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Obesity and the built environment: A re-appraisal

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Abstract

The built environment (BE) has been viewed as an important determinant of health. Numerous studies have linked BE exposure, captured using a variety of methods, to diet quality and to area prevalence of obesity, diabetes, and cardiovascular disease. First-generation studies defined neighborhood BE as the area around the home. Second-generation studies turned from home-centric to person-centric BE measures, capturing an individual's movements in space and time. Those studies made effective uses of global positioning system (GPS) tracking devices and mobile phones, sometimes coupled with accelerometers and remote sensors. Activity space (AS) metrics explored travel paths, modes and destinations to assess BE exposure that was both person and context specific. However, as measures of the contextual exposome have become ever more fine-grained and increasingly complex, connections to long-term chronic diseases with complex etiologies, such as obesity, are in danger of being lost. Further, few studies on obesity and BE have included intermediate energy-balance behaviors, such as diet and physical activity, or explored the potential roles of social interactions or psychosocial pathways. Emerging survey-based applications that identify habitual destinations and associated travel patterns may become the third generation of tools to capture health-relevant BE exposures in the long term.

Keywords

exposome; built environment; home-centered; activity space; mobile technologies; KARMA; obesity; diabetes

1. Introduction

The built environment (BE) has been defined as the human-modified space in which people conduct their daily lives.(1) Measuring and quantifying human exposure to the neighborhood BE has been accomplished in a variety of ways.(2–11) Current studies on obesity and the BE owe much to the development of geographic information systems (GIS) (2, 12, 13) and the widespread use of global positioning system (GPS) devices.(14–18) Elements of the neighborhood BE tend to be categorized into the food environment and the physical activity (PA) environment.(19) The food environment has been conceptualized in

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terms of physical access to local supermarkets, groceries, fast food restaurants, or convenience stores.(19) The PA environment refers to area walkability, greenness, blue water, land use mix, and access to recreational facilities.(19)

Much of the work on health and the BE, conducted over the past two decades, has focused on neighborhood-level BE features and their likely impact on poor diets, lack of exercise, and higher obesity prevalence.(19–23) Most studies were home-centric, meaning that the density of or distances to destinations of interest were measured in relation to the individuals' homes.(2, 13) Whereas aspects of the neighborhood PA environment did predict walking and lower body weights,(23–28) there was little to link the food environment to diet or diet-related health outcomes, such as obesity, diabetes, and cardiovascular disease (CVD). Physical access to supermarkets around the home was unrelated to diet quality or obesity rates.(2, 20, 29–41) There is preliminary evidence that activity space (AS) metrics are also unrelated to diet, obesity, or diabetes.(17, 18) Indeed, there is a growing understanding, with respect to the evaluation of the food environment in particular, that the BE only comprises a small slice of the larger context of the food environment.

Capturing the full contextual exposome, the totality of BE exposures at the individual level, has been described as fundamental to a better understanding of diets, obesity, and diabetes.(42–46) The promise of evaluations of the BE was to show a causal link between elements of the BE, or changes in the BE over time, and obesity or other health outcomes.(42–46) To that end, evaluations of BE exposures have sought to develop methods to more accurately and completely capture elements of the BE. Accordingly, such BE measurement tools have become increasingly more sophisticated using wearable GPS devices, often augmented with travel diaries, travel logs, Google street views, or other mobile technologies.(9, 14, 15, 18, 23, 26, 28, 44, 45, 47–56) These approaches allow the capture of near instantaneous measures of exposure to the BE not only around the home location but also at work, school, and along travel routes.(14, 15, 18, 44, 45, 47–51, 56) Mobile technologies have become increasingly atomized, allowing researchers to capture the minutiae of daily activities in time and space, sometimes at time resolutions of 10 seconds or less. By contrast, measures of diet quality, PA, and health have not followed suit. Standard methods of dietary intake assessment, such as food recalls, or food frequency questionnaires were generally not used.(2, 4–6, 11, 19, 57–59) Instead, the frequency of consuming "healthy" and "unhealthy" foods per day was one proxy for diet quality.(11) Health outcomes, when included in BE studies, were limited to body weight, with only a few studies examining diabetes or cardiovascular outcomes.(60–62)

The almost exclusive focus on quantifying BE exposure, together with cross sectional study designs, (19) has limited the ability to draw causal inferences regarding potential links between BE exposure and obesity.(45, 56) Furthermore, there seems to be a conceptual disconnect between current measures of BE exposure and the long-term trajectories of body weight. Fine-grained mobile technologies capturing detailed movement in space and time of at time resolutions of 10 seconds or less may prove highly useful in predicting risk factors for positive or negative behavior change when paired with spatiotemporally synced ecological momentary assessment (EMA).(63) However, as the measures of BE exposome become instantaneous and increasingly time-specific, links to chronic diseases with long onset periods and complex etiologies, such as obesity and diabetes, is in danger of being lost. Describing the evolving concept of BE exposure in relation to obesity is the topic of this review.

2. Evolving measures of BE exposure

2.1 Home as the center for BE exposures

Interest in health geography began in the early 1990s as researchers sought to establish evidence for geographic disparities in health outcomes.(12, 64) Concurrently, there was a renewed interest in social determinants of health as well as in the socioeconomic and demographic factors that influence where people live.(12, 13) The earliest investigations into the BE and health often relied on neighborhood-level socioeconomic measures such as indexes of socioeconomic position derived from the Census Bureau in the United States, the Townsend index, Carstairs index, and Index of Multiple Deprivation in the United Kingdom and the Socio-Economic Indexes for Areas in Australia, among others.(65–70) These indexes were often composite indicators for area-level poverty or wealth, based on socio-demographic data on poverty, employment, education, incomes, among other metrics.(64–72) In these studies, an individual's neighborhood was often defined by some administrative boundary (e.g. census tracts in the United States) in which the individual's home was located.(64, 71, 72) Often, actual addresses were geocoded to the centroid of the geographic administrative unit.

Early studies combined individual addresses with area-based, socio-demographic data. The density of fast food restaurants or supermarkets, and structural environment features, such as land use mix or availability of parks and trails were calculated per administrative unit.(7, 13, 19, 58, 73) However, care was needed in choosing the most relevant level of aggregation as both the scale and shape of the defined geographic units could influence the observed association introducing a form of statistical bias known as the modifiable areal unit problem.(74) The mismatch in geographic scales was resolved through hierarchical modeling.(12, 64, 75)

Later studies used pre-specified buffer zones, such as 400- or 800-meter buffers around an individual's home using GIS software packages. (7, 13, 19, 58, 73) Here the issue was between the nearest supermarket and the actual destination supermarket. While the location of the nearest supermarket could be readily obtained from GIS data, the location of the destination supermarket could only be ascertained through a survey.(19, 36, 76–78) Those studies undermined the main premise of density metrics by showing that people did not shop at the nearest supermarket and did not eat at the nearest fast food restaurant.(19, 36, 76–78) Those findings were instrumental in shifting attention to AS captured in space and time.

The postulated links between home BE and individual or neighborhood-level health are summarized in Figure 1. Elements of BE exposure were linked cross-sectionally to the prevalence of obesity, hypertension, diabetes, dyslipidemia, and metabolic syndrome.(2, 19, 34, 37, 61, 79, 80) With respect to the PA environment, studies have generally found that greater land use mix, higher residential density, higher walkability scores, and more green space were all associated with lower BMIs. Other measures of the BE such as road traffic and noise have been associated with a higher likelihood of having hypertension or dyslipidemia.(34) However, there was less evidence to link local PA resources, such as recreational facilities with body weight or hypertension.(34) Moreover the few examples of longitudinal evaluations of the PA environment and changes in body weight have produced null or inconsistent findings.(34, 81)

The evidence on the association between the food environment and obesity was even less consistent.(2, 34) Studies suggested that a higher density of supermarkets or full-service restaurants was associated with lower body weight while higher densities of convenience stores or fast food restaurants were associated with higher body weight.(2, 20, 29–31, 34–41) However, other studies have not observed the same association between supermarket density and lower BMIs.(32, 33, 36, 39) Still more studies have been unable to replicate the findings between fast food restaurants or convenience stores and higher BMIs.(32, 39, 40)

Many early home-centric BE studies had several notable limitations with respect to their study design, measurement of the BE, and their consideration of BE-health pathways. First, the majority of early BE and health studies utilized a cross-sectional study design, which does not allow for a causal interpretation for observed associations between the BE and health.(81) Second, home-centric analyses can capture the BE features and resources within an individual's neighborhood; however, proximity does not allow one to infer usage.(19, 36) For example, people do not shop for food in their immediate neighborhood but will instead travel great distances to the supermarket or fast food restaurant of choice.(36) Third, the choice of BE variables can influence the magnitude and direction of the observed association between BE and health – not all such metrics are predictive of health.(82) Relatedly, investigators should be more transparent regarding the variables and methods used to quantify the BE.(83) A recent systematic review examined 113 studies (encompassing 1937 tests of association) that sought to evaluate the relationship between the retail food environment and health.(83) The authors found that the reporting of methods was quite poor for more than half of the studies included in the review and that the wide diversity in methods led to an array of conclusions.(83) Fourth, some of the theoretical pathways through which features of the BE become internalized to influence health are not always readily apparent.(49) Additionally, as indicated in Figure 1, most early studies focused on the relationship between BE and health with few evaluating its effect on any energy balance behaviors. Few early studies had any actual measures of diet or physical activity and those that did usually evaluated these outcomes separately without consideration of the mediating role these energy balance behaviors might have on the BE-health relationship. Fifth, some studies do not adequately disentangle the physical attributes of the BE from the demographic and socioeconomic environments.(84) For example, studies have shown that the socioeconomic indicator, residential property values, is associated with both perceived proximity to neighbor PA environment features as well as health.(31, 36, 40, 41, 76, 84–86)

Some of these limitations can be overcome through the usage of person-centric analysis that incorporate individual-level behaviors (e.g. diet and physical activity), demographics (e.g. race and culture), socioeconomic status (e.g. property values and educational attainment), and psychosocial factors (e.g. attitudes and perceptions). Researchers should also move to directly examine the intermediary pathways through which BE features might operate to influence health via person-centric attributes. These methodological additions will aid researchers in understanding how individual-level characteristics influence a person's exposure to BE elements in space and time and how the BE hinders or helps facilitate health-promoting behaviors.

2.2. Person as the center of BE exposure

Acknowledging that an individual's home neighborhood cannot capture the full extent of health-related BE exposures, researchers turned to more advanced GPS technologies to track movements in space and time.(14, 15, 18, 44, 45, 47–51, 56) Cumulative mobility over a given time period is the basis for constructing AS areas.(18) These AS-derived areas are then supplemented with travel diary data to provide context for the GPS tracks, such as the reason for the trip, identified destination, and any participation in PA or foods consumed.(50)

Several different measures of AS have been used. The radius of gyration is defined as the average distance of a set of GPS points or tracks to the most frequented location.(87) The standard deviational ellipse of a set of GPS-recorded points is defined as the area which covers approximately 68 percent of GPS points and is centered on the average of the point pattern.(88) Convex hulls are defined as polygons that contain all GPS points or tracks and have no angles greater than 180 degrees.(89) Studies have also utilized a non-parametric method known as 2D kernel density estimation where a symmetrical kernel function is superimposed over a cluster of GPS points centered around its mean.(90) The set of overlapping kernel density functions are then superimposed to create a continuous density surface.(90) Other methods include mapping GPS points along street networks, buffered street networks, daily path areas, and more.(18)

The literature examining whether BE features captured in an individual's AS are more predictive of health than home-centric defined features is relatively nascent.(14, 15, 18, 44, 45, 47–51, 56) In some cases AS-defined food and structural environment features have been shown to be more predictive of health behaviors than those captured in the home neighborhood. A study examining fast food outlet density and consumption of saturated fats, whole grains, as well as fruits and vegetables found that the density captured via the AS was positively associated with saturated fat intake and negatively associated with whole grains.(18) No such associations were observed using fast food outlet density captured in the 0.5 mile street network buffer.(18) However, two studies conducted in New York City produced counterintuitive results with one finding that higher noise density in AS-defined neighborhoods was associated with lower systolic and diastolic pressure and the other finding that home-centric food environments were more predictive of body mass index and blood pressure.(48, 49)

These disparate findings may be demonstrative of the utility of AS BE measures in various settings or highlight differences in the operationalization of the AS techniques. For example, Zenk (2011) found that AS defined by daily path areas were predictive of diet but standard deviational ellipse was not.(18) In addition, GPS monitoring and travel diaries place a heavy burden on participants and produce high volume data with thousands of data points. These data must then be cleaned and consolidated into useful metrics, for which there are many, with varying predictability based on setting and the health outcome(s) of interest. This varied predictability may also be due, in part, to the timing and duration of BE exposure covered by the AS measures. For example, a given GPS path may be predictive of physical activity or diet quality for that day or week but may be less predictive or long-term behavior or chronic diseases that are the result of the totality of behaviors over a protracted period of time (e.g. obesity, diabetes).

In order to overcome issues with the timing of BE exposures relative to the distal outcomes of interest, investigators have increasingly turned to exposure momentary assessment (EMA) to capture real-time, proximal dietary and physical activity decision-making as well as mood as they occur in a real-world setting.(63, 91–95) EMA is able to capture dynamic behaviors as they occur throughout the day and can allow investigators to observe the array of risk factors that precipitate a change in behavior that are spatiotemporally linked to the GPS-derived area measures.(63, 91–95)(63, 91–95) This method of data collection often uses short message services or applications via mobile devices and therefore can often be coupled with GPS and accelerometer data. EMA represents an exciting and rapidly growing field of exposure and outcome assessment which is readily applicable to the study of BE and health and complements new and evolving GPS-derived metrics.(63, 91–95)

2.3. Energy balance pathways

Any observable relationship between the BE and obesity should first, logically, have some observable effect on upstream energy balance behaviors, such as diet and physical activity (Figure 2).(11) Several studies have examined the role that the PA environment plays on physical activity and use of active modes of transport to commute to work or school. One feature of the PA environment that has been consistently linked to increased PA, specifically, walking, is neighborhood walkability,(23–26) Walkability is typically defined by land use mix, residential density, retail floor area density, and street connectivity.(27, 28) With respect to the food environment, several studies have examined whether the composition of healthy and unhealthy food outlets, often referred to as the Retail Food Environment Index, in the home neighborhood was associated with diet quality. Several studies have observed that proximity to supermarkets, grocery stores, and sit-down restaurants was associated with high diet quality,(37, 38, 96–98) while proximity to convenience stores and fast food restaurants have been associated with poor quality diets.(2, 20, 99) However, as observed with obesity and diabetes, the relationship between the home food environment and diet quality has not always been consistent.(2)

While there are several studies that have evaluated the effect of BE exposures on health and health behavior separately, there are far fewer that have formally evaluated the potential mediating role of health behaviors in the BE-health relationship. International research examining the interplay amongst the BE, health behaviors, and health provide evidence that PA mediates the effect of the PA environment on health.(100–103) A study of Belgian adults examined the potential mediating effect of accelerometer-assessed PA and sedentary behavior on the relationship between walkability and adiposity.(100) They found that moderate-to-vigorous PA as well as walking and cycling for transport significantly mediated the relationship between walkability and both BMI as well as waist-to-height ratio; however, no such mediating relationship was found for sedentary behaviors.(100) A study of New Zealand adults found that PA and sedentary behaviors played a significant mediating role of the effect of street connectivity and neighborhood destination accessibility on BMI and waist circumference.(101) A third study found that light and moderate-to-vigorous PA mediated the relationship between elements of the urban walking environment and BMI among a group Japanese adults age 65–84 years.(102) With respect to cardio-metabolic outcomes, a study using a representative sample of adults in South Australia found that the effect of walkability and road network buffers on glycosylated hemoglobin (HbA1c) was significantly mediated by self-reported PA levels.(103) However, it is worth noting that since the walkability index has been derived from elements in the environment that relate to walking, it should be expected that, by design, walking and walkability will be correlated. Therefore, the observed associations between walkability and PA levels may represent a form of autocorrelation. To our knowledge there are few, if any, examples of formal mediational analyses of PA in the relationship between BE and obesity, diabetes, or metabolic syndrome in United States-based, adult populations. Moreover, there are no equivalent studies that have examined the mediating role of diet, food shopping, or cooking behaviors on the BE and health relationship either in the United States or internationally. However, such studies evaluating mediational effects of dietary behaviors may not prove fruitful if BE exposure assessment relies on home-centric measures alone.

Early evaluations of the neighborhood BE assumed that, much like the PA environment, the health-relevant food environment comprised the food stores and restaurants around the home.(2, 4, 8, 13, 19, 57) Yet, the current body of evidence evaluating the food environment and health shows that this was an overly simplistic model.(2, 4, 8, 13, 19, 36, 57) It is now understood that the built elements of the food environment only comprise a small slice of the wider context of the food environment. Other factors at the individual-level (e.g. socioeconomic status, cultural and religious norms, perceptions and attitudes), store and restaurant-level, (e.g. affordability, availability, convenience, and marketing), and even local, state, and federal levels (e.g. social, income, and food policies) are more predictive of where individuals shop.(19, 36, 104–108) Many studies fail to account for the diet cost at various food outlets as well as differences in individual purchasing power. Moreover, home-centric measurement fails to capture meals that may be consumed in the vicinity of the workplace or school leading to incomplete assessment of the food environment to which an individual is exposed. Therefore, more thorough investigations of the relationship between the food environment and health should include diet and diet cost in their analyses as well as extend capture of food environment exposures to wear people live, work, and spend their leisure time.

2.4. Psychosocial pathways

Individual-level psychosocial factors such as perceptions (e.g. neighborhood attractiveness or availability of fresh produce), attitudes, social cohesion, as well as self-rated health and wellness can aid researchers in elucidating how individuals interact with and internalize their environment (Figure 3).(2, 109–115) Indeed where objective, GIS-based assessments of the BE have failed to produce consistently significant associations with health outcomes, such as obesity and diabetes, perceived metrics such as the availability of supermarkets have been shown to be far more predictive.(2) Collection of survey-based psychosocial measures may also assist in accurately capturing individual-level utilization of BE resources better than objective, GIS-based measures alone.(2, 109)

Individual perceptions of the built environment have been shown to be correlated with objective measures of the BE(109, 116) as well as measures of socioeconomic status(117) and are predictive of health.(2, 109–115, 118) One study found that a four-item food environment assessment tool, which measured an individual's perceptions of healthy food access, matched very closely with actual access in a low-income population.(116) However, the degree to which perceived and objective measures of the BE match up may vary by population in a systematic way.(109) Caspi and colleagues found that mismatch between perceived and objective BE measures was high but also observed that perceived supermarket access was more predictive of fruit and vegetable consumption than objective measures such as supermarket proximity.(109) A similar relationship has been observed with perceived and objective measures of the structural environment and levels of PA with the perceived presence of facilities, sidewalks, shops, area traffic each showing a positive association with level of PA.(113) Likewise other self-rated measures of BE, such as attractiveness, noise, and crime, were associated individual property values, which in turn correlated highly to neighborhoods with a high prevalence of obesity.(117)

Positive attitudes, self-efficacy, and social supports have been demonstrated to be positively associated healthy eating and higher levels of PA.(55, 77, 119–126) One study found that participants who strongly agreed that a healthy diet was important to them had a healthier diet overall compared to those participants who disagreed or strongly disagreed.(127) This attitude-diet relationship was found to be present regardless of the average cost of a healthy diet at the supermarket.(127) Studies examining psychosocial factors predictive of PA levels have found that self-efficacy and social supports are associated with greater levels of activity.(55, 119, 125, 126) Interestingly, studies that have jointly examined both perceived or objective measures of the BE and psychosocial factors have found a synergistic relationship between the BE, self-efficacy, and social supports.(55, 119, 125, 126) Those individuals possessing positive psychosocial characteristics and living in environments conducive to physical activity showed the greatest levels of PA or participation in active transport to work or school.(55, 119, 125, 126)

While psychological factors have shown to be related to both BE features as well as health, more work is needed to understand how the perceived environment and positive attitudes mediate the effects of the BE on health. Furthermore, there is limited evidence evaluating the role that mental health and wellbeing play in mediating the effects of the BE on health. One study found that the presence of depressive symptoms changed both the strength and the direction of the association between the perceived structural environment and PA levels.(128) To our knowledge there are no studies that examine the how effect of the food environment on diet quality and health outcomes is mediated by individual perceptions, attitudes, and mental health. Such studies should use dynamic, person-centric measures of the food environment to capture the full extent of exposure at home, work, school, and during commutes as well additional contextual factors such as prices, policies, marketing, and cultural and religious norms.

EMA, now viewed as a new and promising behavioral outcome of BE exposure,(63) is concordant in space and time with spatiotemporally-driven GPS measures of the BE exposome such as AS metrics. EMA has helped to shift attention from dietary quality or body weight to momentary, place-driven impulses, behavioral triggers, or environmental cues. These triggers may be predictive of longer-term health outcomes, such as obesity and diabetes. While the EMA may provide answers to the relationship between BE and risk factors for behavior change, such methods may have less utility in providing insights into how the neighborhood BE or larger BE exposome influence chronic diseases with protracted onset periods. Such long-term chronic diseases have etiologies that are highly complex and result from the accumulation of exposures to the BE as well as socioeconomic status, behavior, and more.(129)

2.5 Residential selection bias

Underpinning many residential BE exposures are the socioeconomic and sociodemographic factors which determine where individuals are able to live and as well as whether and where they are able to relocate.(19, 74, 130) Historical patterns of residential segregation, a prominent manifestation of structural racism, have dramatically shaped the human geography of much of the world and have been linked to health disparities.(131, 132) Relatedly, inequities in educational and work opportunities as well as intergenerational accumulation of wealth also play a key role in where individuals locate as well as how they interact with the BE.(133) Two individuals may occupy the same physical residential space or AS but experience very different social or economic environments.(133) Therefore, careful confounding control is needed as there are a number of socioeconomic and sociodemographic factors that are associated with both where a person lives and their risk of obesity, which, in turn, may vary based on the shape and scale of the define area.(74, 130) Interestingly, the incongruence in area-level socioeconomic advantage or disadvantage between residential BE versus AS BE and its relationship to health is currently an active area of research that, to date, has produced mixed findings.(91, 134)

It is also worth noting that much of the extant research into the relationship between the BE and health has been conducted in the United States and other high income countries.(135) The investigation into whether such findings are applicable to low and middle income countries are still in their infancy.(135) As with high income countries, care must be taken in such evaluations to consider the larger social and political context behind where people live. Moreover, the development of new technologies to assess the BE should be flexible and adaptive enough for use in both settings.

3. Obesity and the BE: The third-generation studies

The shift from home-centric BE exposure measurement to a more flexible, person-centered approach was intended to provide better information on the extent of health-relevant BE exposures throughout the day. These GPS-driven approaches have demonstrated great utility in predicting PA, such as walking, as well as use of active transport.(23–26, 37, 38, 96–98) Moreover, the evaluation of GPS data and metrics continues to evolve and show great promise in predicting risk factors for behavior change when combined with spatiotemporally-linked outcome assessment methods such as EMA.(63) However, wearable GPS monitoring devices tend to produce big data that can be computationally intensive and difficult to operationalize into metrics predictive of health based on the outcome of interest, population, and setting. Such computational challenges are represented in Aiello and colleagues (2019) who evaluated the relationship between food purchase behavior and health outcomes using 1.6 billion geocoded food purchases.(136) Moreover, the cost of GPS monitoring is such that it cannot be readily scaled up to large longitudinal cohort studies. There is therefore a need for more efficient tools to assess the context of habitual interactions with the BE.(45, 56)

It is also worth considering the potential privacy concerns which arise with the use of continuous GPS monitoring techniques.(137) While there are several methods researchers have implemented to mask the exact location of their participants to prevent privacy breaches, each method comes with its own strengths and weaknesses as well as different associated reidentification risks.(137) There is currently no universally accepted geographic masking method for confidential locations.(137)

Chaix (2012) described the concept of “contextual expology” as a subdiscipline of BE research focusing on the spatiotemporal configuration of BE exposures and accurate mapping of spatial behavior.(56) With this in mind, the Residential Environment and COROnary Heart Disease (RECORD) study developed the Visualization and Evaluation of Route Itineraries, Travel Destinations, and Activity Spaces (VERITAS) as an interactive web mapping application that geolocates participant’s self-reported habitual destinations.(56) VERITAS has proven useful in identifying highly frequented locations which can then be operationalized in several ways such as creating convex AS polygons, buffered areas, or travel paths using street networks.(56) In addition, a validation study of VERITAS against continuous GPS monitoring data found that GPS data fell within 500 meters of a VERTIAS-identified location for approximately 86% of the RECORD study population.(45) While highly promising as an BE exposure assessment tool, to date, no study has used VERITAS-derived BE measures to examine health or health behavior. In addition, the VERITAS questionnaire does not ask participants to provide the path they travel to go to and from their key destinations.(45, 56)

A new tool, the Knowledge-based Activity Reporting and Mapping Application or KARMA, is a dynamic, cloud-based, interactive application which addresses some of the gaps identified in VERITAS. KARMA, like VERITAS, allows participants to self-report key destinations that they frequent most using an interactive, web-based tool with the in-person help of a trained interviewer. However, unlike VERITAS, KARMA uses the Google application programming interface (API) to then map the most logical travel path, based on travel mode, which is then able to be modified by the participant if necessary. This allows KARMA to evaluate flexible AS, buffered dwell points, as well as travel paths. In addition, KARMA allows participants to input the timing of travel and activities throughout a given day allowing researching to examine the duration of time spent at each dwell point or in transit.

KARMA was developed within the Seattle Obesity Study III (SOS III), which seeks to critically examine the interplay between the BE, diet quality, PA, and diet-related health outcomes. As such SOS collects both self-reported and objective measures of diet quality, PA, and BMI. Expanding beyond more traditional survey-based evaluations of diet, which usually only measure adequate fruit and vegetable intake, SOS III is able to collect detailed data on habitual dietary patterns using food frequencies questionnaires and assign objective diet quality scores using the Healthy Eating Index.(11, 138)PA was measured at baseline via Actigraph accelerometer (ActiGraph™ , Pensacola, CA) devices as well as was self-reported, allowing us to correct these self-reported metrics longitudinally.(139) Moreover, SOS III also collects information on an array of demographic, socioeconomic, and psychosocial factors (Figure 3). This puts the SOS III study in the unique position to address some of the existing gaps in the BE literature related to the mediating roles of health behaviors and psychosocial factors in the BE-health relationship.

4. Conclusion

As our understanding of how individuals interact with the BE, and how these interactions are internalized, becomes increasingly complex so too must our conceptual models of obesity and the BE. Studies examining the effects of the BE on obesity and diabetes must consider how these effects are enhanced or mitigated via health behaviors, socioeconomic status, and psychosocial factors. The assessment of the BE must expand beyond the immediate home environment to encompass a variety of other locations and destinations of travel. Streamlined, efficient, destination-focused, web-based tools such as VERITAS and KARMA may become the next generation of tools to assess habitual BE exposure in long-term studies of weight trajectories, obesity and diabetes.

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Abbreviations:

API	application programming interface
AS	activity space
BE	built environment
BMI	body mass index
CVD	cardiovascular disease
GPS	global positioning system
PA	physical activity
RECORD	Residential Environment and Coronary Heart Disease

SOS III	Seattle Obesity Study III
VERITAS	Visualization and Evaluation of Route Itineraries, Travel Destinations, and Activity Spaces
KARMA	Knowledge-based Activity Reporting and Mapping Application
RFE	retail food environment

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Study Importance Questions

What is already known about this subject?

- Previous reviews of the built environment have provided comprehensive summaries of the state of knowledge regarding the relationship between the physical environment and food environment on their impact on poor diets, lack of exercise, and higher obesity prevalence.

What are the new findings in your manuscript?

- The present review provides an in-depth examination of the evolution of our conceptual understanding of the built environment and obesity, a call for a closer examination of the role of energy balance pathways, technological advances in the capture of built environment exposures, and suggestions for promising new avenues of research.

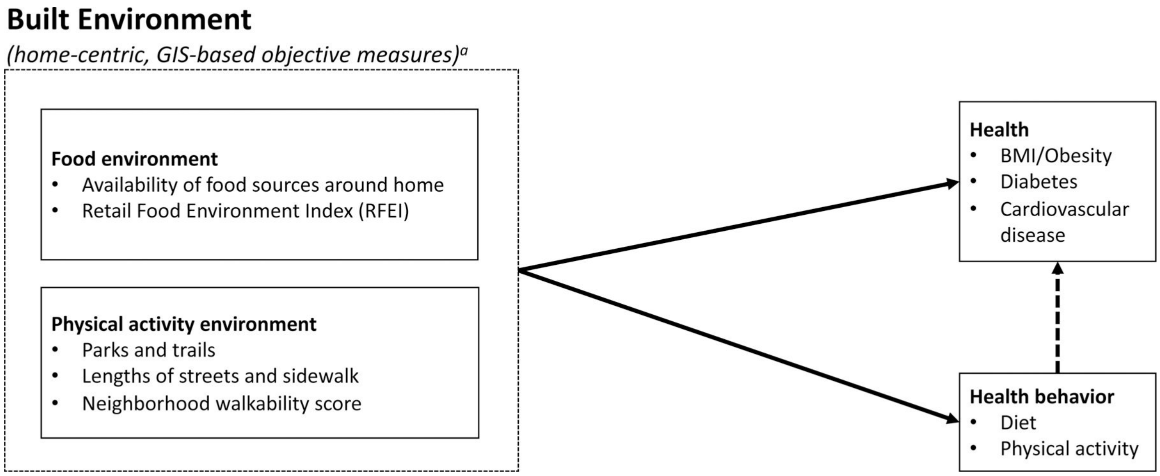

Figure 1.

Conceptual model of home-centric analyses linking the built environment to health

Note: Bulleted items are provided as examples and are not meant to represent an exhaustive list. Dashed arrow indicates the mediating role of health behaviors on the association between the built environment and health that was not directly evaluated by early studies.

a. Defined as fixed radius buffers around home address (e.g. 400 or 800-meter buffers)

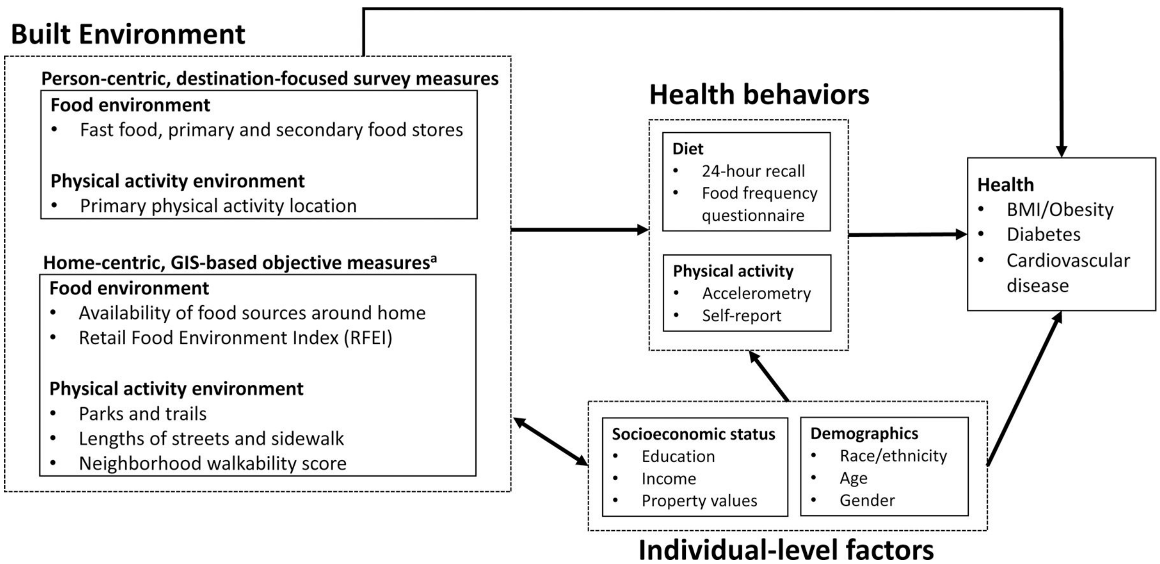

Figure 2.

Conceptual model of SOS home- and person-centric analyses linking the built environment to health

Note: Bulleted items are provided as examples and are not meant to represent an exhaustive list.

a. Defined as fixed radius buffers around home address (e.g. 400 or 800-meter buffers)

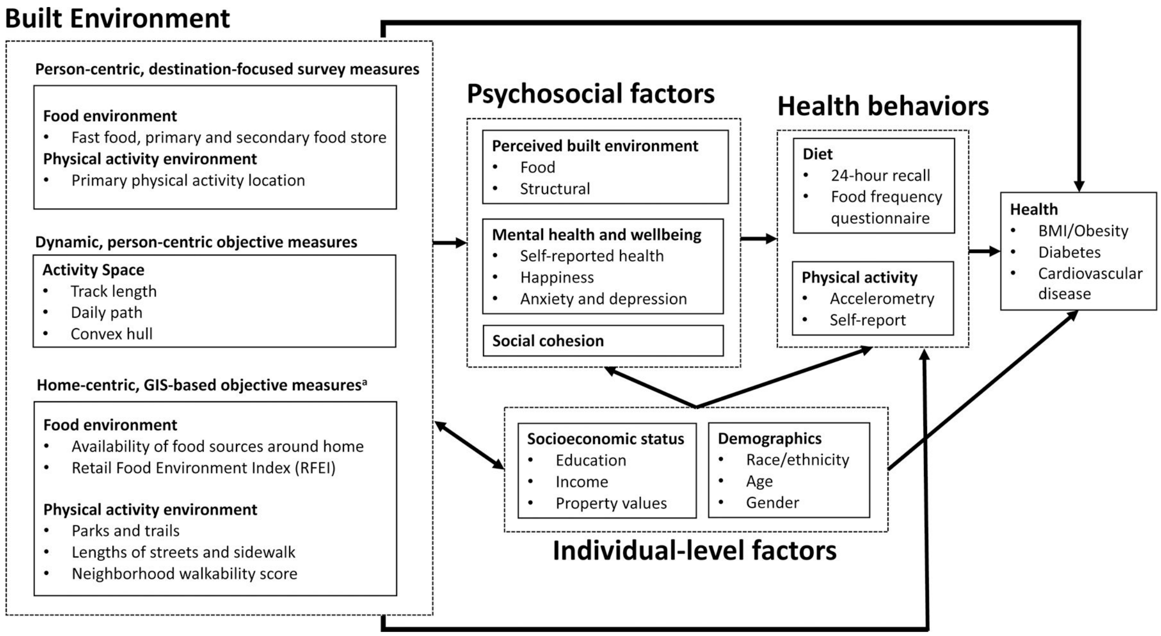

Figure 3.

Conceptual model of home- and person-centric (dynamic and destination-focused) analyses linking the built environment to psychosocial factors and health

Note: Bulleted items are provided as examples and are not meant to represent an exhaustive list.

a. Defined as fixed radius buffers around home address (e.g. 400 or 800-meter buffers)