Mobility Patterns, Activity Spaces, and Tuberculosis in Nairobi, Kenya

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Abstract

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Background:

Tuberculosis (TB) remains one of the leading infectious causes of morbidity and mortality globally. Annually, over 3 million people develop TB but are not diagnosed and not initiated on treatment. This case-detection gap critically impedes global efforts to end the TB epidemic, as individuals with undiagnosed TB may be contributing to ongoing transmission. Active case finding (ACF) offers one approach to close this gap by screening and diagnosing TB in the community and reaching priority groups. Highly mobile individuals are one population that may be at higher risk for TB and could potentially benefit from targeted ACF. A second challenge for implementing ACF is to determine where to deploy ACF activities in a community. Activity spaces, which are locations where an individual spends their time, can provide possible venues in which to conduct ACF. Our goal in this analysis of mobility patterns and activity spaces is to evaluate TB with regards to geographic risk factors in an urban, high-burden setting.

Methods:

This analysis leverages data from a population-based TB prevalence survey conducted in Nairobi, Kenya, from May to December 2022. Location-based activity spaces data and data on mobility patterns were collected as part of a questionnaire administered to eligible study participants. The primary outcome of the survey was the prevalence of bacteriologically-confirmed pulmonary TB among those ages 15 years and older. Several dimensions of mobility were captured, including mode

of transportation, distance and length of commute, and use of transit hubs. Latent class analysis was performed to identify two latent mobility classes. Reported activity spaces were recorded and categorized into six broad categories. Logistic regression was used to evaluate the association between mobility patterns and categorized activity spaces and odds of pulmonary TB. The adjusted analysis included age and sex. Secondary analysis explored odds of positive symptom screen.

Results:

The prevalence survey enrolled a total of 6371 participants, with 23.6% completing the work commute questions and 89.3% reporting activity spaces. Overall, the majority of respondents walked to work (68.3%) or used a bus or taxi (28.8%). There was a significant difference in transportation and commute between men and women and among age groups. Reported activity space also varied significantly by age and sex. In the unadjusted analysis, older age groups, male sex (OR 2.94, 95%CI 1.89, 4.58), and reporting a social activity space (OR 2.15, 95%CI 1.15, 4.03) were all significantly associated with a diagnosis of active TB. Mobility factors were not significantly associated with active TB diagnosis, nor was membership in the 'mobile' latent class. Adjusting for age and sex: age group 45 – 54 (OR 2.44, 95%CI 1.05, 5.69), male sex (OR 2.88, 95%CI 1.71, 4.85), and reporting a social activity space (OR 1.95, 95%CI 1.02, 3.72) were significantly associated with higher odds of active TB.

Conclusions:

In this analysis, we did not find a significant association between mobility patterns and TB. However, we did find a strong positive association between reported 'social' activity spaces and active TB diagnosis. Identification of 'social' activity spaces provides important insight into possible venues for ACF activities, both in Nairobi, Kenya, and possibly other high-burden urban settings. Investigating the extent of this association and other geographic risk factors can help form a data-driven approach for optimizing spatially-targeted ACF.

Introduction:

Tuberculosis (TB) remains one of the leading infectious causes of death globally, with an estimated 10.6 million incident cases and 1.3 million deaths in 2022.[1] Diagnosed cases of TB increased to 7.5 million in 2022 after several years of COVID-19 pandemic-related disruptions, still leaving over 3 million people annually who develop TB but who are not diagnosed and never initiated on treatment.[1] This case-detection gap critically impedes global efforts to end the TB epidemic as individuals with undiagnosed TB, including those with detectable *M. tuberculosis* but without clinically-recognized symptoms (also known as "subclinical TB"), are likely to be contributing significantly to ongoing transmission and are at higher risk for death if treatment is delayed or not initiated.[2,3] Identification of those individuals with high risk of TB in the community and systematic screening through active case finding (ACF) can help to achieve earlier diagnosis and treatment and possibly prevent onward transmission.[4] ACF aims to diagnose TB in people outside of health facilities, in the community, and among populations at risk—versus passive case finding whereby only those individuals with symptoms who seek care at health facilities are tested.[4,5]

Mobile individuals, and in particular migrants, are one segment of the population that may be at higher risk for TB and could potentially benefit from screening through ACF.[6–8] For example, rural-to-urban migrants in western China face both personal and structural barriers that delay TB diagnosis[9] and migrant mineworkers in southern Africa experience some of the highest TB incidence rates in the world due to exposure to multiple risk factors, such as HIV and poverty, and to frequent health care disruptions.[10] Mobility has also been implicated in the emergence and dispersal of novel drug-resistant strains of TB.[11,12] In addition to international and labor migration, mobility on a smaller scale, such as one's daily commute to work or school, may be a factor contributing to the TB epidemic. Several studies from Cape Town, South Africa, of CO2 levels and social contacts suggest public transportation as one possible site for TB transmission.[13–15] Similarly, in Lima, Peru, the risk of TB among workers in the informal public transport sector was found to be significantly higher than in the general population.[16,17] Despite playing a potentially important, and varied, role in the transmission of TB, there remain large gaps in our understanding of human mobility as a risk factor for TB across different settings or even how to properly measure it.[18,19] The first aim of this study is to describe mobility profiles across different demographic groups in our study population in Nairobi and evaluate its association with active TB disease.

A second challenge for implementing ACF, after identifying a priority population for screening, is to determine where to deploy ACF activities in a community. Traditional ACF may encompass a range of activities such as door-to-door screening or community mobilization,[4,20] though these activities are geographically untargeted and may be a less efficient use of resources. In contrast, a spatially-targeted ACF strategy focuses on a particular geographic area or locale with suspected high burden of disease, with the potential benefit of needing to screen fewer people to identify a TB case (number needed to screen).[21] Activity spaces, which are locations or sites where an individual spends their time, present one possible solution to the open question of where to geographically deploy ACF. One study in Japan mapped 'activity spaces' for patients with culture-positive TB residing in Shinjuku City between 2003-2011 and located the peak density of cases at the Shinjuku Railway Station that was over 12 times greater than average.[22] In a study in a rural Ugandan township, 6 out of 15 (40%) genotype-matched TB clusters shared potential epidemiologic links based on either a shared physical location or geographically neighboring location (within 100 meters) in the time leading up to diagnosis.[23] Likewise, in a case-control study in Lima, Peru, activity spaces were obtained from both multidrug-resistant (MDR) TB cases and negative controls and demonstrated that person-time (in hours) in healthcare venues, school, and transportation venues was significantly associated with MDR TB diagnosis.[24] The second aim of this study, with the question in mind of "where to find individuals at high risk of TB", is to evaluate the reported activity spaces of our study population, particularly among those found to have active TB disease.

Emerging strategies of disease control require understanding the role and impact of human mobility and activity spaces on the TB epidemic, both at an individual and population level,[11,18] and to tailor interventions such as active case finding to populations who are at increased risk.[25,26] Our goal in this analysis of mobility and activity spaces data, collected in conjunction with a TB prevalence survey, is to evaluate TB with regards to geographic risk factors in an urban, high-burden setting.

Methods:

This analysis leverages data from a population-based TB prevalence survey conducted in Nairobi, Kenya, as part of the TB Aerobiology, Immunology, and Transmission (TBAIT) study.[27] Location-based activity spaces data and data on mobility patterns were collected as part of a questionnaire administered to eligible study participants. Below we describe the study design for the main prevalence survey, our measurements of mobility, and the statistical analysis.

Prevalence survey study design

The TB prevalence survey was a cluster-based cross-sectional survey that enrolled participants from May to December 2022. The primary aims of the survey were to determine the prevalence of bacteriologically-confirmed pulmonary tuberculosis among those ages 15 years and older in Nairobi and to evaluate changes in TB prevalence rates compared to 2015 (the year of Kenya's first national TB prevalence survey). In addition to a symptom screen and digital chest X-ray and subsequent sputum collection x2 (if eligible), each enrolled participant completed a series of surveys including a household socioeconomic survey and COVID-19 questionnaire, as well as mobility-specific questions which captured self-reported data on work commute, overnight trips, changes in residence, and activity spaces.

Study setting

The prevalence survey was conducted in Nairobi County, specifically in nine of the 10 clusters previously surveyed during the 2015-16 Kenya National TB Prevalence Survey.[28] The geographic boundaries of each cluster were the same across both surveys. Nairobi County is an urban setting with variations in housing and density both within and across clusters. Several clusters consisted of predominantly informal settlements.

Study subjects

Individuals were eligible for enrollment if they were ages 15 years and older and must have resided in a household within a study cluster for at least 30 days prior to the survey date. All enrolled participants provided informed consent. A sample size of 6480 adults was expected across all nine clusters with a target of 720 adults enrolled per cluster.

Data collection

Pre-survey activities included engagement visits and sensitization with county officials and local authorities, identification of community resource persons for assistance with community mobilization, and mapping of cluster borders. Study clusters were surveyed one at a time over two-week periods. To identify eligible residents, mobilization teams performed a door-to-door census in each cluster until they reached a target of 650-790 persons per cluster. Each household member was enumerated on a listing questionnaire, and the head of the household completed a household

socioeconomic questionnaire. GPS coordinates of each household were collected during the door-to-door census.

Eligible household members were invited to a nearby mobile field site where additional surveys (including the mobility and activity spaces questionnaire) were administered as well as a TB symptom screen and digital chest X ray. Those participants with an abnormal radiograph or positive symptom screen (reporting a cough of any duration) were eligible for sputum collection. Two sputum samples were collected from each sputum-eligible participants: a 'spot' sputum during the mobile field site visit and a 'morning' sputum collected at the participant's home the following morning. Specimens were transported daily to one of two labs: either the National TB Reference Laboratory (NTRL) or the Center for Respiratory Diseases Research at the Kenya Medical Research Institute (CRDR-KEMRI), where direct sputum smears were performed and molecular testing with GeneXpert MTB/RIF Ultra (Cepheid, Sunnyvale, CA, USA). Specimens underwent sputum AFB-culture using Mycobacterium Growth Indicator Tubes (MGIT 960, Becton, Dickinson and Company, Franklin Lakes, NJ, USA).

In the primary analysis of the prevalence survey, a study participant was defined as having prevalent pulmonary TB if the Xpert Ultra result was positive (at a semiquantitative level that was greater than 'trace positive' [i.e., very low, low, medium, or high]) or at least one sputum culture was positive for *M. tuberculosis*. In contrast, in this analysis of mobility patterns and activity spaces, all participants with a positive *Mtb* culture or positive Xpert Ultra result (including 'trace positive') were considered to be positive.

All participants with a positive culture or positive Xpert Ultra result (including 'trace positive') were referred to local health clinics for TB treatment.

Measurement of human mobility and activity spaces

Several components of geographic mobility were collected via questionnaire. First, dimensions of mobility relating to daily commute, specifically commuting to work, were obtained from the subset of participants who reported a work location. These data include mode of transportation (e.g. walk, bus, taxi, etc.), distance of commute (in kilometers), length of commute (in hours), expense (in Kenyan shillings), and use of transit hubs. Second, participants were asked about overnight trips in

the past month, including frequency, duration, and reason for travel. Third, participants were asked about changes in residence over the past 5 years. Finally, data on activity spaces were collected, as participants were asked to list the top four places where they spent their waking hours, as well as the top four places they visit in the community on weekdays and on weekends. The activity space data were collected as free text responses and manually categorized into one of six categories: home, work, school, market, social, or church for this analysis.

Statistical analysis

We first generated descriptive summary statistics for mobility patterns and activity spaces for the total population and stratified by sex (female & male) and age group (15-24, 25-34, 45-54, 55-64, and 65+). We then used logistic regression to evaluate the association between demographic characteristics, mobility patterns, 'mobility' class membership, and reported activity spaces with our primary outcome of prevalent pulmonary TB, i.e. odds of being a TB case. The adjusted analysis included age and sex. Secondary analysis explored these same independent variables with odds of positive symptom screen (e.g. cough of any duration, fever, night sweats, or weight loss).

For clarification, in the regression analysis, reporting a particular category of activity space does not necessarily mean that that activity space category was the first reported place. The activity space exposure variables indicate any reporting of a particular activity space, whether it be in the top 4 places where people spent their waking hours or the top 4 places visited on weekdays or the top 4 places visited on weekends. So long as that category was reported, this would count as a positive exposure to an activity space.

Latent class analysis (LCA) was performed to construct one latent variable from six of our observed variables capturing various features of mobility (**Table S1**) that could identify different 'mobility' subgroups or profiles within our population, similar to an analysis of geographic mobility of participants with TB in Uganda.[18] Models with between 1-4 latent classes were tested, and we selected the best fitting latent class model based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Results:

Study population

The 2022 Nairobi Prevalence survey was conducted from May to December 2022 across nine neighborhoods in Nairobi, enrolling a total of 6371 participants (83% enrollment out of 7644 eligible). Of those enrolled, 1504 participants (23.6%) completed the work commute questionnaire and 5687 (89.3%) completed questions regarding activity spaces. Demographic characteristics of participants in the prevalence survey and the subgroup that answered questions regarding activity spaces were similar with respect to age (median age 33), sex, occupation, marital status, and education. Only those who provided an answer to the survey question "Where do you work" were administered the work commute questions. This subgroup was younger (median age 30), had a greater percent that were male, were more likely to be employed in the private sector or be a student, and more likely to be single or never married. **Table 1**.

Work commute

The work commute questionnaire was completed by a subset of 1504 participants of the prevalence survey. Overall, the majority of respondents walked to work (68.3%) or used a bus or taxi (28.8%), with only a small fraction riding boda boda (motorbike taxis) or using other means of transportation. There was a significant difference in mode of transportation between men and women (p-value <0.001), with women more likely to walk then men (73.6% vs 62.3%) and less frequently using the bus or taxi (24.5% vs 33.5%). Across age groups, bus/taxi ridership was highest among those ages 15-24 (34.7%) and lowest among those ages 45-54 (22.2%). Median commute distance overall was 2km [IQR 1-5]. One third of commuting trips (32.7%) were below 1km. Men, on average, had a longer commute distance then women (mean 7.6km vs 5.2km) and longer commute time (mean 1.85 hours vs 1.32 hours). Only 241 of the total participants (3.8%) reported spending time at a transit station, with a median time of 10 minutes [IQR 5-30]. **Table 2**.

Activity spaces

A subset of 5687 participants responded to the activity spaces questions, which include listing the top 4 places they spent most of their waking hours in the past year, top 4 places visited most often on weekdays, and top 4 places visited most often on weekends. The question structure did not explicitly ask for participants to rank these places by the amount of time they spent there. These responses were manually coded into one of six activity space categories where possible. For the top

4 places where participants spent their waking hours, there were a total of 4542/5687 (79.9%) categorized activity spaces for the first reported place, 904/1497 (60.4%) for the second reported place, 231/539 (42.9%) for the third reported place, and 94/332 (28.3%) for the fourth reported place. Overall, reported activity space categories for the first reported place were home (65.4%), work (25.6%), school (4.3%), market (3.9%), social (0.6%), and church (0.2%). These categories differed significantly by sex, with men more frequently citing a workplace than women (33.7% vs 21.4%), as well as age group, with older groups more frequently reporting work. For the second, third, and fourth reported places, market and social activity spaces were reported more frequently. **Table 3**. Reported activity spaces varied across neighborhoods. **Figure 1**. A two-mode network of shared activity space categories within a single neighborhood is shown in **Figure 2**.

Latent class analysis – classification of mobility

A model with two latent classes was selected as it had a better fit compared to a single class based on a lower Bayesian Information Criterion (BIC) and Akaike's Information Criterion (AIC). **Table S2**. Models with three and four latent classes did not converge after 300 iterations. One class was characterized as "higher mobility" and the other "lower mobility" based on greater estimated marginal probability for the following features: using the bus, taxi, or other mode of transportation besides walking (69.6% vs 3.1%), commuting distance greater than 2km (92.0% vs. 6.3%), and commute time greater than 0.5 hours (97.0% vs 69.7%). Each participant was assigned group membership to their most likely 'mobility' class based on posterior probabilities. **Table S3 & Figure 3**.

Association of SES, mobility, & activity spaces with TB diagnosis, symptoms, and care-seeking

In total, there were 83 enrolled participants with a positive diagnosis of TB (either positive Xpert Ultra including 'trace positive' and/or positive *Mtb* culture). Of these, 16/83 (19.3%) participated in the mobility survey and 73/83 (88.0%) reported activity spaces.

In the unadjusted analysis, older age groups, male sex (OR 2.94, 95%CI 1.89, 4.58), being divorced (OR 3.10, 95%CI 1.48, 6.48), positive HIV status (OR 5.31 95%CI 2.34, 12.08), and reporting a social activity space (OR 2.15, 95%CI 1.15, 4.03) were all significantly associated with a diagnosis of active TB in the prevalence survey. Mobility factors, specifically mode of transportation, commute distance, and commute time, were not significantly associated with active TB diagnosis, nor was membership

in the 'higher mobility' latent class. Adjusting for age and sex: age group 45 – 54 (OR 2.44, 95%CI 1.05, 5.69), male sex (OR 2.88, 95%CI 1.71, 4.85), and reporting a social activity space (OR 1.95, 95%CI 1.02, 3.72) were significantly associated with higher odds of active TB diagnosis. Reporting a social activity space was also significantly associated with reporting any of the four TB screening symptoms (OR 1.44, 95%CI 1.14, 1.82) in adjusted analyses. **Table 4**.

Discussion:

In this analysis, we compared the mobility patterns and activity spaces of people with bacteriologically-confirmed TB and community controls across nine clusters in Nairobi, Kenya. While mobility patterns differed significantly by sex and across age groups and between neighborhoods, we did not find a significant association between the specific measures of geographic mobility captured in this study, nor the constructed latent class consisting of "mobile" individuals, with respect to greater odds of active TB diagnosis. However, we did find a strong positive association between reported 'social' activity spaces and TB. Adjusting for age and sex, individuals reporting a 'social' activity space, for example bars, had almost two times greater odds of having TB. Reporting other activity spaces, such as home, school, market, and church, was not significantly associated with greater odds of TB diagnosis. Taken together, our results provide evidence for a geographic risk factor for TB that is not related to work commute but instead associated with reporting time spent at 'social' activity spaces.

While the World Health Organization conditionally recommends community-wide systematic screening for TB in high burden settings (areas with an estimated TB prevalence of 0.5% or higher),[4] large-scale ACF trials have shown mixed effectiveness in reducing population-level TB prevalence.[20,29] For example, two community cluster-randomized trials, ZAMSTAR[30] and TREATS[31], showed no effect on TB prevalence from enhanced case finding and door-to-door screening, respectively. Meanwhile, the ACT3 study[32] demonstrated a 44% reduction in TB prevalence in Ca Mau Province, Vietnam, after three years of community-wide ACF. Uncertainty regarding the effectiveness of ACF activities, in these cluster-randomized trials as well as other non-randomized trials, highlight ongoing challenges in the design, implementation, and evaluation of ACF interventions.[29] Two predicaments to solve in optimizing ACF for any setting would be which groups to prioritize and where to target efforts.

Identification of 'social' activity spaces, in this study, as being locations more likely to be frequented by individuals diagnosed with TB provides an important insight into possible venues for ACF activities, both in Nairobi, Kenya, and possibly other high-burden urban settings. Rather than an untargeted approach that does not focus on specific geographic areas, a spatially-targeted approach would deploy ACF activities to specific locations known or suspected of being TB transmission 'hotspots'.[21,33] Other studies have pointed to healthcare facilities and markets as important venues for likely TB transmission.[23,24,34] We found reporting 'social' activity spaces, particularly bars, to be highly associated with TB diagnosis among participants in our prevalence survey. Investigating the extent of this association and identifying particular bars or social venues can help to inform national and local TB programs on where exactly to screen for TB or possibly implement structural modifications, such as improved ventilation, to reduce the risk of TB transmission. Combining granular activity spaces data with results from a recent prevalence survey or modelled TB incidence estimates[35] can provide a data-driven approach to spatial targeting of ACF in a community.

Our study has several limitations. Participation in the work commute survey was limited to only those who provided a site or location for employment, leading to a large degree of selection bias when collecting mobility data. Summary statistics of mobility characteristics were not representative of the total population, with responses totaling less than a quarter of all participants. Moreover, daily commute and mobility are not constrained to only travel to and from work. Individuals may move about outside of their homes for any number of reasons, work or non-work related. Capturing data on all types of movement, not only work commute, can give a more comprehensive picture of an individual's mobility patterns and associated risks and exposures. Second, our study was limited by the unstructured responses allowed for reporting activity spaces hindering our ability to extract detailed geographic information on specific physical venues. Abstract locations, for example "Work place" or "market", could not be geo-located, thus our analysis was constrained to broad categories of activity spaces, such as home, work, social, market, etc. It is also likely for some degree of bias to have been introduced via our post-hoc categorization of activity spaces. Additionally, specifying a more explicit time frame for activity spaces, such as in the past 30 days prior to diagnosis, may help with both recall and point towards sites of possible recent transmission. Third, our analysis focused on the primary outcome of bacteriologically-confirmed TB diagnosis, either by sputum culture and/or Xpert Ultra. With only a small number of positive cases found overall in the prevalence survey (~1%), and even fewer positive cases that completed the mobility questionnaire (n=73), we were very likely

to have been underpowered to identify significant differences in exposures between TB cases and controls.

Future work to investigate the association of mobility and activity spaces with TB, particularly with the goal of informing targeted active case finding activities, may benefit from a more quantitative and detailed approach at capturing dynamic patterns of movement. Studies utilizing GPS tracking, for example, have reported on travel patterns and activity spaces of patients with MDR-TB,[36] pregnant women,[37] residents of malaria-endemic regions,[38] and young adults with high risk of HIV acquisition.[39] Comprehensive evaluation of mobility, however, will likely require not only GPS tracking but also qualitative interviews in a mixed methods approach to truly understand the varied contexts and attributes relating to travel. Travel diaries, GPS loggers, and focused interviews in tandem will likely bring out more useful and relevant information with regards to human movement and exposures. Furthermore, implementation studies will be critical for understanding the acceptability of TB screening in community venues. Understanding heterogenous patterns of mobility and activity in various contexts, settings, and environments and among different sub-populations may help to identify those groups with the highest risk of TB exposure and where to find them.

In summary, mobility patterns and activity spaces offer distinct perspectives on human behavior not traditionally captured in standard epidemiological studies. Investigating these geographic characteristics, at both the individual and population level, can not only offer insights on risks and exposures for TB transmission but also provide practical insights for optimizing targeted active case finding strategies.

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Conflicts of Interest:

All authors report no potential conflicts.

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Table 1. Sociodemographic characteristics of participants

	Overall Prevalence survey N = 6371 enrolled	Work Commute survey N = 1504 (23.6%)	Activity spaces survey N = 5687 (89.3%)
Age, median [IQR]	33 [24 – 42]	30 [19 – 41]	33 [24 – 43]
Age group			
15 – 24	1663 (26.1%)	568 (37.8%)	1481 (26.0%)
24 – 34	1901 (29.8%)	367 (24.4%)	1693 (29.8%)
35 – 44	1450 (22.8%)	280 (18.6%)	1292 (22.7%)
45 – 54	751 (11.8%)	203 (13.5%)	678 (11.9%)
55 – 64	393 (6.1%)	64 (4.3%)	348 (6.1%)
65+	213 (3.3%)	22 (1.5%)	195 (3.4%)
Sex			
Female	4184 (65.7%)	793 (52.7%)	3720 (65.4%)
Male	2187 (34.3%)	711 (42.3%)	1967 (34.6%)
HIV status (self-reported)			
Positive	138 (3.3%)	28 (2.7%)	120 (3.1%)
Negative	4016 (96.7%)	1008 (97.3%)	3726 (96.9%)
Number of household members	2 [2 – 4]	3 [2 – 4]	3 [2 – 4]
Occupation			
Self-employed	2774 (43.6%)	591 (39.4%)	2482 (43.7%)
Employed by government	84 (1.3%)	57 (3.8%)	77 (1.4%)
Employed in private sector	615 (9.7%)	375 (25.0%)	557 (9.8%)
Pupil/student	584 (9.1%)	424 (28.2%)	500 (8.8%)
Housewife	880 (13.8%)	6 (0.4%)	786 (13.8%)
Unemployed	1311 (20.6%)	21 (1.4%)	1182 (20.8%)
Other	120 (1.9%)	28 (1.9%)	100 (1.8%)

Table 2. Work commute patterns by sex and age group (n=1504)

	Overall	Male	Female	p-value	15 – 24	25 – 34	35 – 44	45 – 54	55 – 64	65+	p-value
Mode											
Walk	1023 (68.3%)	442 (62.3%)	581 (73.6%)	**<0.001**	361 (63.9%)	255 (69.7%)	192 (68.8%)	152 (74.9%)	48 (75.0%)	15 (68.2%)	**0.001**
Bus/Taxi	431 (28.8%)	238 (33.5%)	193 (24.5%)		196 (34.7%)	91 (24.9%)	77 (27.6%)	45 (22.2%)	15 (28.8%)	7 (31.8%)	
Boda boda	31 (2.1%)	19 (2.7%)	12 (1.5%)		5 (0.9%)	12 (3.3%)	10 (3.6%)	3 (1.5%)	1 (1.6%)	0	
Other	14 (0.9%)	11 (1.6%)	3 (0.4%)		3 (0.5%)	8 (2.2%)	0	3 (1.5%)	0	0	
Commute distance (km)											
<= 1	492 (32.7%)	211 (29.7%)	281 (35.4%)	**<0.001**	167 (29.4%)	121 (33.0%)	92 (32.9%)	88 (43.3%)	20 (31.3%)	4 (18.2%)	**0.003**
1-2	363 (24.1%)	167 (23.5%)	196 (24.7%)		132 (23.2%)	103 (28.1%)	74 (26.4%)	32 (15.8%)	15 (23.4%)	7 (31.8%)	
2-5	344 (22.9%)	149 (21.0%)	195 (24.6%)		155 (27.3%)	68 (18.5%)	63 (22.5%)	38 (18.7%)	15 (23.4%)	5 (22.7%)	
5-10	186 (12.4%)	106 (14.9%)	80 (10.1%)		64 (11.3%)	46 (12.5%)	40 (14.3%)	25 (12.3%)	9 (14.1%)	2 (9.1%)	
>10	119 (7.9%)	78 (11.0%)	41 (5.2%)		50 (8.8%)	29 (7.9%)	11 (3.9%)	20 (9.9%)	5 (7.8%)	4 (18.2%)	
Commute cost											
0 Ksh	1029 (68.4%)	449 (63.2%)	580 (73.1%)		351 (61.8%)	263 (71.7%)	197 (70.4%)	153 (75.4%)	48 (75.0%)	77 (77.3%)	**0.014**
<50	68 (4.5%)	32 (4.5%)	36 (4.5%)	**<0.001**	39 (6.9%)	5 (1.4%)	11 (3.9%)	9 (4.4%)	3 (4.7%)	1 (4.6%)	
50-99	102 (6.8%)	54 (7.6%)	48 (6.1%)		47 (8.3%)	26 (7.1%)	18 (6.4%)	9 (4.4%)	1 (1.6%)	1 (4.6%)	
100-199	198 (13.2%)	114 (16.0%)	84 (10.6%)		89 (15.7%)	44 (12.0%)	38 (13.4%)	19 (9.4%)	6 (9.4%)	2 (9.1%)	
200+	107 (7.1%)	62 (8.7%)	45 (5.7%)		42 (7.4%)	29 (7.9%)	16 (5.7%)	13 (6.4%)	6 (9.4%)	1 (4.6%)	
Commute time											
<= 0.5 hours	281 (18.7%)	117 (16.5%)	164 (20.7%)	**0.003**	94 (16.6%)	77 (21.0%)	45 (16.1%)	46 (22.7%)	14 (21.9%)	5 (22.7%)	0.457
0.5 - 1	898 (59.7%)	419 (58.9%)	479 (60.4%)		343 (60.4%)	216 (58.9%)	178 (63.6%)	114 (56.2%)	34 (53.1%)	13 (59.1%)	
1-2	254 (16.9%)	129 (18.1%)	125 (15.8%)		110 (19.4%)	55 (15.0%)	42 (15.0%)	31 (15.3%)	12 (18.8%)	4 (18.2%)	
>2	71 (4.7%)	46 (6.5%)	25 (3.2%)		21 (3.7%)	19 (5.4%)	15 (5.4%)	12 (5.9%)	4 (6.3%)	0	
Transit hub time (mins)											
0-5	71 (29.5%)	35 (35.4%)	36 (35.0%)	0.174	19 (29.7%)	21 (30.0%)	16 (25.0%)	6 (27.3%)	5 (35.7%)	4 (57.1%)	0.532
6-10	57 (23.7%)	34 (24.6%)	23 (22.3%)		13 (20.3%)	13 (18.6%)	20 (31.3%)	8 (36.4%)	3 (21.4%)	0	
11-20	43 (17.8%)	21 (15.2%)	22 (21.4%)		12 (18.8%)	13 (18.6%)	12 (18.8%)	3 (13.6%)	3 (21.4%)	0	
21-30	21 (8.7%)	16 (11.6%)	5 (4.9%)		10 (15.6%)	7 (10.0%)	1 (1.6%)	1 (4.5%)	1 (7.1%)	1 (14.3%)	
31-60	13 (5.4%)	8 (5.8%)	5 (4.9%)		4 (6.3%)	4 (5.7%)	5 (7.8%)	0	0	0	
Over 60 mins	36 (14.9%)	24 (17.4%)	12 (11.7%)		6 (9.4%)	12 (17.1%)	10 (15.6%)	4 (18.2%)	2 (14.3%	2 (28.6%)	

Table 3. Categorized activity spaces by sex and age group (n=4252)

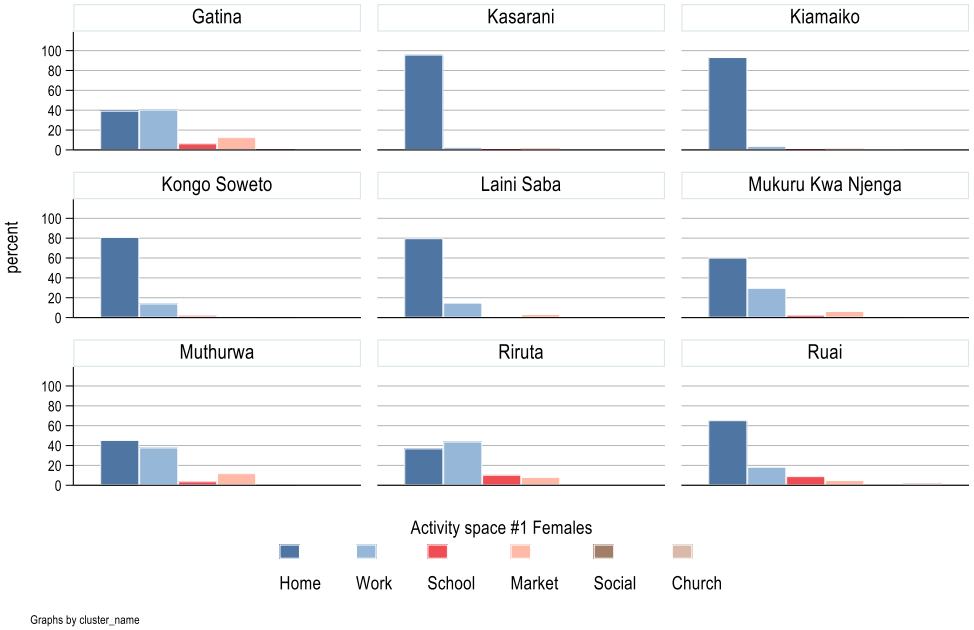
	Overall	Male	Female	p-value	15 – 24	25 – 34	35 – 44	45 – 54	55 – 64	65+	p-value
Place #1											
Home	2972 (65.4%)	915 (58.7%)	2057 (68.9%)	**<0.001**	794 (68.5%)	884 (65.1%)	668 (64.6%)	320 (57.6%)	189 (67.5%)	117 (76.0%)	**<0.001**
Work	1163 (25.6%)	525 (33.7%)	638 (21.4%)		127 (11.0%)	376 (27.7%)	327 (31.6%)	216 (38.9%)	86 (30.7%)	31 (20.1%)	
School	197 (4.3%)	84 (5.4%)	113 (3.8%)		187 (16.1%)	6 (0.4%)	3 (0.3%)	1 (0.2%)	0	0	
Market	175 (3.9%)	14 (0.9%)	161 (5.4%)		39 (3.4%)	82 (6.0%)	31 (3.0%)	14 (2.5%)	4 (1.4%)	5 (3.3%)	
Social	27 (0.6%)	17 (1.1%)	10 (0.3%)		9 (0.8%)	10 (0.7%)	3 (0.3%)	5 (0.9%)	0	0	
Church	8 (0.2%)	3 (0.2%)	5 (0.2%)		3 (0.3%)	1 (0.1%)	2 (0.2%)	0	1 (0.4%)	1 (0.7%)	
Place #2											
Home	218 (24.1%)	82 (28.3%)	136 (22.2%)	**<0.001**	48 (22.1%)	59 (23.6%)	51 (24.4%)	37 (27.2%)	15 (21.1%)	8 (38.1%)	**<0.001**
Work	312 (34.5%)	113 (39.0%)	199 (32.4%)		37 (17.1%)	89 (35.6%)	86 (41.2%)	66 (48.5%)	28 (39.4%)	6 (28.6%)	
School	81 (9.0%)	37 (12.8%)	44 (7.2%)		76 (35.0%)	4 (1.6%)	1 (0.5%)	0	0	0	
Market	236 (26.1%)	34 (11.7%)	202 (32.9%)		43 (19.8%)	77 (30.8%)	59 (28.2%)	25 (18.4%)	25 (35.2%)	7 (33.3%)	
Social	39 (4.3%)	19 (6.6%)	20 (3.3%)		7 (3.2%)	15 (6.0%)	9 (4.3%)	6 (4.4%)	2 (2.8%)	0	
Church	18 (2.0%)	5 (1.7%)	13 (2.1%)		6 (2.8%)	6 (2.4%)	3 (1.4%)	2 (1.5%)	1 (1.4%)	0	
Place #3											
Home	80 (34.6%)	29 (37.2%)	51 (33.3%)	0.362	17 (29.8%)	18 (31.6%)	25 (44.6%)	13 (34.2%)	3 (20.0%)	4 (50.0%)	**0.029**
Work	17 (7.4%)	8 (10.3%)	9 (5.9%)		3 (5.3%)	5 (8.8%)	4 (7.1%)	5 (13.2%)	0	0	
School	9 (3.9%)	5 (6.4%)	4 (2.6%)		7 (12.3%)	0	0	2 (5.3%)	0	0	
Market	66 (28.6%)	21 (26.9%)	45 (29.4%)		18 (31.6%)	14 (24.6%)	18 (32.1%)	11 (29.0%)	3 (20.0%)	2 (25.0%)	
Social	17 (7.4%)	4 (5.1%)	13 (8.5%)		3 (5.3%)	8 (14.0%)	2 (3.6%)	1 (2.6%)	3 (20.0%)	0	
Church	42 (18.2%)	11 (14.1%)	31 (20.3%)		9 (15.8%)	12 (21.1%)	7 (12.5%)	6 (15.8%)	6 (40.0%)	2 (25.0%)	
Place #4											
Home	65 (69.2%)	23 (65.7%)	42 (71.2%)	0.740	15 (75.0%)	14 (63.6%)	18 (72.0%)	12 (85.7%)	2 (25.0%)	4 (80.0%)	0.769
Work	3 (3.2%)	1 (2.9%)	2 (3.4%)		0	1 (4.6%)	0	1 (7.1%)	1 (12.5%)	0	
School	1 (1.1%)	0	1 (1.7%)		0	1 (4.6%)	0	0	0	0	
Market	10 (10.6%)	3 (8.6%)	7 (11.9%)		2 (10.0%)	3 (13.6%)	3 (12.0%)	0	2 (25.0%)	0	
Social	5 (5.3%)	3 (8.6%)	2 (3.4%)		1 (5.0%)	1 (4.6%)	1 (4.0%)	1 (7.1%)	1 (12.5%)	0	
Church	10 (10.6%)	5 (14.3%)	5 (8.5%)		2 (10.0%)	2 (9.1%)	3 (12.0%)	0	2 (25.0%)	1 (20.0%)	

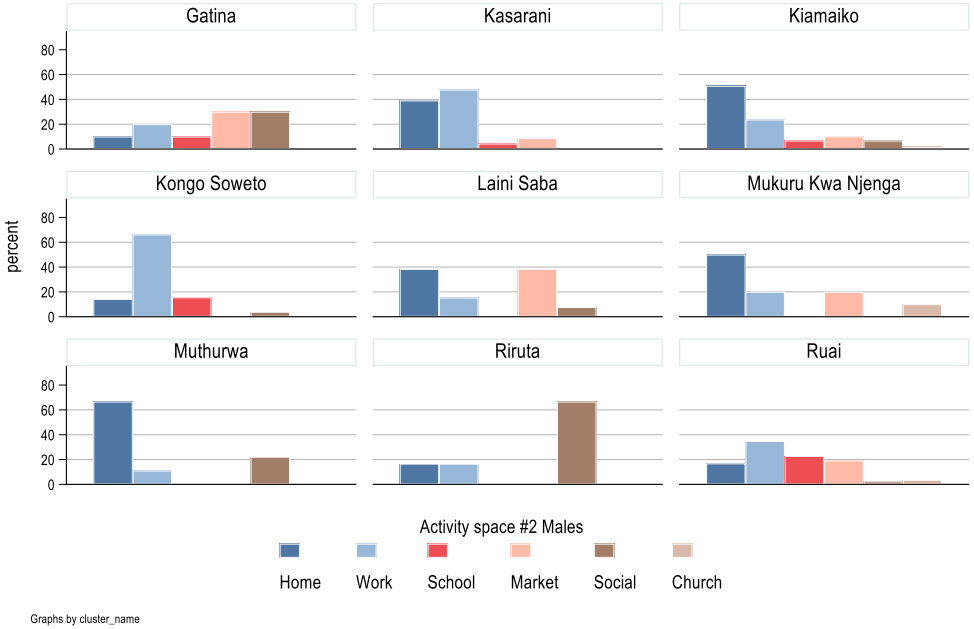
Table 4. Association of mobility & activity spaces with active TB diagnosis and positive symptom screen

	Bacteriologically-confirmed TB (n=5686)				Reporting any symptoms (n=5683)			
	Unadjusted OR	**p-value**	**Adjusted OR**	**p-value**	**Unadjusted OR**	**p-value**	**Adjusted OR**	**p-value**
Age group								
15 – 24	Ref		Ref		Ref		Ref	
24 – 34	2.16 (1.07, 4.36)	**0.032**	1.83 (0.85, 3.97)	0.124	0.97 (0.81, 1.17)	0.776	0.98 (0.79, 1.22)	0.882
35 – 44	2.31 (1.12, 4.79)	**0.024**	1.73 (0.76, 3.95)	0.196	1.20 (0.99, 1.45)	0.066	1.17 (0.94, 1.46)	0.166
45 – 54	2.85 (1.29, 6.31)	**0.010**	2.44 (1.05, 5.69)	**0.038**	1.81 (1.46, 2.24)	**<0.001**	1.84 (1.44, 2.35)	**<0.001**
55 – 64	2.72 (1.05, 7.07)	**0.040**	1.76 (0.58, 5.32)	0.320	1.79 (1.37, 2.34)	**<0.001**	1.93 (1.44, 2.59)	**<0.001**
65+	1.42 (0.31, 6.47)	0.647	1.07 (0.23, 5.08)	0.932	2.06 (1.48, 2.86)	**<0.001**	2.07 (1.45, 2.97)	**<0.001**
Sex								
Male	Ref		Ref		Ref		Ref	
Female	0.34 (0.22, 0.53)	**<0.001**	0.35 (0.21, 0.59)	<0.001	0.89 (0.78, 1.02)	0.101	0.99 (0.85, 1.14)	0.861
Mobility (Latent classes)*								
Class 1 – Higher mobility								
Class 2 – Lower mobility	1.20 (0.45, 3.22)	0.713			0.84 (0.64, 1.10)	0.210		
	Ref				Ref			
Mode*								
Walk	Ref				Ref			
Bus/taxi	0.59 (0.16, 2.10)	0.417			0.81 (0.59, 1.11)	0.193		
Boda boda	2.81 (0.35, 22.31)	0.329			1.65 (0.73, 3.75)	0.231		
Other	1				0.79 (0.18, 3.57)	0.761		
Commute distance (km)*								
<= 1	Ref				Ref			
1-2	0.17 (0.02, 1.34)	0.092			0.93 (0.65, 1.32)	0.668		
2-5	0.89 (0.29, 2.75)	0.843			0.88 (0.61, 1.26)	0.473		
5-10	0.33 (0.04, 2.63)	0.294			0.78 (0.49, 1.24)	0.294		
>10	0.51 (0.06, 4.14)	0.531			0.68 (0.39, 1.22)	0.196		
Commute time (hours)*								
<= 0.5	Ref				Ref			
0.5 – 1	1.88 (0.42, 8.50)	0.407			0.77 (0.54, 1.08)	0.130		
1 – 2	0.55 (0.05, 6.12)	0.628			0.75 (0.48, 1.17)	0.209		
> 2	1.99 (0.18, 22.31)	0.576			1.08 (0.57, 2.04)	0.822		
Activity Spaces								
Home	0.95 (0.59, 1.51)	0.814	1.07 (0.65, 1.76)	0.778	0.80 (0.69, 0.91)	**0.001**	0.83 (0.72, 0.96)	**0.010**
Work	0.86 (0.53, 1.41)	0.553	0.55 (0.31, 0.98)	**0.042**	1.05 (0.91, 1.20)	0.524	0.94 (0.80, 1.10)	0.411
School	0.16 (0.02, 1.15)	0.069	0.18 (0.02, 1.37)	0.098	0.86 (0.66, 1.11)	0.243	1.01 (0.75, 1.37)	0.939
Market	0.81 (0.47, 1.39)	0.445	1.02 (0.57, 1.81)	0.955	0.92 (0.79, 1.07)	0.272	1.00 (0.84, 1.19)	0.971
Social	2.15 (1.15, 4.03)	**0.016**	1.95 (1.02, 3.72)	**0.043**	1.42 (1.14, 1.78)	**0.002**	1.44 (1.14, 1.82)	**0.002**
Church	0.62 (0.38, 1.01)	0.054	0.86 (0.51, 1.46)	0.573	0.99 (0.86, 1.13)	0.860	1.00 (0.86, 1.18)	0.957

*Only a smaller subset responded to the mobility survey (n=1499 and n=1485, respectively). Mobility was not included in the adjusted analyses.

Figure 1. Activity spaces (reported places #1 and #2) by sex across 9 neighborhoods





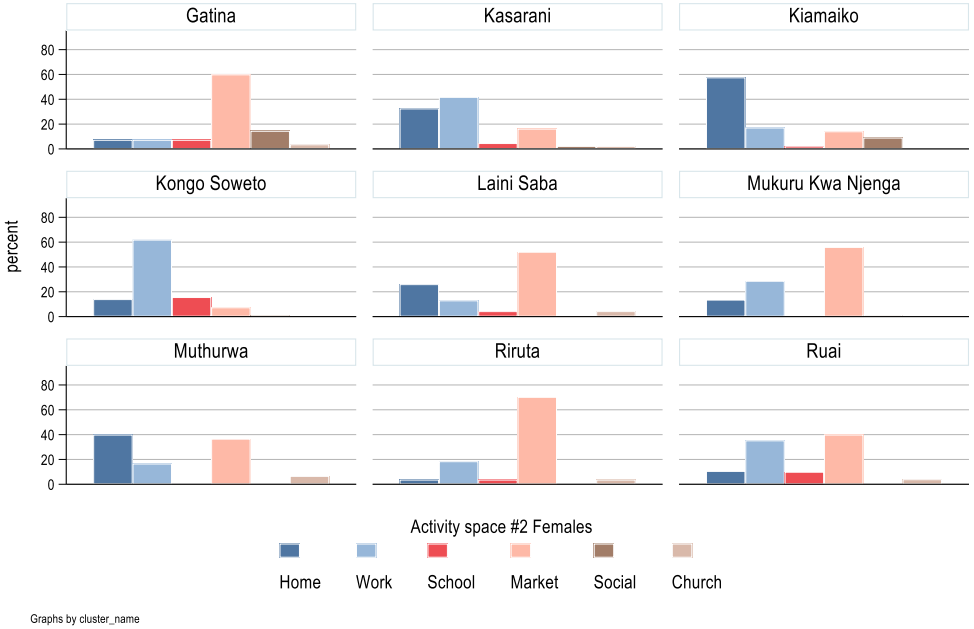


Figure 2. Visualization of a two-mode (bipartite) network with shared activity space categories

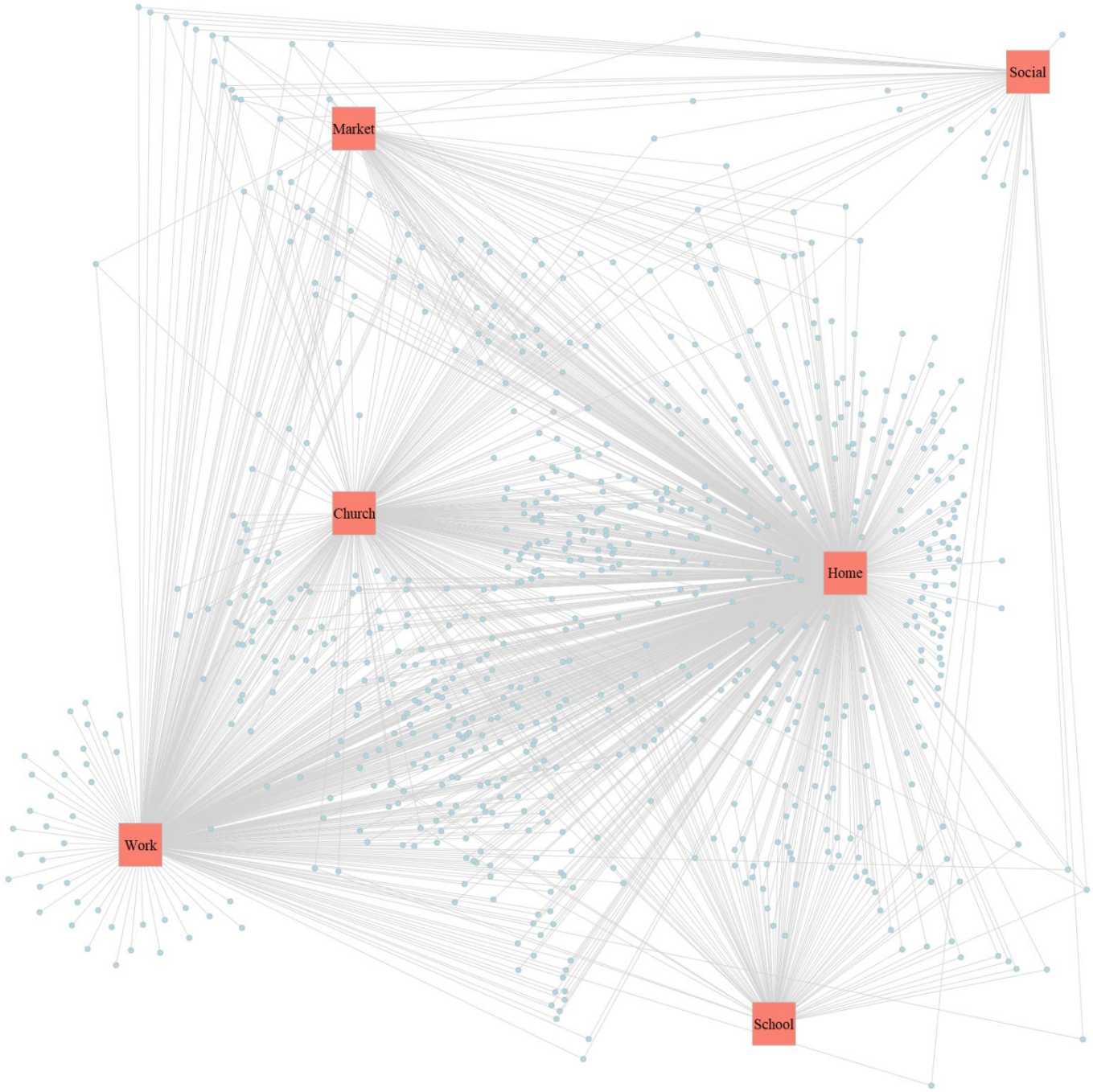
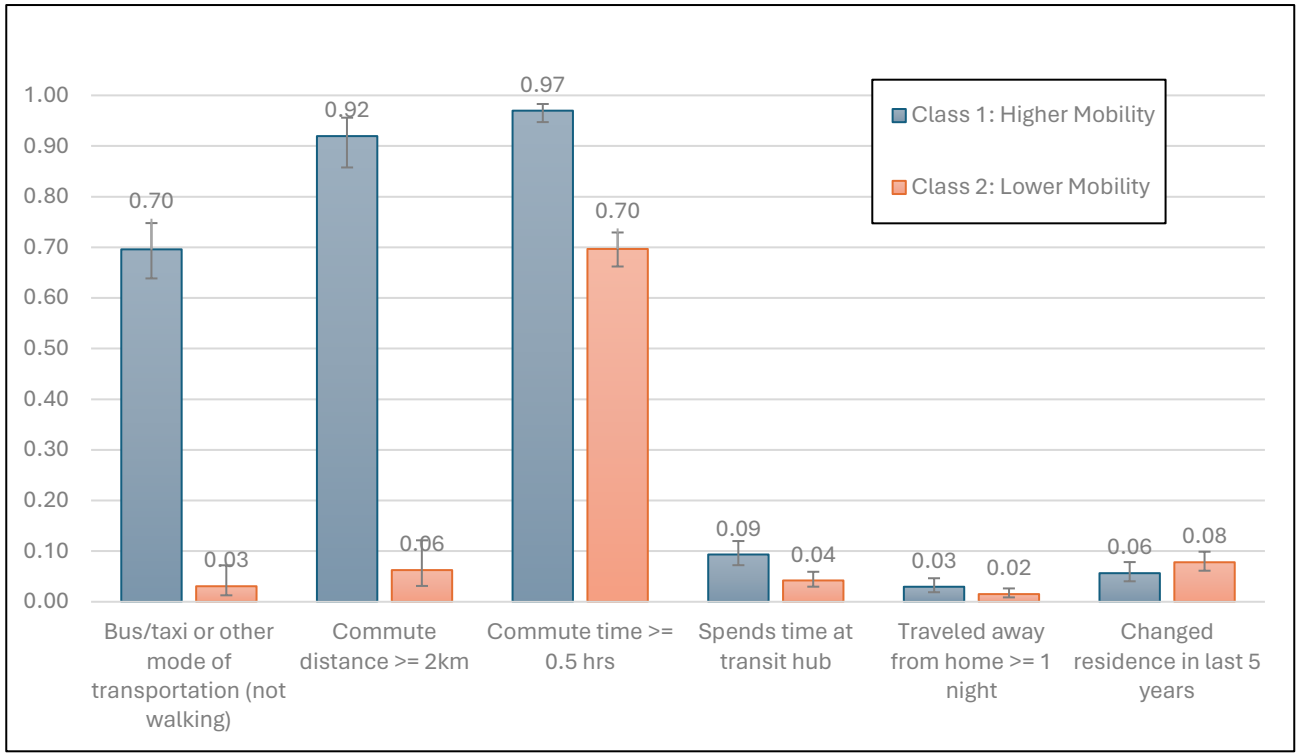


Figure 3. Marginal probabilities for mobility features in each latent class of mobility



Supplement

Table S1. Features of geographic mobility

Variable	Higher mobility	Lower mobility
Mode of transportation (working commute)	Bus, taxi, or other vehicles	Walk
Commute distance *Sensitivity analysis*: *different thresholds*	> 2km	<= 2km
Commute time *Sensitivity analysis*: *different thresholds*	> 0.5 hour	<= 0.5 hour
Transit hub – Do you use a transit hub (e.g. bus station or taxi rank)	Yes	No
Travel away from home in past month, # of nights	1 or more nights	0 nights
Residence change – Have you changed your residence at any point the last 5 years	Yes	No

Table S2. LCA model selection: # classes, degrees of freedom, BIC, AIC

Number of Latent Classes	Degrees of freedom	Bayesian Information Criterion	Akaike's Information Criterion
1	6	7174.1	7142.2
2	13	6446.3	6377.2
3	20	No convergence	
4	27		

Table S3. Estimated marginal probabilities for individual features in each latent class of mobility

	Class 1 (Higher mobility) Mean (95%CI)	**Class 2 (Lower mobility) Mean (95%CI)**	**Difference (Class 1 – Class 2)**
Commute distance > 2km	0.92 (0.86 – 0.96)	0.06 (0.03 – 0.12)	0.86
Bus/taxi or other mode of transportation (not walking)	0.70 (0.64 – 0.75)	0.03 (0.01 – 0.07)	0.67
Commute time > 0.5 hours	0.97 (0.95 – 0.98)	0.70 (0.66 – 0.73)	0.27
Spends time at transit hub	0.09 (0.07 – 0.12)	0.04 (0.03 – 0.06)	0.05
Traveled away from home >= 1 night in last month	0.03 (0.02 – 0.05)	0.02 (0.01 – 0.03)	0.01
Changed residence in last 5 years	0.06 (0.04 – 0.08)	0.08 (0.06 – 0.10)	-0.02