would be destroyed. Providing informed consent for data that will be used by many researchers over an extended period of time is often not feasible and raises new questions about how to address ethical issues related to using these new forms of data.[64] Ethical issues associated with new forms of media and digital devices have been explored since the inception of the Internet. Recent surveys suggest that IRBs are divided with respect to whether these issues are unique, and relatively few institutions have developed formal guidelines to address them.[65] Leadership from groups such as the NIH to help academic institutions develop a common set of principles and practices that could be implemented would be optimal. In the meantime, given the current milieu, it will be incumbent on researchers to continue to seek out strategies for ensuring that participants fully understand the attendant risks involved when using mHealth devices and programs.

Other challenges and future directions, and possible solutions for key challenges, are summarized in Table 2. The broadening definitions and focus of “built environment” research to include “man-made” social and media environments that have become increasingly ubiquitous also deserve further attention. Finally, it is increasingly important to find strategies to shrink the “digital divide” among socioeconomically underserved populations.[66,67]

The complex challenges described herein set the stage for transformative approaches to scientific discovery, application, and translation in the field. Through building partnerships across health behaviors, levels of impact, and relevant sectors, including the technology industry, the promise of the technologic advances described for measuring and modifying environmental contexts for active living and healthy eating may be realized more fully.

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References

1. Stokols D, Grzywacz JG, McMahan S, Phillips K. Increasing the health promotive capacity of human environments. Am J Health Promot. 2003;18(1):4–13. [PubMed: 13677958]
2. King AC. Harnessing the power of technology to promote population-wide physical activity. 3rd International Conference on Ambulatory Monitoring of Physical Activity and Movement 2013; published abstract. http://www.umass.edu/sphhs/sites/default/files/ICAMPAM-Speakers-3.29.13.pdf.
3. Swan M Emerging patient-driven health care models: an examination of health social networks, consumer personalized medicine and quantified self-tracking. Int J Environ Res Public Health. 2009;6(2): 492–525. [PubMed: 19440396]
4. Glanz K, Murphy S, Moylan J, et al. Improving dietary self-monitoring and adherence with hand-held computers: a pilot study. Am J Health Promot. 2006;20(3):165–170. [PubMed: 16422134]
5. Atienza AA, King AC, Oliveira BM, et al. Using hand-held computer technologies to improve dietary intake. Am J Prev Med. 2008;34(6): 514–518. [PubMed: 18471588]
6. King AC, Ahn DK, Oliveira BM, et al. Promoting physical activity through hand-held computer technology. Am J Prev Med. 2008;34(6): 138–142. [PubMed: 18201644]
7. Fox S, Duggan M. Tracking for Health. 2013 www.pewinternet.org/2013/11/26/part-three-tracking-for-health/.
8. Li I, Dey A, Forlizzi J. A stage-based model of personal informatics systems. Paper presented at Proceedings of the 28th International Conference on Human Factors in Computing Systems-CHI 2010; 2010 Apr 10 15; Chicago IL.
9. Health Data Exploration Project. Personal data for the public good: new opportunities to enrich understanding of individual and population health. Irvine CA: University of California-Irvine, University of California-San Diego, 2014
10. Hirsch JA, James P, Robinson JRM, et al. Using MapMyFitness to place physical activity into neighborhood context. Front Public Health. 2014;2:19. [PubMed: 24653982]
11. Tsai C, Lee G, Raab F, et al. Usability and feasibility of PmEB: a mobile phone application for monitoring real time caloric balance. Paper presented at Proceedings of the First International Conference on Pervasive Computing Technologies for Healthcare 2006; Innsbruck, Austria.
12. Greene J, Sacks R, Piniewski B, et al. The impact of an online social network with wireless monitoring devices on physical activity and weight loss. J Prim Care Community Health. 2013;4(3):189–194. [PubMed: 23799706]
13. Ertin E, Stohs N, Kumar S, et al. AutoSense: unobtrusively wearable sensor suite for inferencing of onset, causality, and consequences of stress in the field. Paper presented at Proceedings of ACM Conference on Embedded Networked Sensing Systems, 2011 Nov 1–4; s.
14. Ali AA, Hossain SM, Hovsepain K, et al. SmokeTrack: automated detection of cigarette smoking in the mobile environment from respiration measurements. Paper presented at Proceedings of ACM Conference on Information Processing in Sensor Networks (IPSN), 2012; Beijing, China.
15. King AC, Hekler EB, Grieco LA, et al. Harnessing different motivational frames to promote daily physical activity and reduce sedentary behavior in aging adults. PLoS One. 2013;8(4):e62613.

16. Kirchner TR, Cantrell J, Anesetti-Rothermel A, et al. Geospatial exposure to point-of-sale tobacco: real-time craving and smoking-cessation outcomes. Am J Prev Med. 2013;45(4):379–385. [PubMed: 24050412]
17. Gustafson A, Christian JW, Lewis S, et al. Food venue choice, consumer food environment, but not food venue availability within daily travel patterns are associated with dietary intake among adults, Lexington Kentucky 2011. Nutr J. 2013;12:17. [PubMed: 23360547]
18. Christian WJ. Using geospatial technologies to explore activity-based retail food environments. Spat Spatiotemporal Epidemiol. 2012;3(4): 287–295. [PubMed: 23149325]
19. Horanont T, Phithakkitnukoon S, Leong TW, et al. Weather effects on the patterns of people's everyday activities: a study using GPS traces of mobile phone users. PLoS One. 2013;8(12):e81153.
20. Hodges S, Williams L, Berry E, et al. SenseCam: a retrospective memory aid In: Dourish P, Friday A, eds. Ubicomp 2006 LNCS. 4206. Berlin: Springer-Verlag, 2006.
21. Kerr J, Marshall SJ, Godbole S, et al. Using the SenseCam to improve classifications of sedentary behavior in free-living settings. Am J Prev Med. 2013;44(3):290–296. [PubMed: 23415127]
22. Vargo J, Stone B, Glanz K. Google walkability: a new tool for local planning and public health research? J Phys Act Health. 2012;9(5): 689–697. [PubMed: 21946250]
23. Frank LD, Saelens BE, Chapman J, et al. Objective assessment of obesogenic environments in youth: geographic information system methods and spatial findings from the Neighborhood Impact on Kids study. Am J Prev Med. 2012;42(5):e47–e55. [PubMed: 22516503]
24. Kerr J, Norman G, Godbole S, et al. Validating GPS data with the PALMS System to detect different active transportation modes. Med Sci Sports Exerc. 2012;44(5S):S2529.
25. Ellis K, Kerr J, Marshall S, et al. Identifying travel behaviors in challenging environments using machine learning algorithms, GPS, and accelerometer data: a validation study. Front Public Health. 2014;2:36. [PubMed: 24795875]
26. Nikzad N, Verma N, Ziftci C, et al. CitiSense: improving geospatial environmental assessment of air quality using a wireless personal exposure monitoring system. Paper presented at Proceedings of the Conference on Wireless Health '12 2012 Oct 23 25; San Diego CA.
27. Gonzalez MC, Hidalgo CA, Barabasi AL. Understanding individual human mobility patterns. Nature. 2008;453(7196):779–782. [PubMed: 18528393]
28. Madan A, Moturu S, Lazer D, et al. Social Sensing: obesity, unhealthy eating and exercise in face-to-face networks. Wireless Health. 2010: 104–110.
29. Madan A, Cebrian M, Lazer D, et al. Social sensing for epidemiological behavior change. Access. 2010:291–300.
30. Madan A, Cebrian M, Moturu S, et al. Sensing the "health state" of a community. IEEE Pervasive Comput. 2012;11:36–45.
31. Ranard BL, Ha YP, Meisel ZF, et al. Crowdsourcing—harnessing the masses to advance health and medicine, a systematic review. J Gen Intern Med. 2014;29(1):187–203. [PubMed: 23843021]
32. Lane ND, Xu Y, Lu H, et al. Exploiting social networks for large-scale human behavior modeling. IEEE Pervasive Comput. 2011;10(4): 45–53.
33. Kumar S, Nilsen W, Abernethy A, et al. mHealth Evidence Workshop —exploring innovative methods to evaluate the efficacy and safety of mobile health. Am J Prev Med. 2013;45(2):228–236. [PubMed: 23867031]
34. McKenzie TL, Cohen DA, Sehgal A, et al. System for Observing Play and Recreation in Communities (SOPARC): reliability and feasibility measures. J Phys Act Health. 2006;3(S1):S208–S222.
35. Santos MP, Rech CR, Alberico CO, et al. Agreement and reliability of an app for observing play and recreation in communities (ISOPARC). Proceedings of the International Congress of Physical Activity and Public Health, Rio de Janeiro Brazil, April 8–11, 2014 http://www.icpaph2014.com/abstracts.pdf.
36. Saint-Maurice PF, Welk G, Ihmels MA, et al. Validation of the SOPLAY direct observation tool with an accelerometry-based physical activity monitor. J Phys Act Health. 2011;8(8):1108–1116. [PubMed: 22039129]

37. Rowe PJ, Schuldheisz JM, van der Mars H. Measuring physical activity in physical education: validation of the SOFIT direct observation instrument for use with first to eighth grade students. Pediatr Exerc Sci. 1997;9(2):136–149.
38. Ridgers ND, Stratton G, McKenzie TL. Reliability and validity of the System for Observing Children's Activity and Relationships during Play (SOCARP). J Phys Act Health. 2010;7(1):17–25. [PubMed: 20231751]
39. Cavanaugh E, Mallya G, Brensinger C, et al. Nutrition environments in corner stores in Philadelphia. Prev Med. 2013;56(2):149–151. [PubMed: 23262362]
40. Centola D An experimental study of homophily in the adoption of health behavior. Science. 2011;334(6060):1269–1272. [PubMed: 22144624]
41. Anderson I, Maitland J, Sherwood S, et al. Shakra: tracking and sharing daily activity levels with unaugmented mobile phones. Mobile Netw Appl. 2007;12(2–3):185–199.
42. Black SR, Schmiege S, Bull S. Actual versus perceived peer sexual risk behavior in online youth social networks. Transl Behav Med. 2013;3(3): 312–319. [PubMed: 24073183]
43. Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. N Engl J Med. 2007;357(4):370–379. [PubMed: 17652652]
44. Fowler JH, Christakis NA. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. BMJ. 2008;337:a2338.
45. Vickey TA, Ginis KM, Dabrowski M. Twitter classification model: the ABC of two million fitness tweets. Transl Behav Med. 2013;3(3):304–311. [PubMed: 24073182]
46. Nilsen W, Riley WT, Heetderks W. News from the NIH: using mobile and wireless technologies to improve health. Transl Behav Med. 2013; 3(3):227–228. [PubMed: 24073170]
47. Norman GJ, Zabinski MF, Adams MA, et al. A review of eHealth interventions for physical activity and dietary behavior change. Am J Prev Med. 2007;33(4):336–345. [PubMed: 17888860]
48. Spring B, Gotsis M, Paiva A, et al. Healthy apps: mobile devices for continuous monitoring and intervention. IEEE Pulse. 2013;4(6):34–40. [PubMed: 24233190]
49. Azar KM, Lesser LI, Laing BY, et al. Mobile applications for weight management: theory-based content analysis. Am J Prev Med. 2013; 45(5):583–589. [PubMed: 24139771]
50. Hekler EB, Buman MP, Dunton GF, et al. Are daily fluctuations in perceived environment associated with walking after controlling for implementation intentions? Psychol Health. 2012;27(9):1009–1020. [PubMed: 22214492]
51. Chen FX, King AC, Hekler EB. "Healthifying" exergames: improving health outcomes through intentional priming. Paper presented at CHI 2014, 2014 Apr 26 May 01; Toronto, ON, Canada.
52. Fox J, Bailenson JN. Virtual self-modeling: the effects of vicarious reinforcement and identification on exercise behaviors. Media Psychol. 2009;12:1–25.
53. Napolitano MA, Hayes S, Russo G, et al. Using avatars to model weight loss behaviors: participant attitudes and technology development. J Diab Sci Tech. 2013;7(4):1057–1065.
54. Centola D, vandeRijt A. Choosing your network: social preferences in an online health community. Soc Sci Med. 2015;1255:19–31. 10.1016/j.socscimed.2014.05.019.
55. Napolitano MA, Hayes S, Bennett GG, et al. Using Facebook and text messaging to deliver a weight loss program to college students. Obesity (Silver Spring). 2013;21(1):25–31. [PubMed: 23505165]
56. Montes F, Sarmiento OL, Zarama R, et al. Do health benefits outweigh the costs of mass recreational programs? An economic analysis of four ciclovia programs. J Urban Health. 2012;89(1):153–170. [PubMed: 22170324]
57. Buman MP, Winter SJ, Baker C, et al. Neighborhood eating and activity advocacy teams (NEAAT): engaging older adults in policy activities to improve built environments for health. Transl Behav Med. 2012:1–5. [PubMed: 24073090]
58. Buman MP, Winter SJ, Sheats JL, et al. The Stanford Healthy Neighborhood Discovery Tool: a computerized tool to assess active living environments. Am J Prev Med. 2013;44(4):e41–e47. [PubMed: 23498112]
59. Winter SJ, Buman MP, Sheats JL, et al. Harnessing the potential of older adults to measure and modify their environments: long-term successes of the Neighborhood Eating and Activity

Advocacy Team (NEAAT) study. Transl Behav Med. 2014;4(2):226–227. 10.1007/s13142-014-0264-1. [PubMed: 24904707]

60. BingoWalk [computer program. Berkeley CA: The Regents of the University of California, 2012
61. Gutman M, Stern P, eds. Putting people on the map Protecting confidentiality with linked social/spatial data. Washington DC: National Academies Press; 2007.
62. Anonymity, privacy, and security online. Pew Research Center; 2013 http://www.pewinternet.org/Reports/2013/Anonymity-online.aspx.
63. De Montjoye YA, Hidalgo CA, Verleysen M, et al. Unique in the crowd: the privacy bounds of human mobility. Sci Rep. 2013;3:1376. [PubMed: 23524645]
64. Arnason V. Coding and consent: moral challenges of the database project in Iceland. Bioethics. 2004;18(1):27–49. [PubMed: 15168697]
65. Buchanan EA. Internet research ethics and IRBs Chicago IL: OHRP Research Forum 2010.
66. Fox S Digital divisions. 2010 http://www.pewinternet.org/Reports/2005/Digital-Divisions.aspx.
67. Viswanath K, Kreuter MW. Health disparities, communication inequalities, and eHealth. Am J Prev Med. 2007;32(5S):S131–S133. [PubMed: 17466818]

Table 1.

Domain Examples of Technology and Environment Assessment and Intervention tools

The "Me" domain (person-level contexts and behaviors)		
Assessment	Self-tracking[4–6] SenseCam[20,21] Personal Activity Location Measurement System (PALMS)[24,25]	Apps that allow users to record data on calorie intake, exercise, medical test results, etc., in conjunction with proximal contextual information Takes pictures every 15–20 seconds, which improves categorization of sedentary behaviors A fully integrated measurement system that is capable of estimating Physical Activity Energy Expenditure (PAEE) by combining activity data collected by accelerometers, heart rate from heart rate monitors and location data collected by GPS data loggers
Intervention	Quantified-Self mobile apps[8,15]	Provide a platform for using dynamic personal data in conjunction with local contextual information to deliver real-time feedback and guidance for behavior change
The "We" domain (aggregated data across people and larger-scale contexts)		
Assessment	Web-based tools and GIS[22,23] Aggregated, de-identified data collection from mobile devices[26–28,34] Crowd-sourcing[31] Social network-based surveillance[40,45]	Web-based tools such as Walk-score, Google Earth, and Google Streetview can create a more comprehensive view of environments Utilized to collect information on travel and other physical activity behaviors; also can be used to facilitate capture of observational surveillance data (e.g., SOPARC) Self-reported information that can be aggregated across large numbers of people to allow tracking of health behavior patterns and determinants on a large scale Researchers can track a variety of behavioral information (e.g., exercise frequency, location information, daily app use patterns) via Twitter and other programs
Intervention	Citizen scientist tools[57–59] Virtual worlds[52] "Stealth" interventions (BingoWalk)[60]	Apps that allow residents to electronically capture barriers to active living and healthy eating in ways that compel action at the environmental and policy levels Virtual environments where users can create a "virtual self" or avatar to help visualize and "practice" healthful activities and accomplishments Example of an electronic game for older adults that incorporates navigation finding and outdoor walking to earn Bingo points

Note: The Personal Activity and Location Measurement System (PALMS) and similar systems can also aggregate physical activity and environmental data over larger-scale locales and populations of relevance to the "We" domain.

GIS, geographic information system; GPS, global positioning system; SOPARC, System for Observing Play and Recreation in Communities.

Table 2.

Challenges and Opportunities

Challenges	Potential solutions and opportunities
Data collection and data expansion	
Lack of GIS infrastructure	Encourage local municipalities and companies to share GIS resources.
Lack of sufficient data on physical activity and dietary behavior	Continue to educate and expand the number of researchers interested in studying physical activity and nutrition behaviors.
Lack of understanding of person-environment interactions	Increase the number of cross-sectoral studies that look at different dimensions of individual's health choices and environments.
Technical considerations	
Keeping up with advancing technology	Centralized resources for researcher with links, critiques, etc. Partner with industry to develop and test cutting-edge technologies.
Cost of technology and equipment	Enroll study participants in cohorts, so you can purchase fewer devices. Consider what costs can and should be covered by participants (e.g., smart phone ownership). Develop standardized protocols for privacy concerns.
Funding issues for longitudinal data collection	Use existing relationships with funders to encourage the inclusion of built environment-related measures into existing longitudinal surveys.
Challenges with the "digital divide" between different socioeconomic populations	Locate, partner with, and use publicly available resources such as library computers, low-fee mobile devices.
Areas for "bridging the gap"	
Collaboration across disciplines	Centralized group to link researchers and practitioners from different disciplines; encourage and incentivize institutional collaborations.
Understanding community and organizational systems, stakeholders, and decision-making approaches	Engage with decision makers who support built environment-technology work. Team up with organizational behavior experts from different community sectors. Work with industry to evaluate technology applications in behavioral health field.
Bridge the gap between assessment and intervention	Work with key audience members and groups to identify leverage points for change and how to integrate change strategies into tech platforms.
Broaden definitions of "built environment" research and focus to enable more comprehensive and potentially effective solutions	Work across disciplines and sectors. Identify and partner with experts from varied disciplines (e.g., planning, transportation, physical activity, food retail).
Expand link between food and activity environments	Model examples of teams that address both food and activity environments; propose an "energy balance" foundation for obesity prevention projects.

GIS, geographic information system.