Neighborhood Environment Profiles Related to Physical Activity and Weight Status among Seniors: A Latent Profile Analysis

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Neighborhoods are multidimensional

- **Walkability** – high residential density, a mix of land uses, good street connectivity, retail design. (Saelens & Handy, 2008; TRB, 2005; Heath et al, 2006)

- **Public transportation** – access to bus and rail stations/stops. (Besser & Dannenberg, 2005)

- **Recreation environments** – access to parks, gyms, recreational facilities (Kaczynski & Henderson, 2007)

- **Microscale features** – quality of environment, pedestrian and cycling facilities, social factors, safety, crime, etc.
Analytical challenges

• Aspects of neighborhood built environment (BE) coexist: they are not independent

• Significant challenge is how to deal with the numerous variables & complexity of BE

• Possible that unique combinations of variables may have different functions for PA.
Several approaches hold promise

- Measure many variables and factor analyze in search of underlying constructs (Cerin, et al., 2009; Cervero et al., 2003)

- Combine disparate variables into a single index (e.g. walkability index) (Frank et al., 2010)

- Explore first and second order interactions between a few variables.

- Identify unique multivariate patterns that subgroups of individuals share. (Yan et al., 2010; Nelson et al., 2006; Norman et al., 2010).
Purpose

• To explore whether distinct neighborhood environment profiles can be derived from a large range of reported BE features from an older adult sample.

• To test whether derived neighborhood environment profiles result in differences in adults’ physical activity and weight status.

Supported by UCSD T32 in Integrated Cardiovascular Epidemiology
Seniors’ Neighborhood Quality of Life Study (SNQLS)
SNQLS Methods

• Epidemiological study of built environment on multiple health outcomes for older adults.

• 66–97 years old, 52.9% female, 29.2% racial/ethnic minority

• Study Regions
  — Seattle–King County, WA (N =360)
  — Baltimore, MD – Washington, DC (N =354)

• Neighborhoods selected to maximize variance in walkability.
  • Low Walk/Low Income, Low Walk/High Income
  • High Walk/Low Income, High Walk/High Income
Neighborhood Environment Walkability Scale (NEWS)

- Residential density
- Land use mix–diversity
- Land use mix–access
- Street connectivity
- Walking & cycling facilities
- Aesthetics
- Pedestrian/traffic safety
- Crime safety

- *Nearest bus or train stop
- *Nearest park
- *Nearest recreation center or ‘gym or fitness facility’

*Selected because of hypothesized association w/PA and policy relevance

NEWS available at: http://sallis.ucsd.edu
Measures

• **Actigraph Accelerometer**
  - Instructed to wear for all waking hours for 7 days
  - Valid day ≥10 valid hours of wear
  - Freedson adult cut-points for MVPA

• **CHAMPS Questionnaire for Older Adults**  
  (STEWART et al. MSSE 2001)
  - Walking for transportation = sum of hours/week of walking for errands.
  - Leisure-time PA = sum of duration of leisure activities (e.g. walking, tennis, swimming, golf) and other moderate- and vigorous-intensity PA for leisure.
  - CHAMPS variables natural log transformed for regression models & antilogged to report geometric mean mins/wk

• **Body mass index (BMI)** calculated using self-reported weight and height.
Statistical Analyses

• Latent Profile Analysis
  — Useful when group membership of individuals is unknown -- must be inferred from response patterns.
  — LPA model conceptualized as a single categorical latent variable and a set of continuous indicators.
  — Divides a sample into mutually exclusive subgroups.
  — Maximizes between group variance & minimizes within group variance based on model fit criteria (usually AIC, BIC, LMR).
  — 11 environmental variables (8 NEWS subscales and 3 NEWS items).
  — Determined # of profiles using model fit, sample size of classes, and interpretability

• Independent analysis for Seattle and Baltimore regions.

• ANCOVA models tested relations between neighborhood profiles and PA & BMI, adjusting for demographics and other covariates
Baltimore Region
Neighborhood profiles for Older Adults in the Baltimore region (z-scores).

- **LWTS**: Low Walkable/Transit Sparse
- **LWRS**: Low Walkable/Recreationally Sparse
- **MWRD**: Moderately Walkable/Recreationally Dense
- **HWRD**: High Walkable/Recreationally Dense
Seattle Region
Neighborhood profiles for Older Adults in the Seattle region (z-scores).

- **LWTR**: Low Walkable, Transit & Recreation
- **LWRS**: Moderately Walkable / Moderately Recreational
- **HWRD**: High Walkable/Recreationally Dense
All models were adjusted for sex, age, ethnicity, annual household income, education, # motor vehicles/adults in household, marital status, number of people in household, and length of time at current address.
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CONCLUSIONS
Overall

- Represents a first step to operationalizing and testing the concept of “activity supportive neighborhoods”.

- Patterns that included a combination of high walkability w/good access to transit, parks and recreation facilities.

- Individuals living in activity–supportive n’hoods had best health and behavioral characteristics in NQLS/SNQLS.

- Results for BMI inconsistent, but direction of activity–supportive neighborhoods to BMI in expected direction.

- Other neighborhood types emerged & associated with PA.
Profile Differences

• Walkability components
  — Differentiated profiles.
  — Consistently associated with PA. (Gebel et al. 2007)
  — Residential density needed to support shops/services. Critical mass.
  — People on the street. Behavioral modeling. (Adams et al. 2006)
  — More destinations & reduced travel burden. (Frank et al, 2003)

• Transit access
  — Differentiated profiles. Large differences between profiles.
  — Public transit users walk 19 minutes more each walking trip (Besser & Dannenberg, 2005)
  — Light rail users lost 6 lb over 18 months. (MacDonald et al, 2010)
Profile Differences Cont.

• Parks and recreation facilities
  — Differentiated profiles.
  — Review found that access to parks associated with increased activity levels (Kaczynski & Henderson, 2007).
  — Within parks, more features (e.g. trails, sports facilities) more activity.

• Microscale features
  — Not as stable as other BE features. Tended to vary more across profiles.
  — More difficult to report.
  — Better measures and research needed.
Why is this important?

• Isolating individual BE variables may underestimate effect sizes. Combined approach may produce stronger associations than single variables.

• “Profiling neighborhoods” may reveal optimal neighborhoods for PA or types for more targeted improvements for public health interventions or policy actions.

• Examining patterns informs ecological models of some of the complex BE combinations present.
Methodological Considerations

• Limitations included:
  — Exploratory approach
  — Non-random sampling
  — Sampling maximized range of BE attributes
  — Reported BE
  — No food environment for BMI
  — No adjustment for residential self-selection
  — Multilevel modeling
  — Unmeasured or objectively-measured variables could produce different characterizations of neighborhoods

• Strengths included:
  — Use of validated measures for BE and PA.
  — Objective PA
  — Evidence of concurrent validity
  — Profiles have practical significance due to the strong associations with health outcomes.
NEXT STEPS

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Activity–supportive neighborhoods:
Examining combined effects of walkability and recreation environments for physical activity across the life span

Table 1. Summary of Original Studies' design and participant characteristics.

<table>
<thead>
<tr>
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<th>SNQLS</th>
<th>NQLS</th>
<th>TEAN</th>
<th>NIK</th>
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<tbody>
<tr>
<td>Principal Investigator</td>
<td>King, Abby</td>
<td>Sallis, James</td>
<td>Sallis, James</td>
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<td>R01 ES014240 NIEHS</td>
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<tr>
<td>Sample Size (N)</td>
<td>728</td>
<td>2199</td>
<td>954</td>
<td>723</td>
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<tr>
<td>Study Design</td>
<td>Cross-sectional</td>
<td>Cross-sectional</td>
<td>Cross-sectional</td>
<td>2-yr Longitudinal</td>
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<td>Sampling Regions</td>
<td>Seattle-King County, WA &amp; Baltimore, MD/Washington DC</td>
<td>Seattle-King County, WA &amp; Baltimore, MD/Washington DC</td>
<td>Seattle-King County, WA &amp; San Diego, CA</td>
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<tr>
<td>Neighborhood Sampling</td>
<td>2 x 2 Matrix of lo/hi Walkability X lo/hi Income</td>
<td>2 x 2 Matrix of lo/hi Walkability X lo/hi Income</td>
<td>2 x 2 Matrix of lo/hi Walkability X lo/hi Income</td>
<td>2 x 2 Matrix of lo/hi Walkability &amp; Parks X lo/hi Nutrition Environment</td>
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<tr>
<td>Age range (yrs)</td>
<td>66-97</td>
<td>20-65</td>
<td>12-16</td>
<td>6-11 (and their parents)</td>
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<tr>
<td>% Female</td>
<td>56.4%</td>
<td>48.2%</td>
<td>50.3%</td>
<td>48-55%</td>
</tr>
<tr>
<td>% Non-white</td>
<td>29%</td>
<td>26%</td>
<td>34.4%</td>
<td>17-20%</td>
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<tr>
<td>% Hispanic</td>
<td>2.8%</td>
<td>3.7%</td>
<td>6.8%</td>
<td>14-20%</td>
</tr>
<tr>
<td>% Overweight/obese¹</td>
<td>58.9%</td>
<td>57.0%</td>
<td>25.6%</td>
<td>24-32%</td>
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<tr>
<td>Accelerometer data (% with ≥5 valid days)</td>
<td>95.6%</td>
<td>96.5%</td>
<td>95.0%</td>
<td>89.3%</td>
</tr>
</tbody>
</table>

¹For youth, overweight is based on ≥85th percentile of BMI-for-age; ²Ranges of estimates across 2x2 quadrants are reported;

* Examine whether profiles can be derived from objective BE measures
Collaborators

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THANK YOU

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