

Recovery in Place: A Multimodal Pilot Study of Neighborhood Context, Life-Space, and Social and Physical Functioning After Lower-Limb Fracture Surgery

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Research Article

Keywords: Older adults, Neighborhood context, Social isolation, Life-space, Activity space, Post-discharge recovery, Multimodal passive sensing

Posted Date: October 27th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11283018/v1>

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Additional Declarations: No competing interests reported.

Abstract

Background

Older adults returning home after lower-limb fracture surgery or hip replacement recover within heterogeneous social and spatial contexts, yet neighborhood conditions are rarely integrated into post-discharge monitoring. Guided by the capability approach and the life-space concept, this study examined recovery as a situated process shaped by residential context, activity space, and changing social and physical function after discharge.

Methods

Eighteen community-dwelling older adults completed eight weeks of monitoring, contributing 1,008 person-days of multimodal sensor data and repeated biweekly clinical assessments. Clinical measures included the Social Isolation Scale, Oxford Hip Score, Oxford Knee Score, Timed Up and Go test, and 30-second chair-stand test. Residential and visited locations were linked to amenity, crime, and Canadian census-derived socioeconomic data. Generalized estimating equations tested associations between socio-spatial exposures and the Social Isolation Scale, Oxford Hip Score, and Oxford Knee Score. Predictive models compared sensor-only, socio-spatial-only, and combined feature sets for all clinical outcomes under random-shuffled and cross-person validation.

Results

Neighborhood material disadvantage was associated with lower social interaction in both residential and activity-space analyses. More location transitions per day were associated with higher social interaction after correction for multiple testing, while other location-derived mobility measures showed exploratory associations. Activity-space exposure to libraries and food establishments was associated with better hip function after correction for multiple testing, whereas similar amenity associations were not observed around the residence. Predictive performance varied by model, outcome, and validation setting. Prediction errors were generally higher under cross-person validation, and socio-spatial features improved prediction for some outcomes and models but not others.

Conclusions

These preliminary findings suggest that post-discharge recovery is shaped by the interaction between changing bodily capacity and the social and spatial environments that become accessible during recovery. Integrating residential and activity-space context may improve interpretation of remote-monitoring data, but larger longitudinal studies are required before clinical application.

1. Background

Older adults who return home following lower-limb fracture surgery or hip replacement face a critical period in which the risks of social isolation and functional decline are sharply elevated [1], [2]. The transition out of acute care frequently disrupts daily routines, mobility, and the social ties that sustain participation in community life, and these losses can derail the broader goal of aging in place [3], [4], [5]. Functional decline refers to reductions in physical status and in the ability to perform basic and instrumental activities of daily living [6], [7], while social isolation describes a thinning of contacts and social networks and is itself linked to morbidity, mortality, and reduced quality of life [2], [8]. The two phenomena may reinforce one another: weakened function constrains opportunities for interaction, and reduced interactions contributes to decline [2]. A structured scoping review of post-hip-fracture recovery identified income, employment, education, and informal support as recurrent social determinants of outcomes, but found that these factors are seldom integrated with longitudinal post-discharge monitoring [9]. We use recovery in place to describe the dynamic process through which changing bodily capacity interacts with the home, neighborhood, mobility systems, social relations, and community resources after discharge.

A growing body of social-science research demonstrates that residential neighborhoods influence older adults' health, mobility, and social participation. Proximity to neighborhood amenities, such as parks and libraries, facilitates engagement and supports mobility [10], [11], whereas concerns about neighborhood insecurity, fear of crime, and limited access to services can suppress outdoor activity and amplify isolation [10], [12]. Census-derived indicators of socioeconomic resources, language, immigration status, and housing tenure are associated with the risk of loneliness and functional limitations among community-dwelling older adults in Canada and elsewhere [13], [14]. A recent scoping review of neighborhood socioeconomic processes and healthy aging concluded that resource-limited neighborhoods are consistently linked to worse outcomes across multiple healthy-aging domains [15]. Furthermore, qualitative work with older adults recovering from disability in resource-limited neighborhoods identifies environmental and infrastructural barriers, perceived safety concerns, and limited informal support as factors shaping recovery [16]. However, this literature remains temporally and spatially limited, with a predominant focus on cross-sectional studies of chronic aging and community-level processes, such as gentrification [17], and less attention to the acute post-discharge period or to the activity spaces older adults actually use. These knowledge and methodological gaps are especially important after fracture, when mobility is abruptly constrained and environmental supports or barriers may be most consequential [3], [18]. During this period, the recovery process unfolds over time through daily movement, patterns of leaving and returning home, access to meaningful places, perceived safety, and the social conditions that make social participation possible or difficult. Therefore, examining both the immediate residential environment and the broader activity space an older adult can reach is required to provide a more situated understanding of recovery in the community [19], [20].

Previous research on older adults' recovery in the community has used remote monitoring but has often remained focused on individual biomedical status, without capturing the relational and environmental

determinants of recovery [21], [22]. Continuous monitoring and artificial intelligence (AI) applied to wearable, smartphone, and home-sensor data offer a promising alternative that can capture day-to-day function outside clinical settings [23], [24]. However, these systems often interpret recovery through individual-level signals, such as falls, vital signs, step counts, and in-home movement, while leaving the surrounding social and environmental context largely unmeasured [24]. A dominant assumption is that reduced-mobility signals indicate that an older adult is experiencing physical decline, when, in reality, mobility may also reflect socio-spatial conditions, such as a lack of nearby amenities or fear of local crime. This assumption is informed by biomedical “age scripts” that frame reduced activity as an expected feature of aging rather than as a situated response to social and spatial constraints [25], [26], [27]. A broader understanding of context is required to capture the plurality of possible meanings in AI system outputs and support their meaningful interpretation [28].

The capability approach and the life-space concept provide a conceptual bridge for understanding recovery as both resource-dependent and spatially situated. Sen’s capability approach distinguishes resources from achieved functioning and emphasizes that resources are converted into well-being through personal, social, and environmental conversion factors [29], [30]. This approach has been used to examine aging in place, social connectedness, and the conditions that enable older adults to pursue lives they have reason to value [31], [32], [33], [34], [35], [36], [37], [38], [39], [40]. In post-discharge recovery, the capability approach shifts analysis from the presence of neighborhood resources to whether older adults can convert those resources into mobility, social participation, and everyday functioning.

Life-space provides the spatial perspective on this process, referring to the geographical area within which a person carries out routine and community activities from the home to the neighborhood and beyond [41]. Its measurement has progressed from diaries and self-report questionnaires to GPS-derived indicators of activity space [19], [42], [43], [44], [45], [46]. The geographical size of life-space should not be interpreted as inherently beneficial or problematic, as a limited life-space may still support recovery when it contains meaningful destinations, accessible resources, and opportunities for social connection. Rather, large reductions in life-space over time have been associated with greater loneliness and diminished psychological well-being [47], [48]. In the post-fracture period, the more salient issue may be whether life-space contracts in ways that diminish access to the places, relationships, and routines that previously supported everyday functioning and recovery [42]. Together, these frameworks position recovery as a situated process shaped by social and spatial context.

Guided by this conceptual framing, this pilot study examined associations of neighborhood context and life-space with social isolation and physical functioning during the early post-discharge recovery period. The study followed community-dwelling older adults for eight weeks after discharge following lower-limb fracture surgery or hip replacement, integrating wearable activity sensors, GPS location data, assessments of social isolation and physical functioning every two weeks, and neighborhood characteristics drawn from municipal amenity data, crime data, and the Canadian census. The analyses examined four areas. (i) Associations of home-neighborhood resources, including social amenities,

safety, and socioeconomic disadvantage, with social isolation and physical functioning in the early post-discharge period. (ii) Changes in these associations after adding personal, social, and economic conversion factors. (iii) Differences between the immediate home neighborhood and realized life-space in relation to these outcomes. (iv) Whether socio-spatial features added exploratory cross-person predictive information beyond wearable sensor features alone.

This study provides a theoretically grounded, longitudinal examination of associations between neighborhood context, GPS-derived activity space, and social and physical functioning during early post-discharge recovery, using multimodal sensor data and repeated clinical assessments. By integrating residential context, activity space, multimodal sensing, and repeated clinical assessment, the study examines recovery in place as a relational process rather than an exclusively individual trajectory.

2. Methods

2.1. Study design overview

This prospective longitudinal observational pilot study followed a cohort of community-dwelling older adults for eight weeks immediately after discharge from hospital following lower-limb fracture surgery or hip replacement. Three streams of data were integrated: continuous multimodal passive sensing of behavior, physiology, and location in the home and community; standardized clinical assessments of social and physical functioning delivered biweekly by a trained research assistant; and neighborhood-level socio-spatial characteristics extracted from publicly available municipal and census data sources for every location each participant visited. The eight-week monitoring window was chosen because the majority of physical recovery after hip fracture or hip replacement takes place during the first one to three months following discharge, the period in which capacity is most acutely constrained and environmental supports or barriers are most consequential [9], [49], [50]. The study was conducted in the Greater Toronto Area, Canada, in accordance with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans, the ICH Guideline for Good Clinical Practice E6, and applicable institutional ethics requirements. It was approved by the Research Ethics Board of the University Health Network (ID 20-5113), and all participants provided written informed consent prior to enrollment.

2.2. Participants and setting

Participants were recruited from a rehabilitation hospital in Toronto, Canada, during their admission for surgical management of a lower-limb fracture or elective hip replacement. Eligibility criteria were age 60 years or older; recent surgical repair of a lower-limb fracture or hip replacement; absence of cognitive impairment as indicated by a Mini-Mental State Examination score of 24 or higher [51]; a residential Wi-Fi connection capable of supporting the monitoring platform; and consent to enrollment prior to hospital discharge so that continuous data collection could begin on the first day at home. Recruitment was carried out by a trained research assistant during the inpatient stay, and informed written consent was obtained at the bedside. As a pilot study designed to test the feasibility and analytic value of integrating

multimodal sensing with neighborhood-level data, a small, purposive sample was sought rather than a target derived from a formal power calculation.

2.3. Multimodal monitoring

Continuous passive monitoring was carried out using a research-grade in-home sensor platform described previously [52]. The platform integrated four cloud-connected devices: a smartwatch (Google Pixel Watch), a smartphone (Motorola Moto G), an under-mattress sleep mat (Withings Sleep), and a wall-mounted passive infrared motion sensor (Proteus M5). The smartphone and smartwatch applications captured GPS coordinates every 10 seconds, triaxial acceleration every second, heart rate every 30 minutes, and continuous step counts, with all signals uploaded to a secure cloud backend every thirty minutes. The under-mattress mat recorded sleep onset, duration, stages, snoring, and nocturnal heart rate, and the wall-mounted sensor recorded in-home motion events throughout the monitoring period. To conserve battery and minimize in-home location tracking, GPS was activated only when participants crossed a predefined geofence around the residence. Devices required minimal participant effort beyond routine recharging and carrying or wearing the smartphone and smartwatch. The platform was deployed on Google Cloud Platform to support scalable data management and extension to larger cohorts, and used non-invasive sensors designed to minimize interference with daily routines. Devices were configured during a pre-discharge home visit. No directly identifying information was stored with the sensor streams; data were pseudonymized and processed on encrypted servers. Daily summary features derived from acceleration, heart rate, step count, GPS location, in-home motion, and sleep signals were used as predictors in the models.

2.4. Social interaction and physical function assessments

Validated clinical assessments were administered every two weeks by a trained research assistant via Microsoft Teams video calls with participants at home, providing reference measures of social interaction and physical function that served as the primary outcomes. These comprised the 6-item Social Isolation Scale (SIS) [53] (higher scores indicate greater social interaction), the 12-item Oxford Hip Score (OHS) [54] and 12-item Oxford Knee Score (OKS) [55] (higher scores indicate better joint function), the 30-second chair-stand test [56] (higher counts indicate better lower-limb strength), and the Timed Up and Go (TUG) test [57] (lower times indicate better mobility).

2.5. Neighborhood-level (socio-spatial) data integration

Each participant's residential location and the locations visited during the eight-week monitoring period were captured as time-stamped latitude and longitude coordinates by the smartwatch when outside the home geofence. These locations were linked to publicly available place-based data to characterize the material and social resources of each participant's life-space. Three exposure profiles were selected to capture complementary dimensions of life-space context: local amenities for participation, neighborhood-level crime representing safety conditions that may enable or constrain movement, and socioeconomic conditions that shape access to resources:

1. Amenity index: For each unique location, including the home and visited locations, points of interest within a 1 km radius were counted using the Google Places Nearby Search application programming interface (API) [58]. Four amenity categories were extracted: parks, libraries, food establishments (restaurants and cafés), and places of worship. These amenity counts indicate local opportunities for social engagement, physical activity, and community participation that the capability approach views as resources.
2. Neighborhood-level crime index: This exposure was based on the Toronto Police Service Neighborhood Crime Rates Open Data [59]. Annual neighborhood-level crime rates for assault, robbery, break-and-enter, auto theft, theft-over, shooting, and homicide, measured per year, were extracted and assigned to each location. To link locations to the crime dataset, latitude and longitude coordinates were reverse-geocoded using the Google Geocoding API [60] to obtain Canadian six-character postal codes. The postal codes were then matched with Toronto Police Service neighborhood data using approximate string matching to accommodate naming inconsistencies.
3. Neighborhood-level socioeconomic index: Data for this exposure were obtained from Statistics Canada [61]. Postal codes were mapped to dissemination areas and then linked to the Census Profile to extract indicators covering household and after-tax income, government-transfer dependence (i.e., the share of income derived from government transfers rather than employment or private income sources), employment and unemployment rates, educational attainment, housing tenure and affordability, housing characteristics, and population composition, including immigrant and visible-minority share and residential mobility. These area-level indicators follow the Ontario Marginalization Index convention [62] and operationalize the material and economic resources of each life-space. The indicators were used as inputs for the composite material-deprivation index (a composite measure of neighborhood socioeconomic disadvantage based on indicators such as income, employment, education, housing, and reliance on government transfers). All linkages used de-identified coordinates and aggregated to the neighborhood level to preserve participant privacy; the full processing pipeline is detailed in [63].

2.6. Statistical analysis and predictive modeling

Two complementary analyses were conducted: explanatory association analyses testing whether each socio-spatial exposure was related to the recovery outcomes, and predictive modeling testing whether sensor-derived behavior, neighborhood context, or their combination could predict outcome scores from a preceding monitoring window.

2.6.1. Association analysis

Social interaction and physical functioning outcomes were modeled as continuous responses. Socio-spatial exposures were operationalized in two ways. First, home-neighborhood exposures characterized the immediate residential environment surrounding each participant's home, referred to as the "immediate life-space." Second, activity-space exposures summarized the locations participants visited

during the monitoring period, with greater weight given to places where they spent more time. These exposures were referred to as the “realized life-space” because they represent the places participants were able to reach and occupy during recovery, rather than the neighborhood resources surrounding the home alone.

For each operationalization, individual amenity counts, neighborhood-level crime rates, and selected Census socioeconomic indicators were entered alongside three composite indices: amenity, crime, and material deprivation (defined as limited neighborhood access to economic and material resources). Associations were estimated using generalized estimating equations clustered by participant at the daily level. The primary estimate was the linear slope per + 1 standard deviation of the standardized exposure, reported with robust 95% confidence intervals. False-discovery-rate control was applied using the Benjamini-Hochberg procedure within each exposure domain by outcome family. Additionally, the season was examined in a sensitivity analysis by comparing summer months, from June through August, with the remainder of the year, because weather may influence outdoor mobility and social participation in the Canadian setting.

Associations between GPS-derived mobility patterns and recovery outcomes were examined as additional activity-space analyses. Four GPS-derived mobility metrics were derived: unique locations visited per day, defined as the count of distinct places visited; location entropy, defined as the evenness of time distributed across visited locations; fraction of time spent away from home, defined as the proportion of the GPS-active day spent outside the residence; and location transitions per day, defined as movements from one stay location to the next. A composite index was also calculated to summarize these four GPS-derived mobility metrics.

2.6.2. Predictive modeling

The preprocessing pipeline for the sensor and neighborhood socio-spatial data, including feature extraction and missing-value imputation, is described in detail in [63], [64]. Briefly, missing sensor observations were replaced using a two-tier within-participant mean-substitution procedure based on within-day and within-week estimates. Three feature sets were compared: sensor only, socio-spatial only, and combined sensor and socio-spatial features. For the combined setting, the candidate pool included 64 features: 44 sensor-derived features and 20 socio-spatial features (Supplementary Material 1). Feature selection was performed within each training fold using recursive feature elimination [65]. The top 48 features, corresponding to 75% of the original candidate pool, were retained to provide modest dimensionality reduction without aggressive feature pruning. The feature sets were used as inputs to the models, while SIS, OHS, OKS, TUG, and 30-second chair-stand measures served as model outcomes.

Two machine learning models were used to compare performance across different model families: a gradient-boosted tree ensemble, CatBoost [66], and a tabular foundation model designed for prediction on tabular datasets, TabPFN [67]. Model generalization was evaluated under two cross-validation settings with progressively stricter boundaries, following recommendations for structured longitudinal data [68]. First, in random-shuffled 5-fold cross-validation, all observations were randomly divided into

five folds regardless of participant. This setting served as a more permissive benchmark because observations from the same participant could appear in both the training and test sets. Second, in cross-person 5-fold cross-validation, participants were divided into five groups. In each iteration, 80% of participants were used for training and the remaining 20% were held out for testing. This process was repeated five times so that each group served as the test set once, providing a stricter test of generalization to participants not seen during training. Model performance was evaluated using mean absolute error (MAE) between predicted and observed scores on each held-out fold. MAE was reported in the original units of each recovery outcome to preserve clinical interpretability. Across-fold means and standard deviations summarized accuracy and stability under each cross-validation scheme.

3. Results

3.1 Participant cohort and baseline characteristics

Eighteen community-dwelling older adults completed the eight-week post-discharge monitoring protocol between March 2022 and September 2025, contributing 1,008 person-days of multimodal sensor data and 72 biweekly clinical assessment visits. The cohort had a mean age of 76.5 years (SD 8.9; range 60–94), was predominantly female (14 of 18; 78%), and most participants lived alone (14 of 18; 78%). Self-reported ethnicity was white for 15 of the 18 participants (83%), Black for 2 (11%), and South Asian for 1 (6%). Index procedures comprised hip replacement (n = 8; 44%), hip fracture (n = 4; 22%), pelvis fracture (n = 3; 17%), and femur fracture (n = 3; 17%). Cohort characteristics, including baseline (first biweekly visit) values and across-visit summaries for the recovery outcomes, are presented in Table 1.

Data coverage was high across the eight-week monitoring window: clinical assessments were completed in full at every biweekly visit, sleep recordings from the under-mattress mat were missing on 1.3% of nights, and smartwatch streams were missing for 17.6% of person-days. Missingness windows aligned closely across smartwatch modalities, consistent with the watch being off-wrist or charging rather than per-modality failure. Missing values were imputed using within-participant means [63].

Participants resided in home neighborhoods spanning a wide range of amenity, crime, and socioeconomic contexts (Table 2). Distribution of home-neighborhood characteristics is reported across amenity counts (within a 1 km radius), neighborhood-level crime rates, selected census socioeconomic indicators, and the three composite indices (amenity, crime, and material deprivation). The composite indices are z-standardized against the city locations used as the reference set; a value of zero denotes the mean of that reference set, and higher values denote more of the measured attribute. Neighborhood-level data were essentially complete: the amenity and crime-rate tables had full coverage, and the small number of missing Census values were imputed using the geographically nearest neighborhood.

3.2 Association analyses

Table 3 reports the adjusted home and activity-space associations between each socio-spatial exposure and the three recovery outcomes. The OHS and OKS were the outcome measures of self-reported joint

function in the association models; the performance-based TUG and chair-stand tests were reserved for the predictive analysis. Three patterns are noteworthy. The strongest signal is that indicators of neighborhood material disadvantage were associated with lower social interaction. Higher shares of household income from government transfers, higher material deprivation, and higher unemployment rates each predicted lower SIS scores in both the home and the activity-space operationalizations. The false-discovery-rate-adjusted q-values for the material-deprivation index and the government-transfer share were below conventional thresholds (Table 3 (a)).

Activity-space analysis showed amenity-related associations that were not observed in the home-based analysis. Greater dwell-weighted exposure to libraries and food establishments was associated with higher Oxford Hip Scores after false-discovery-rate correction (Table 3(b)). Exposure to food establishments and places of worship showed nominal associations with higher Oxford Knee Scores, but neither survived correction (Table 3(c)). These amenity associations were observed in the activity-space analyses but not in the home-neighborhood analyses. A counterintuitive pattern emerged for average household income: higher neighborhood values were associated with lower OHS in the activity-space analysis and lower OKS in both home-neighborhood and activity-space analyses after false-discovery-rate correction. The other income indicators did not show equally consistent evidence. Each composite index was first entered alone in a single-domain model (reported in Table 3 under “Overall composite indices”), and the amenity, crime, and material-deprivation indices were then entered together in a combined model (reported under “All domains combined”), so that each domain estimate could be read both on its own and after accounting for the other two domains.

An exploratory comparison of summer monitoring (June through August) with the remainder of the year showed two nominal associations in opposing directions: social interaction was higher in summer months than across the rest of the year (adjusted $\beta = +2.40$, $p = .008$; unadjusted $\beta = +2.26$, $p = .012$), while the OHS was lower during summer (adjusted $\beta = -2.07$, $p = .006$; unadjusted $\beta = -1.88$, $p < .001$). The OKS showed no association with summer (adjusted $\beta = -1.47$, $p = .253$). Only 4 of the 18 participants (22%) were monitored during the summer window. These estimates are therefore exploratory and may reflect differences between the small groups monitored in and outside summer rather than seasonal effects, and results should be interpreted with caution.

3.3 GPS-derived mobility

Table 4 reports associations between GPS-derived mobility metrics and the three recovery outcomes. More location transitions per day were associated with higher social interaction after false-discovery-rate correction; the other GPS-derived mobility measures showed no corrected associations with SIS, OHS, or OKS. For SIS, unadjusted associations were positive for the composite index, unique locations, location entropy, and location transitions, though only transitions reached conventional significance. After adjustment for age and household composition, these associations strengthened, and location transitions per day survived false-discovery-rate control. The composite index, unique locations, and location entropy reached or approached conventional significance, while time away from home was

unrelated to SIS. No GPS-derived mobility metric was associated with OHS or OKS. Thus, higher social interaction co-occurred more consistently with visiting varied locations and moving between places than with the duration of time spent away from home.

3.4 Predictive modeling

Table 5 reports MAE for CatBoost and TabPFN across four feature-set combinations under two cross-validation settings: random-shuffled 5-fold, randomly pooling observations across participants, and cross-person 5-fold, keeping each participant's observations within a single fold for cross-person generalization. Under random-shuffled 5-fold, TabPFN generally had lower MAE than CatBoost. Combined features reduced MAE relative to sensor-only features for every CatBoost outcome, while TabPFN results varied by outcome. Adding socio-spatial features to the sensor pool reduced error for CatBoost on every outcome under random-shuffled validation, while the effect for TabPFN varied by outcome. Under cross-person 5-fold, MAE was substantially higher across all settings, reflecting the difficulty of generalizing to held-out participants given the small cohort and the individualized nature of post-discharge recovery. Under cross-person validation, socio-spatial-only or combined features reduced MAE for some outcomes and models, but increased it for others. The contribution of neighborhood context to prediction in unseen participants was therefore inconsistent.

The cross-person feature-importance ranking that informed the top-48 feature subset is reported in Supplementary Material 2 (a) to (e). Neighborhood socioeconomic and crime indicators accounted for most of the highest-ranked features, including neighborhood unemployment rate, mean total individual income, the percentage of renter households, the percentage of residents aged 15+ without a high school diploma, the percentage of residents aged 15+ with a bachelor's degree or higher, the theft-over-\$5,000, and the break-and-enter rates. A small number of sensor features (mean wrist acceleration, overnight movement events, and mean daily steps) appeared among the highest-ranked features for the chair-stand and TUG outcomes. These rankings should be interpreted as exploratory descriptions rather than stable estimates of predictor importance.

4. Discussion

Summary of findings. This study examined how residential context and GPS-derived activity space were associated with social and physical recovery during the eight weeks after discharge for lower-limb fracture surgery or hip replacement. We conceptualize recovery in place as a dynamic process produced through interactions between changing bodily capacity and mobility, neighborhood resources, safety, socioeconomic context, and spatial conditions of everyday life based on Sen's capability approach [29], [30] and the life-space framework [41]. Three findings support this relational interpretation, indicating that social recovery, in particular, appears to be influenced by these interactions. First, indicators of neighborhood material disadvantage were consistently associated with lower self-reported social interaction in both the home neighborhood and the activity space, and these associations persisted after adjustment for age and household composition. Second, time-weighted exposure to community

amenities across visited locations was associated with better physical recovery only when measured across the activity space rather than around the home. Third, GPS-derived mobility measures were positively associated with social interaction, while the amount of time spent away from home was not. Combining sensor and socio-spatial features in cross-person predictive modeling reproduced these patterns of recovery in place, and the features driving the rankings were dominated by neighborhood socioeconomic and safety indicators rather than individual sensor signals.

Interpretation through the capability and life-space frameworks. The association between neighborhood material disadvantage and social interaction is consistent with the capability approach's central distinction between resources and what people are able to do with them. For instance, the material-deprivation index, the share of household income from government transfers, and the unemployment rate were each associated with lower SIS in both the home and the activity space, persisted after adjustment for age and household composition, and survived false-discovery-rate correction within the (domain $\times$ outcome) family. Within Sen's framework, these indicators characterize aspects of the social and economic environment that may shape whether potential opportunities become usable.

Comparing residential-neighborhood and activity-space operationalizations further clarifies the role of place. Dwell-weighted exposure to libraries, food establishments, and places of worship was associated with better OHS and OKS, whereas none of these associations was visible at the residence-neighborhood space. In this study, the residential neighborhood space represents the structural context into which a person is discharged; the activity-space represents environments actually encountered during recovery. This is consistent with May et al.'s original framing of life-space as the locations a person actually occupies [41]. The difference between these spaces is theoretically informative because spatial availability and realized exposure are not equivalent. Activity space is also endogenous to health: better function may enable a person to reach more destinations, while the destinations reached may support or constrain subsequent recovery. The data reveal this coupling between bodily capacity and place but cannot determine its direction.

The GPS-derived mobility findings further specify which dimensions of the realized activity space were associated with social interaction signal. Diversity of places visited, evenness of time across them, and the number of stay-to-stay transitions were each positively associated with SIS; the amount of time spent away from home was not. These findings suggest that the diversity and structure of mobility, rather than simply time outside the residence, may be more closely related to social interaction. The associations strengthened after adjustment for age and household composition, indicating that these covariates may have suppressed part of the observed relationship. From a capability perspective, the findings are consistent with the possibility that access to varied environments supports social functioning. However, GPS data captures movement rather than the opportunities or choices available to participants and should not be interpreted as capability.

A counter-intuitive finding requires interpretation within the same frameworks. Higher neighborhood income indicators were associated with worse OHS and OKS in both operationalizations. From a capability perspective, resources do not translate directly into improved functioning; their value depends on the personal, social, and environmental conditions through which they can be converted into meaningful opportunities. Such environments may offer material advantages while providing fewer opportunities to incorporate movement into everyday routines—particularly during recovery, when mobility is temporarily constrained. The observed association may therefore reflect a mismatch between socioeconomic advantage and spatial accessibility, rather than an adverse effect of neighborhood income itself. Because density, walkability, and individual access to resources were not directly measured, this interpretation remains hypothesis-generating but highlights the need for future research.

The cross-person predictive analyses provide a complementary indication that recovery cannot be fully characterized from individual sensor signals alone. In most comparisons, models combining sensor and socio-spatial features predicted social and physical outcomes more accurately than sensor-only baselines. Neighborhood socioeconomic and crime indicators also featured prominently in the model rankings, whereas sensor measures assumed greater importance for the chair-stand and Timed Up and Go outcomes. This distinction suggests that sensor signals may be especially informative for performance-based physical outcomes, while broader social and self-reported physical functioning may be more intelligible when the environments in which recovery occurs are also considered. Taken together, the association, mobility, and predictive analyses converge on a view of recovery as a situated process produced through the interaction of bodily capacity and place. This interpretation is consistent with the capability approach, in which environmental resources and conversion conditions shape achieved functionings, and with a life-space perspective, in which observed mobility reflects the relationship between individual capacity and the environments that become reachable during recovery. The predictive results are best viewed as a demonstration of the potential value of incorporating socio-spatial context when interpreting sensor-derived indicators of recovery in place.

Comparison with prior literature. The association between neighborhood material disadvantage and lower social interaction is consistent with a broader literature linking neighborhood socioeconomic conditions to social engagement and loneliness in older adults [11], [69], [70]. The present study extends this literature by demonstrating the same socio-spatial-to-social-interaction signal under cross-person cross-validation and by showing that the signal is carried by a composite material-deprivation index following the Ontario Marginalization Index convention [62].

The differentiation of home-based and activity-space exposures is rarely reported in the post-discharge recovery literature, where the residential location is typically used as the sole place-based proxy. Cornwell and Cagney [19] showed that older adults' GPS-derived activity space carries information about social engagement that the residence does not, and Chaix [71] outlined the methodological case for mobile sensing in environmental health research. The present results extend these observations to clinical recovery outcomes: dwell-weighted exposure to libraries, food establishments, and places of

worship was associated with better OHS and OKS scores when measured at the activity space but not at the home.

The GPS-derived mobility findings add nuance to prior measurement research in this area. Existing studies have used questionnaire-based life-space scores [43] and the time spent away from home [47], [48] generally reporting positive associations with social well-being. Among the four GPS-derived mobility patterns, those that index the diversity and evenness of movement (number of unique locations, location entropy, and number of stay-to-stay transitions) were associated with higher self-reported social interaction, while the metric that captured only the amount of time outside the home was not. This pattern operationalizes quantitatively the observation by Douma and colleagues [42] that life-space size matters less than the meaningfulness of the destinations within it.

The predictive-modeling contribution of socio-spatial features extends a prior sensor-only modeling effort in this population. The earlier work on the same population [64] reported baseline predictive performance for the same recovery outcomes using only daily wearable and in-home sensor features, and the cross-person scheme produced substantially larger errors than the within-cohort k-fold scheme. The present study reproduces that pattern and shows that adding neighborhood socio-spatial features further reduces cross-person error for the social and several physical outcomes beyond the sensor-only baseline. The convergence is consistent with broader work showing that local environmental conditions add measurable value when combined with individual-level sensor data [72], [73].

Implications. These pilot findings support further investigation of socio-spatial influences on post-discharge recovery in larger, more diverse samples and with longitudinal designs capable of clarifying directionality. For remote-monitoring research, several of the strongest amenity–recovery associations were apparent only when exposures were measured across participants’ activity spaces rather than around their residences. Systems based solely on residential address may therefore miss relevant features of the environments with which individuals actually engage, whereas incorporating GPS-derived activity spaces may provide a more contextually informative interpretation of sensor data. From a community-planning and population-health perspective, the associations between material disadvantage and post-discharge social interaction further suggest that recovery is shaped by environmental conditions rather than being a purely individual process. Clinical implications remain preliminary and require replication before implications to practice can be stated.

Strengths and limitations. This study has several strengths. First, it integrates continuous multimodal sensor monitoring, GPS-derived activity-space measures, neighborhood-level socio-spatial data, and validated clinical assessments within a single cohort. This integrated analytical design allowed recovery in the community to be examined across behavioral, spatial, environmental, and clinical dimensions. Second, the use of longitudinal multimodal sensor data provided a dense, day-to-day account of recovery outside the clinical setting. Third, the study used a common analytical framework to compare home-neighborhood and activity-space exposures directly. Lastly, the study provides insights using intensive, multi-week monitoring of a understudied period of recovery for community-dwelling older adults.

Several limitations should be acknowledged. The cohort size was small and included a limited range of fracture types, restricting subgroup analysis. Although the sample size was modest, it reflects the practical challenges of recruiting and sustaining longitudinal monitoring in this post-discharge population. Participants were recruited from a single urban setting, the Greater Toronto Area, and were predominantly female and predominantly white, with a high proportion living alone. These characteristics limit the generalizability of the findings to other socioeconomic, ethnic, geographic, and household configurations. The eight-week monitoring window captures the immediate post-discharge phase and may not reflect medium- or long-term recovery trajectories. The observational design restricts causal inference; the reported associations describe patterns of co-occurrence between neighborhood exposures and recovery outcomes, not the mechanisms through which neighborhood context may influence recovery.

Measurement-related limitations warrant additional caution. Sensor streams from the smartwatch had non-trivial missingness consistent with off-wrist time rather than per-modality failure and were handled by within-participant imputation; residual measurement error cannot be ruled out. The activity-space exposures depend on smartwatch GPS that was geofenced to conserve battery, so days spent entirely at home contribute no activity-space information. Neighborhood-level variables were derived from publicly available datasets that may contain coding or temporal inaccuracies. The summer-versus-rest contrast rests on a small subset of participant-visits and should be read as exploratory. The counter-intuitive association between higher neighborhood income and worse OHS and OKS scores may reflect confounding by higher-income neighborhoods, lower walkability, and the cohort's age distribution, which cannot be disentangled at this sample size. Lastly, the study does not directly establish whether limited movement was chosen or constrained. The findings therefore illustrate how contextual conditions and realized functionings co-vary.

5. Conclusions

In this eight-week pilot of community-dwelling older adults following lower-limb fracture surgery or hip replacement, material disadvantage across residential and activity-space contexts was associated with lower social interaction, while several amenity exposures were associated with better OHS and OKS only when measured across participants' realized activity spaces. Location diversity and stay-to-stay transitions, rather than time away from home alone, were also associated with social interaction. Exploratory predictive models further indicated that socio-spatial features added information beyond sensor-only measures. Our findings position post-discharge recovery as a situated process emerging through the interaction of changing bodily capacity and the environments that become accessible during recovery. Larger longitudinal studies are required before clinical application, but integrating residential and activity-space context may ultimately improve the interpretation of remote-monitoring data and reduce the risk of attributing environmentally constrained mobility solely to individual decline.

Abbreviations

AI: Artificial intelligence

API: Application programming interface

CI: Confidence interval

GPS: Global Positioning System

MAE: Mean absolute error

OHS: Oxford Hip Score

OKS: Oxford Knee Score

SD: Standard deviation

SIS: Social Isolation Scale

TUG: Timed Up and Go

Declarations

Ethics approval and consent to participate

The study was conducted in accordance with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans, the ICH Guideline for Good Clinical Practice E6, and applicable institutional ethics requirements. It was approved by the Research Ethics Board of the University Health Network (ID 20-5113), and all participants provided written informed consent prior to enrollment.

Consent for publication

Not applicable.

Availability of data and materials

The dataset used in this study is publicly available at <https://doi.org/10.5281/zenodo.18307745>.

Competing interests

The authors declare that they have no competing interests.

Funding

This work was supported by funding awarded to C.H.C. and S.S.K. from the Centre for Aging + Brain Health Innovation (CABHI), as well as Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grants awarded to C.H.C. and S.S.K.

Authors' contributions

C.H.C. and A.A. designed the study. A.A. developed the MAISON platform, managed data collection, created and curated the dataset, and made the dataset publicly available. A.A. conducted the statistical analysis and machine-learning modeling, with review and input from C.H.C. and S.S.K. P.J. and D.M. contributed to the socio-spatial framing and supported interpretation of the results, with input from A.A. A.A. drafted the manuscript with contributions from P.J. and D.M. All authors reviewed and approved the final manuscript.

Acknowledgements

The authors acknowledge Dherya Jain and Zara Hasan for their support throughout the data collection process, including sensor installation and removal, and periodic clinical assessments.

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Tables

Table 1. Baseline characteristics of the study cohort.

Characteristic	Value
N participants	18
N biweekly assessments	72
Monitoring per participant, weeks	8
Total person-days of sensor data	1,008
Age, years, mean (SD) [range]	76.5 (8.9) [60-94]
Female sex, n (%)	14 (78)
Lived alone, n (%)	14 (78)
White, n (%)	15 (83)
<i>Fracture/index procedure, n (%)</i>	
Hip replacement	8 (44)
Hip fracture	4 (22)
Pelvis fracture	3 (17)
Femur fracture	3 (17)
<i>Baseline outcomes (first biweekly visit), mean (SD)</i>	
Social Isolation Scale (SIS) total	23.7 (4.0)
Oxford Hip Score (OHS) total	29.3 (8.1)
Oxford Knee Score (OKS) total	30.7 (10.3)
Timed Up and Go (TUG), seconds	21.8 (14.5)
30-second chair-stand, repetitions	8.1 (3.2)
<i>Across all biweekly visits, mean (SD) [range]</i>	
Social Isolation Scale (SIS) total	23.8 (3.9) [15-30]
Oxford Hip Score (OHS) total	28.4 (7.9) [17-47]
Oxford Knee Score (OKS) total	30.3 (9.7) [15-48]
Timed Up and Go (TUG), seconds	19.6 (12.6) [7-59]
30-second chair-stand, repetitions	9.8 (3.4) [1-17]

Table 2. Participants' home-neighborhood exposure characteristics.

Characteristic	Mean (SD)	Range [min, max]	Median
<i>Social amenities</i>			
Libraries (count)	9.06 (5.06)	[2.00, 17.00]	8.00
Parks (count)	11.56 (3.90)	[7.00, 19.00]	10.00
Food establishments (count)	8.50 (5.70)	[1.00, 20.00]	8.00
Places of worship (count)	8.67 (5.71)	[2.00, 19.00]	7.00
Amenity index (z)	0.15 (0.73)	[-0.99, 1.92]	0.01
<i>Crime</i>			
Assault rate	992.90 (684.13)	[316.62, 2,617]	791.54
Auto-theft rate	278.81 (220.86)	[45.16, 870.61]	216.01
Break-and-enter rate	224.92 (92.30)	[109.88, 402.74]	206.14
Homicide rate	2.87 (5.45)	[0.00, 15.90]	0.00
Robbery rate	131.08 (127.47)	[12.92, 443.19]	89.00
Shooting rate	9.41 (10.69)	[0.00, 34.08]	7.55
Theft-over rate	74.71 (53.31)	[17.28, 196.80]	53.08
Crime index (z)	-0.20 (0.61)	[-0.80, 0.97]	-0.39
<i>Census / socioeconomic</i>			
Avg household income, 2020 (\$)	116,307 (59,289)	[50,068, 315,522]	107,112
Avg after-tax income, 2020 (\$)	54,957 (18,975)	[26,161, 107,387]	46,385
Median full-time employment income (\$)	77,312 (15,776)	[41,853, 122,022]	75,435
Income from govt transfers (%)	14.27 (10.84)	[3.00, 51.00]	10.50
Employment rate (%)	57.80 (10.44)	[34.00, 83.00]	57.00
Unemployment rate (%)	12.46 (5.26)	[5.00, 23.00]	11.50
One-person households (%)	44.73 (15.00)	[18.68, 67.85]	49.97
Avg income, one-person households (\$)	66,586 (24,982)	[21,800, 108,887]	60,817
Immigrants (%)	42.17 (9.89)	[14.17, 61.60]	42.68
Recent immigrants (%)	8.16 (5.02)	[0.00, 20.88]	8.16
Visible minority (%)	44.56 (22.72)	[10.23, 84.71]	42.48
Renter households (%)	54.93 (25.07)	[13.79, 99.81]	54.41

Spending 30%+ on shelter (%)	37.35 (14.04)	[14.03, 64.19]	39.60
Moved in past year (%)	19.12 (13.29)	[3.43, 52.39]	12.98
Avg rooms per dwelling	3.70 (1.35)	[2.00, 6.00]	3.00
Bachelor degree or higher (%)	55.15 (17.22)	[27.08, 76.72]	61.85
Material-deprivation index (z)	0.25 (1.47)	[-2.02, 4.49]	0.21

Table 3. Home and activity-space associations between neighborhood socio-spatial exposures and three recovery outcomes: (a) Social Isolation Scale (SIS); (b) Oxford Hip Score (OHS); (c) Oxford Knee Score (OKS). Adjusted linear generalized estimating equation (GEE) coefficients of β per +1 standard deviation (SD) of the standardized exposure, with 95% confidence intervals (CI), p-values, and Benjamini-Hochberg false-discovery-rate q-values. Estimates with $p < .05$ are shown in bold.

(a)

Exposure	Home, adj beta [95% CI] (p; q)	Activity-space, adj beta [95% CI] (p; q)
<i>Social amenities</i>		
Libraries	+0.41 [-1.00, +1.82] (p=0.570; q=0.632)	-0.24 [-1.49, +1.01] (p=0.706; q=0.706)
Parks	-0.64 [-2.74, +1.45] (p=0.547; q=0.632)	-1.28 [-3.29, +0.74] (p=0.213; q=0.427)
Food establishments	-1.46 [-2.93, -0.00] (p=0.050; q=0.300)	-0.49 [-2.33, +1.35] (p=0.605; q=0.706)
Places of worship	-1.27 [-2.88, +0.34] (p=0.122; q=0.365)	+0.28 [-0.71, +1.28] (p=0.574; q=0.706)
<i>Crime</i>		
Assault	+0.37 [-0.42, +1.17] (p=0.358; q=0.827)	+0.24 [-0.76, +1.23] (p=0.641; q=0.996)
Auto theft	-1.05 [-2.02, -0.09] (p=0.032; q=0.325)	-0.05 [-1.99, +1.88] (p=0.956; q=0.996)
Break and enter	-0.34 [-1.59, +0.92] (p=0.601; q=0.827)	-0.00 [-1.92, +1.91] (p=0.996; q=0.996)
Homicide	-0.53 [-2.88, +1.83] (p=0.662; q=0.827)	-0.70 [-3.13, +1.72] (p=0.570; q=0.996)
Robbery	+0.05 [-0.91, +1.00] (p=0.921; q=0.921)	-0.08 [-1.09, +0.94] (p=0.881; q=0.996)
Shooting	-1.16 [-3.21, +0.89] (p=0.268; q=0.827)	-1.55 [-3.81, +0.71] (p=0.178; q=0.996)
Theft over	-0.16 [-1.39, +1.07] (p=0.800; q=0.889)	-0.10 [-1.82, +1.62] (p=0.912; q=0.996)
<i>Census / socioeconomic</i>		
Avg household income	+0.50 [-1.26, +2.27] (p=0.575; q=0.752)	+1.12 [-0.98, +3.23] (p=0.296; q=0.335)
Avg after-tax income	+1.10 [-1.06, +3.27] (p=0.316; q=0.511)	+1.46 [-0.58, +3.50] (p=0.161; q=0.249)
Median full-time employment income	+1.20 [-1.22, +3.61] (p=0.331; q=0.511)	+1.54 [-0.88, +3.96] (p=0.213; q=0.284)
Share of income from government transfers (%)	-2.30 [-3.41, -1.20] (p=0.000; q=0.001)	-2.73 [-3.63, -1.84] (p=0.000; q=0.000)
Employment rate	+1.16 [-0.62, +2.94] (p=0.201; q=0.427)	+1.55 [-0.38, +3.48] (p=0.114; q=0.194)

Unemployment rate	-1.68 [-3.13, -0.22] (p=0.024; q=0.131)	-2.15 [-3.78, -0.52] (p=0.010; q=0.041)
One-person households (%)	+0.13 [-1.30, +1.56] (p=0.857; q=0.910)	+0.91 [-0.54, +2.35] (p=0.217; q=0.284)
Avg income, one-person households	+1.59 [+0.15, +3.03] (p=0.031; q=0.131)	+1.92 [+0.60, +3.23] (p=0.004; q=0.024)
% immigrant	+0.06 [-1.32, +1.43] (p=0.937; q=0.937)	-1.72 [-3.78, +0.33] (p=0.100; q=0.190)
% recent immigrant	-0.94 [-2.61, +0.73] (p=0.269; q=0.508)	-1.51 [-3.06, +0.04] (p=0.056; q=0.136)
% visible minority	-1.39 [-3.23, +0.46] (p=0.142; q=0.344)	-2.23 [-3.98, -0.49] (p=0.012; q=0.041)
% renter	-1.47 [-3.18, +0.25] (p=0.094; q=0.266)	-1.70 [-3.30, -0.10] (p=0.038; q=0.107)
% spending 30%+ on shelter	+0.61 [-0.87, +2.09] (p=0.421; q=0.596)	+0.66 [-0.54, +1.85] (p=0.284; q=0.335)
% moved in past year	+0.31 [-1.15, +1.77] (p=0.678; q=0.768)	+0.29 [-1.25, +1.82] (p=0.715; q=0.715)
Avg rooms per dwelling	+0.39 [-1.17, +1.96] (p=0.622; q=0.755)	+0.46 [-1.07, +2.00] (p=0.553; q=0.588)
% Aged 15+ with bachelor's degree or higher	+1.43 [-0.20, +3.06] (p=0.085; q=0.266)	+1.69 [-0.13, +3.50] (p=0.069; q=0.146)
Overall composite indices (each domain summarized; single-index models)		
Amenity index	-1.32 [-3.10, +0.46] (p=0.147; q=0.220)	-1.18 [-3.11, +0.74] (p=0.229; q=0.344)
Crime index	-0.44 [-1.82, +0.94] (p=0.534; q=0.534)	-0.35 [-1.86, +1.16] (p=0.649; q=0.649)
Material-deprivation index	-2.14 [-3.58, -0.71] (p=0.003; q=0.010)	-2.38 [-3.96, -0.79] (p=0.003; q=0.010)
All domains combined: amenity + crime + census indices, mutually adjusted		
Amenity index	-0.33 [-1.70, +1.04] (p=0.637; q=0.803)	+0.07 [-1.48, +1.61] (p=0.932; q=0.932)
Crime index	-0.15 [-1.28, +0.99] (p=0.803; q=0.803)	+0.54 [-0.81, +1.89] (p=0.435; q=0.652)
Material-deprivation index	-1.98 [-3.29, -0.67] (p=0.003; q=0.009)	-2.61 [-3.87, -1.36] (p=0.000; q=0.000)

(b)

Exposure	Home, adj beta [95% CI] (p; q)	Activity-space, adj beta [95% CI] (p; q)
<i>Social amenities</i>		
Libraries	+0.76 [-3.06, +4.57] (p=0.698; q=0.869)	+2.87 [+0.62, +5.12] (p=0.012; q=0.037)
Parks	+2.20 [-1.42, +5.82] (p=0.233; q=0.869)	+0.00 [-2.46, +2.46] (p=0.999; q=0.999)
Food establishments	+0.62 [-2.80, +4.04] (p=0.724; q=0.869)	+3.69 [+1.31, +6.06] (p=0.002; q=0.014)
Places of worship	+0.02 [-2.74, +2.78] (p=0.991; q=0.991)	+2.80 [-0.02, +5.62] (p=0.052; q=0.103)
<i>Crime</i>		
Assault	-0.97 [-2.96, +1.02] (p=0.341; q=0.379)	-0.90 [-4.69, +2.90] (p=0.644; q=0.747)
Auto theft	-2.34 [-4.76, +0.08] (p=0.058; q=0.115)	-0.21 [-3.84, +3.41] (p=0.908; q=0.908)
Break and enter	-3.58 [-6.87, -0.29] (p=0.033; q=0.106)	-1.87 [-6.42, +2.69] (p=0.422; q=0.704)
Homicide	-1.61 [-3.54, +0.32] (p=0.103; q=0.147)	-1.33 [-3.70, +1.03] (p=0.269; q=0.704)
Robbery	-1.10 [-3.07, +0.86] (p=0.272; q=0.339)	-0.77 [-4.34, +2.80] (p=0.673; q=0.747)
Shooting	-3.55 [-6.16, -0.94] (p=0.008; q=0.076)	-2.61 [-6.10, +0.88] (p=0.143; q=0.704)
Theft over	-2.73 [-5.33, -0.14] (p=0.039; q=0.106)	-2.31 [-6.51, +1.90] (p=0.283; q=0.704)
<i>Census / socioeconomic</i>		
Avg household income	-2.83 [-4.77, -0.89] (p=0.004; q=0.071)	-3.60 [-5.81, -1.40] (p=0.001; q=0.023)
Avg after-tax income	-2.79 [-5.21, -0.36] (p=0.024; q=0.207)	-3.55 [-6.28, -0.83] (p=0.011; q=0.091)
Median full-time employment income	-2.62 [-5.43, +0.19] (p=0.068; q=0.385)	-3.52 [-6.50, -0.53] (p=0.021; q=0.118)
Share of income from government transfers (%)	+1.63 [-1.39, +4.65] (p=0.291; q=0.825)	+1.74 [-1.10, +4.59] (p=0.230; q=0.322)
Employment rate	+1.03 [-1.80, +3.85] (p=0.476; q=0.969)	-1.50 [-4.15, +1.14] (p=0.265; q=0.322)

Unemployment rate	-1.77 [-5.01, +1.47] (p=0.285; q=0.825)	+1.93 [-0.99, +4.85] (p=0.196; q=0.322)
One-person households (%)	+0.25 [-2.90, +3.39] (p=0.878; q=0.969)	+1.11 [-2.48, +4.70] (p=0.545; q=0.580)
Avg income, one-person households	-0.50 [-2.91, +1.90] (p=0.681; q=0.969)	-2.45 [-4.82, -0.09] (p=0.042; q=0.179)
% immigrant	+0.38 [-3.29, +4.04] (p=0.841; q=0.969)	+1.96 [-0.68, +4.59] (p=0.145; q=0.309)
% recent immigrant	-0.59 [-3.68, +2.50] (p=0.710; q=0.969)	+1.53 [-1.55, +4.61] (p=0.329; q=0.373)
% visible minority	+1.33 [-1.85, +4.52] (p=0.411; q=0.969)	+2.04 [-1.14, +5.21] (p=0.208; q=0.322)
% renter	-0.17 [-3.18, +2.84] (p=0.912; q=0.969)	+2.25 [-0.19, +4.69] (p=0.071; q=0.201)
% spending 30%+ on shelter	+0.31 [-3.93, +4.54] (p=0.888; q=0.969)	+2.38 [-0.10, +4.85] (p=0.060; q=0.201)
% moved in past year	-0.71 [-4.87, +3.45] (p=0.737; q=0.969)	+0.63 [-2.55, +3.82] (p=0.697; q=0.697)
Avg rooms per dwelling	+0.02 [-3.42, +3.47] (p=0.989; q=0.989)	-1.63 [-4.47, +1.20] (p=0.259; q=0.322)
% Aged 15+ with bachelor's degree or higher	-2.34 [-5.84, +1.15] (p=0.189; q=0.804)	-2.22 [-5.86, +1.43] (p=0.233; q=0.322)
Overall composite indices (each domain summarized; single-index models)		
Amenity index	+0.95 [-2.18, +4.09] (p=0.551; q=0.648)	+2.23 [-0.20, +4.65] (p=0.072; q=0.181)
Crime index	-2.93 [-5.76, -0.10] (p=0.042; q=0.127)	-2.05 [-6.59, +2.49] (p=0.377; q=0.377)
Material-deprivation index	+0.76 [-2.52, +4.05] (p=0.648; q=0.648)	+2.66 [-0.70, +6.02] (p=0.121; q=0.181)
All domains combined: amenity + crime + census indices, mutually adjusted		
Amenity index	+1.43 [-1.89, +4.76] (p=0.398; q=0.598)	+1.30 [-1.35, +3.95] (p=0.337; q=0.337)
Crime index	-3.26 [-6.14, -0.38] (p=0.026; q=0.079)	-3.46 [-7.22, +0.30] (p=0.071; q=0.141)
Material-deprivation index	+0.57 [-3.26, +4.39] (p=0.772; q=0.772)	+3.30 [-0.56, +7.16] (p=0.094; q=0.141)

(c)

Exposure	Home, adj beta [95% CI] (p; q)	Activity-space, adj beta [95% CI] (p; q)
<i>Social amenities</i>		
Libraries	+2.02 [-2.38, +6.42] (p=0.368; q=0.731)	+2.26 [-0.78, +5.30] (p=0.144; q=0.217)
Parks	-1.35 [-5.18, +2.47] (p=0.488; q=0.731)	-1.97 [-5.03, +1.09] (p=0.207; q=0.248)
Food establishments	+1.60 [-2.18, +5.38] (p=0.407; q=0.731)	+3.36 [+0.44, +6.27] (p=0.024; q=0.060)
Places of worship	+2.03 [-1.82, +5.88] (p=0.301; q=0.731)	+3.51 [+0.34, +6.67] (p=0.030; q=0.060)
<i>Crime</i>		
Assault	-1.16 [-4.25, +1.92] (p=0.460; q=0.575)	+0.09 [-4.66, +4.84] (p=0.970; q=0.983)
Auto theft	-1.04 [-4.68, +2.60] (p=0.575; q=0.575)	-0.47 [-4.52, +3.57] (p=0.819; q=0.983)
Break and enter	-1.40 [-5.76, +2.96] (p=0.528; q=0.575)	-0.26 [-4.78, +4.26] (p=0.910; q=0.983)
Homicide	-3.44 [-5.49, -1.39] (p=0.001; q=0.010)	-2.98 [-5.19, -0.77] (p=0.008; q=0.083)
Robbery	-1.08 [-4.11, +1.94] (p=0.483; q=0.575)	-0.21 [-4.84, +4.42] (p=0.929; q=0.983)
Shooting	-1.39 [-5.51, +2.72] (p=0.507; q=0.575)	-2.83 [-6.11, +0.45] (p=0.090; q=0.451)
Theft over	-2.12 [-5.29, +1.04] (p=0.189; q=0.395)	+0.05 [-4.58, +4.68] (p=0.983; q=0.983)
<i>Census / socioeconomic</i>		
Avg household income	-3.85 [-6.01, -1.69] (p=0.000; q=0.004)	-3.40 [-5.62, -1.18] (p=0.003; q=0.046)
Avg after-tax income	-3.52 [-6.23, -0.81] (p=0.011; q=0.061)	-3.38 [-6.01, -0.74] (p=0.012; q=0.102)
Median full-time employment income	-3.66 [-7.19, -0.13] (p=0.042; q=0.144)	-2.87 [-6.26, +0.51] (p=0.096; q=0.234)
Share of income from government transfers (%)	-0.81 [-4.02, +2.41] (p=0.623; q=0.963)	-0.39 [-3.72, +2.94] (p=0.819; q=0.938)
Employment rate	+0.09 [-3.60, +3.77] (p=0.964; q=0.979)	+2.51 [-0.31, +5.32] (p=0.081; q=0.229)

Unemployment rate	+0.31 [-3.34, +3.95] (p=0.869; q=0.979)	-0.38 [-3.92, +3.15] (p=0.831; q=0.938)
One-person households (%)	+2.16 [-1.03, +5.36] (p=0.184; q=0.446)	+1.73 [-2.05, +5.52] (p=0.368; q=0.652)
Avg income, one-person households	-2.81 [-6.24, +0.62] (p=0.108; q=0.307)	-2.22 [-4.61, +0.16] (p=0.068; q=0.229)
% immigrant	+2.13 [-1.70, +5.95] (p=0.275; q=0.520)	+1.21 [-3.13, +5.55] (p=0.586; q=0.783)
% recent immigrant	+1.12 [-2.76, +5.00] (p=0.571; q=0.963)	+2.67 [-1.61, +6.94] (p=0.222; q=0.471)
% visible minority	+0.79 [-3.58, +5.16] (p=0.723; q=0.979)	+1.81 [-2.66, +6.28] (p=0.428; q=0.661)
% renter	+0.06 [-3.86, +3.98] (p=0.976; q=0.979)	+0.14 [-3.40, +3.69] (p=0.938; q=0.938)
% spending 30%+ on shelter	+4.56 [+2.23, +6.89] (p=0.000; q=0.002)	+2.79 [+0.07, +5.52] (p=0.045; q=0.190)
% moved in past year	+3.46 [+0.37, +6.55] (p=0.028; q=0.119)	+3.65 [+0.33, +6.97] (p=0.031; q=0.176)
Avg rooms per dwelling	-2.03 [-5.51, +1.46] (p=0.255; q=0.520)	-1.57 [-5.10, +1.96] (p=0.384; q=0.652)
% Aged 15+ with bachelor's degree or higher	-0.06 [-4.28, +4.16] (p=0.979; q=0.979)	-1.06 [-5.02, +2.90] (p=0.599; q=0.783)
Overall composite indices (each domain summarized; single-index models)		
Amenity index	+1.44 [-2.73, +5.61] (p=0.498; q=0.747)	+0.68 [-3.37, +4.74] (p=0.742; q=0.888)
Crime index	-2.58 [-6.32, +1.17] (p=0.177; q=0.531)	-1.26 [-6.00, +3.48] (p=0.602; q=0.888)
Material-deprivation index	+0.37 [-3.34, +4.07] (p=0.846; q=0.846)	+0.29 [-3.76, +4.35] (p=0.888; q=0.888)
All domains combined: amenity + crime + census indices, mutually adjusted		
Amenity index	+2.24 [-1.76, +6.24] (p=0.272; q=0.408)	+0.80 [-2.98, +4.58] (p=0.679; q=0.830)
Crime index	-2.96 [-6.16, +0.23] (p=0.069; q=0.206)	-1.60 [-6.16, +2.97] (p=0.493; q=0.830)
Material-deprivation index	-0.24 [-3.56, +3.08] (p=0.889; q=0.889)	+0.48 [-3.95, +4.92] (p=0.830; q=0.830)

Table 4. Associations between GPS-derived mobility measures and recovery outcomes (Social Isolation Scale, SIS; Oxford Hip Score, OHS; Oxford Knee Score, OKS). Unadjusted and adjusted (age and household composition) linear generalized estimating equation coefficients of β per +1 standard deviation (SD), with 95% confidence intervals (CI), p-values, and Benjamini-Hochberg false-discovery-rate q-values. Estimates with $p < .05$ are shown in bold.

GPS-derived mobility measures	Outcome	Unadjusted β (p)	Adjusted β [95% CI] (p; q)
GPS-derived mobility index (composite)	SIS	+0.84 (p=0.321)	+1.47 [+0.05, +2.89] (p=0.042; q=0.063)
	OHS	+1.68 (p=0.237)	+1.51 [-0.95, +3.97] (p=0.228; q=0.386)
	OKS	+1.13 (p=0.557)	+0.79 [-2.30, +3.89] (p=0.616; q=0.616)
Unique locations / day	SIS	+1.08 (p=0.138)	+1.36 [-0.00, +2.71] (p=0.050; q=0.063)
	OHS	+1.35 (p=0.339)	+1.23 [-1.14, +3.60] (p=0.309; q=0.386)
	OKS	+1.05 (p=0.592)	+0.95 [-1.99, +3.89] (p=0.528; q=0.616)
Location entropy	SIS	+1.02 (p=0.194)	+1.56 [+0.19, +2.93] (p=0.026; q=0.063)
	OHS	+1.80 (p=0.226)	+1.45 [-1.16, +4.06] (p=0.277; q=0.386)
	OKS	+2.10 (p=0.325)	+1.56 [-1.68, +4.81] (p=0.345; q=0.616)
Fraction of time away from home	SIS	-1.05 (p=0.071)	-0.83 [-2.53, +0.87] (p=0.337; q=0.337)
	OHS	+0.73 (p=0.465)	-0.06 [-2.09, +1.97] (p=0.953; q=0.953)
	OKS	-0.12 (p=0.924)	-1.71 [-4.59, +1.17] (p=0.245; q=0.616)
Location transitions / day	SIS	+1.81 (p=0.015)	+2.15 [+0.78, +3.53] (p=0.002; q=0.011)
	OHS	+1.80 (p=0.202)	+1.98 [-0.78, +4.73] (p=0.159; q=0.386)
	OKS	+0.80 (p=0.716)	+1.13 [-2.65, +4.91] (p=0.558; q=0.616)

Table 5. Predictive performance of CatBoost and TabPFN across four feature-set combinations under two cross-validation schemes: (a) random-shuffled 5-fold and (b) cross-person 5-fold. Mean absolute error (MAE) is reported as mean $\pm$ standard deviation across folds, in the original units of each recovery outcome. The four feature sets are: sensor only; socio-spatial only (amenities, crime, and census socioeconomic indicators); sensor + socio-spatial combined; and the top 48 features of the combined pool selected through recursive feature elimination inside each training fold.

(a)

Outcome	Model	sensor only	socio-spatial only	sensor + socio-spatial	top-48 of sensor + socio-spatial
Social Isolation Scale (SIS)	CatBoost	1.47 $\pm$ 0.06	1.38 $\pm$ 0.11	1.09 $\pm$ 0.09	1.06 $\pm$ 0.10
	TabPFN	0.79 $\pm$ 0.11	1.39 $\pm$ 0.10	0.78 $\pm$ 0.09	0.78 $\pm$ 0.09
Oxford Hip Score (OHS)	CatBoost	2.99 $\pm$ 0.25	2.20 $\pm$ 0.12	1.66 $\pm$ 0.10	1.63 $\pm$ 0.09
	TabPFN	1.13 $\pm$ 0.09	2.22 $\pm$ 0.12	1.16 $\pm$ 0.05	1.14 $\pm$ 0.04
Oxford Knee Score (OKS)	CatBoost	3.33 $\pm$ 0.14	2.73 $\pm$ 0.11	1.94 $\pm$ 0.11	1.95 $\pm$ 0.07
	TabPFN	1.38 $\pm$ 0.12	2.74 $\pm$ 0.11	1.38 $\pm$ 0.07	1.38 $\pm$ 0.08
Timed Up and Go (TUG)	CatBoost	3.26 $\pm$ 0.17	2.04 $\pm$ 0.19	1.74 $\pm$ 0.11	1.71 $\pm$ 0.13
	TabPFN	1.44 $\pm$ 0.12	2.05 $\pm$ 0.20	1.07 $\pm$ 0.08	1.11 $\pm$ 0.12
30-second chair-stand	CatBoost	1.21 $\pm$ 0.07	1.35 $\pm$ 0.08	0.83 $\pm$ 0.07	0.80 $\pm$ 0.06
	TabPFN	0.51 $\pm$ 0.09	1.35 $\pm$ 0.08	0.48 $\pm$ 0.07	0.46 $\pm$ 0.05

(b)

Outcome	Model	sensor only	socio-spatial only	sensor + socio-spatial	top-48 of sensor + socio-spatial
Social Isolation Scale (SIS)	CatBoost	3.28 ± 1.11	3.36 ± 1.04	3.53 ± 1.05	3.35 ± 1.27
	TabPFN	3.80 ± 0.92	2.99 ± 1.08	3.05 ± 1.10	3.08 ± 1.15
Oxford Hip Score (OHS)	CatBoost	7.93 ± 2.84	6.93 ± 2.89	7.54 ± 3.08	7.72 ± 3.19
	TabPFN	8.99 ± 2.43	7.25 ± 2.92	7.43 ± 3.01	7.53 ± 2.85
Oxford Knee Score (OKS)	CatBoost	8.17 ± 2.40	9.20 ± 2.18	9.10 ± 2.68	8.63 ± 2.15
	TabPFN	9.01 ± 3.67	9.66 ± 1.88	9.70 ± 1.86	9.75 ± 2.21
Timed Up and Go (TUG)	CatBoost	8.51 ± 1.92	11.06 ± 3.85	11.08 ± 4.29	10.79 ± 3.83
	TabPFN	10.75 ± 3.53	9.14 ± 1.85	7.27 ± 1.63	7.62 ± 1.53
30-second chair-stand	CatBoost	2.97 ± 0.67	2.98 ± 0.61	3.00 ± 0.83	2.79 ± 0.99
	TabPFN	3.44 ± 0.68	2.72 ± 1.01	2.63 ± 0.97	2.58 ± 0.91

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