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# Beyond Shelter: Housing Instability, Health-Related Quality of Life, and Mental Health as Public Policy Priorities

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# Abstract

Housing instability has emerged as a significant social determinant of health. While prior research links distinct forms of instability, such as homelessness and foreclosure, to adverse health outcomes, few studies examine how multiple forms of housing instability, in the form of affordability, stable occupancy, and safety and decency, simultaneously affect mental well-being. We explore how multidimensional housing instability and health-related quality of life (HQoL) jointly relate to perceived stress, depression, and anxiety. Using a representative survey (N = 850) of Fort Bend County residents and Machine Learning Gradient Boosting Regression, we find that the contributions of housing instability, HQoL, their interaction, and socio-demographic covariates, with tuned hyperparameters and hold-out validation, achieved high out-of-sample fit ($R^2 \approx 0.88–0.93$). Perceived quality of life and HQoL were the strongest predictors across outcomes, while housing instability showed a mainly conditional association: the interaction between higher housing instability and worse HQoL substantially increased predicted stress, anxiety, and depression, with the largest effects for perceived stress.  Education and income were modestly protective, and basic demographics added little once living conditions and quality of life were included. We find that these patterns vary spatially, with stronger correlations between health and place in certain geographic areas compared to others within our area of analysis, underscoring that structural housing conditions and health-related quality of life are central to understanding psychological distress and support integrating “housing vital signs” and stability-first housing interventions into population health and clinical practice.


# 1. Introduction

In recent times, macroeconomic shifts, financial crises, and shrinking social assistance programs have exacerbated housing instability—generally understood as the loss of secure, stable housing—in the U.S. (1–3). Amid increasing housing instability, scholars have turned to investigating its consequences on health. Although previous research has linked specific types of housing instability, such as foreclosures (4) and homelessness (5), to poorer health outcomes (6) only a few studies have examined the simultaneous impact of multiple forms of housing instability on health (5, 7–17).

We extend the current literature by employing a comprehensive measure of housing instability (4). We offer a multidimensional measure that synthesizes the central mechanisms emphasized in the literature: affordability, stable occupancy, and safety. We believe each of these three mechanisms summarizes a distinct pathway through which housing instability shapes the daily experiences of individuals. Affordability, for example, means that housing costs can be sustained without compromising essential needs, highlighting the financial strain caused by instability. Stable occupancy protects households from involuntary displacement due to economic or other factors, which underscores the importance of continuity. Decent and safe housing encompasses the physical environment necessary to ensure health, security, and daily functioning (4). Our use of this multidimensional measure allows us to explore a more holistic definition of housing instability in relation to health, which would otherwise be obscured by a one-dimensional measure of instability (e.g., foreclosure or homelessness).

In addition to this multidimensional measure of housing instability, we also integrate health-related quality of life (HQoL) into the study to assess how these factors jointly influence mental health outcomes. HQoL is a standardized scale that measures health-related quality of life across five dimensions: mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. In essence, HQoL captures the extent to which individuals manage daily life and work as a common denominator.

What is the impact of housing instability and HQoL on mental health? Using original survey data, this paper sheds light on this question by developing a comprehensive model that analyzes the multifaceted ways in which housing instability and HQoL influence perceived stress, depression, and anxiety. Methodologically, this paper takes advantage of recent advances in Machine Learning and implements Gradient Boosting Regression, which provides a more robust approach when the goal is predictive performance, as it can automatically capture complex relationships and interactions in the data without requiring prespecified functional forms.

Through our analysis, we find that housing instability interacts with HQoL and amplifies perceived stress, anxiety, and depression. The contribution of the interaction is stronger among perceived stress, followed by anxiety and depression, which suggests that symptoms of mental health respond to instability in different ways. Furthermore, we find that these patterns vary spatially, with stronger correlations between health and place in certain geographic areas compared to others within our area of analysis. For example, housing instability clusters with multiple mental health and health related quality of life burdens in the southwestern area of Fort Bend County, our area of focus, which may require specific, place-based housing interventions. The results also demonstrate geographically uneven risk patterns not aligned with our expectations, such as areas where mental health burdens are elevated despite lower housing instability. This pattern may point to other important stressors that residents may experience, such as long commutes or stressful jobs. These findings have important implications for health and place research and policy, suggesting that effective interventions must be geographically targeted, especially when resources may be limited.

## 2. Mental Health

# 2.1. Housing

Researchers examining community health outcomes have increasingly focused on the influence of social determinants of health, referring to the non-medical, biological factors that influence health outcomes (18–22). These non-medical factors tend to include the conditions in which people are born, where they live, and where they work. Some common determinants include socioeconomic status, education, access to healthcare, as well as structural and systemic factors, such as housing policies and economic inequality (3, 19). Housing is a fundamental non-medical determinant of health as it shapes the environments where individuals spend much of their lives, significantly influencing health outcomes (3). Beyond being a basic need for shelter, the stability, quality, and affordability of housing serve as the foundation for both individual and community health. Housing itself represents one of the most

consequential places in people's lives. It is a deeply personal and intimate environment where people spend a vast amount of their time. For some individuals, that place—or those housing conditions—can be either a source of stability or chronic stress that ultimately shapes health outcomes.

As prior work demonstrates, housing instability directly contributes to and exacerbates a wide range of health issues, can undermine community cohesion, and perpetuates significant health disparities (5, 23). Scholars have identified multiple ways in which housing instability manifests, but three dimensions are particularly salient for understanding its impact on health: lack of affordability, lack of safety and decency, and lack of stable occupancy (4). Together, these dimensions capture the financial pressures, inadequate housing conditions, and residential disruptions that create interrelated pathways shaping mental health and overall well-being within the home.

Housing instability can emerge through affordability or economic strain, where the financial burden of securing and maintaining housing creates significant mental health risks. Difficulty paying rent or mortgage, high housing costs, and the expenses associated with moving can deplete savings and increase debt, leading to heightened stress and anxiety (8, 24, 25). High housing costs often force tradeoffs with other essentials, such as nutritious food or medical care, which indirectly contribute to declining physical and mental health over time (12, 26). Moreover, in communities where budgetary limitations restrict government assistance, individuals face even greater challenges in obtaining and maintaining affordable housing (27).

Lack of stable occupancy is another disruptive form of housing instability. Frequent moves, eviction, foreclosure, doubling up, and homelessness generate disruptions that undermine mental health (10, 13, 16, 28, 29). The uncertainty and repeated disruption of moving can provoke or exacerbate anxiety, depression, and other mental health conditions (15, 30, 31). Unstable housing, through frequent moves, erodes social networks, undermining essential sources of emotional support and community ties (32–34). Feelings of loneliness and isolation are common outcomes, and these are strongly associated with depressive symptoms and anxiety disorders. Housing instability can further interrupt access to consistent medical care, as families are forced to switch healthcare providers, undermining both physical and mental health. Over time, the absence of stable occupancy perpetuates a cycle of disrupted relationships, economic precarity, and diminished quality of life, which collectively reinforce mental health disparities.

The quality and safety of housing represent another pathway through which housing instability contributes to adverse mental health outcomes. The stigma associated with living in unsafe or inadequate housing can also negatively affect self-esteem and self-worth (35). Individuals may experience shame, social withdrawal, or an inability to invite others into their homes, which limits opportunities for community support and increases the risk of long-term mental health issues. Perceived neighborhood hazards and inadequate home safety and decency can heighten vigilance and disrupt sleep, which directly contribute to anxiety, stress, and depressive symptoms and indirectly undermine

overall psychological well-being (36, 37). Over time, the lack of a decent and safe home environment can lead to chronic mental health issues.

Taken together, prior findings suggest a strong and consistent connection between housing instability and health. The three dimensions of housing instability—lack of affordability, lack of safety and decency, and lack of stable occupancy—operate through distinct pathways, but they also overlap and reinforce one another. Financial strain can limit access to adequate and safe housing. Similarly, unsafe housing conditions can intensify the stress of residential instability, and frequent moves or evictions often compound economic pressures and disrupt social ties. These overlapping mechanisms create a cycle in which poor housing conditions and instability heighten stress, depression, and anxiety, while also undermining physical health, social networks, and economic security. We build on this literature by examining how these interconnected forms of housing instability—which begins in the home—shape mental health outcomes in Fort Bend County. In particular, we examine perceived stress, depression, and anxiety, which are frequent measures used to understand mental health (38, 39).

## 2.1. Health-Related Quality of Life

Mental health risks worsen not only because of housing instability but also because of the way instability interacts with Health-Related Quality of Life (HQoL). HQoL refers to an individual's overall perception of their physical, mental, and social well-being as it relates to the impact of health conditions, symptoms, and treatments on their ability to function in daily life (40, 41). The three dimensions of housing instability—affordability, lack of stable occupancy, and unsafe or indecent conditions—interact with the physical dimensions of HQoL, such as pain, discomfort, mobility, and self-care. In turn, the deterioration of physical health feeds into and magnifies depression, anxiety, and stress (23, 42).

HQoL interacts with our three dimensions of housing instability, affecting mental health outcomes. For instance, those managing chronic conditions may face affordability pressures that force difficult trade-offs between paying for housing and covering health care costs (12, 26). These tradeoffs heighten the risk of treatment interruptions, medication non-adherence, and inadequate nutrition for those with chronic conditions, exacerbating existing health problems. Repeated moves or the loss of stable occupancy undermine continuity of care for chronic conditions, interrupting scheduled check-ups, established treatment routines, and the stable provider relationships necessary for effective management of long-term illnesses or disabilities. Likewise, living in unsafe or indecent housing magnifies pre-existing HQoL problems. Environmental hazards, such as mold, and structural deficiencies, such as leaks, worsen respiratory conditions, chronic pain, and may limit mobility (43, 44). Similarly, exposure to neighborhood hazards amplifies sleep disruption and fatigue (36). In combination, these dynamics create a reinforcing cycle in which housing instability exacerbates already fragile health, pushing individuals into progressively worse HQoL trajectories, and intensifying HQoL conditions, accelerating their decline.

The worsening of HQoL and housing instability creates additional strain on mental well-being. Chronic pain, mobility limitations, fatigue, and illness not only reduce independence and quality of life but also

foster feelings of frustration, helplessness, and loss of control (45). When everyday tasks become difficult or impossible, individuals face mounting stress and diminished self-efficacy, which in turn elevates the risk of anxiety and depression (45). Sleep disruption, persistent discomfort, and the inability to sustain normal routines further erode emotional regulation (46). In this way, the interaction between HQoL and housing instability feeds directly into psychological distress, reinforcing a cycle in which housing instability and poor health magnify mental health challenges. These considerations lead us to the following hypothesis:

H1

As housing instability increases and health-related quality of life decreases, the prevalence of mental health concerns such as perceived stress, depression, and anxiety will increase.

## 3. Data and Methods

## 3.1. Site Selection

This research stems from NIH's AIM-AHEAD Public-Private Partnerships initiative between local health departments and institutions of higher education. For this project, we partnered with the Fort Bend County Department of Health and Human Services. Fort Bend County, Texas, is one of the fastest-growing and most dynamic regions in the state, characterized by a blend of urban and rural communities, with the latter encompassing approximately 60% of the total land area. As development progresses, these communities are experiencing significant changes, including new housing developments, shifts in land use, and evolving demographics. These transformations necessitate a focus on improving access to health services, especially as limited county resources are increasingly redirected to serve expanding urban and suburban areas.

## 3.2. Data

The data come from a representative survey using a dual-frame random sample of adults living in Fort Bend County, consisting of a landline sample generated by list-assisted random-digit dialing and a cellphone sample delineating local call boundaries and billing ZIP Codes to indicate users' current residence. The survey was conducted between March 11 and April 4, 2025, by ReconMR, a member of the American Association for Public Opinion Research transparency initiative and a HIPAA-certified research firm. Instrument and data collection protocols were approved by the university's Institutional Review Board, and informed consent was obtained. The data collection achieved its target of 850 completions, with a ± 3.3 margin of error. Responses were split mainly between cell phones (780) and landlines (70). Of this split, 393 interviews were collected by telephone and 457 via text-to-web; 49 interviews were conducted in Spanish.

Gender quotas were essentially met (47% male, 52% female; 9% prefer not to say). The language distribution skews slightly towards English-only, more than planned (63% vs. 58% quota), with 37% of

respondents speaking other languages at home. Race/ethnicity quotas were well aligned for Whites (28%), Blacks (28%), and Hispanics (28%), while Asians fell short of its 21% target (12% achieved); a residual 138 cases were “other/refused,” and small counts appear for American Indian/Alaska Native and Native Hawaiian/Pacific Islander as expected. Age shows an overrepresentation of younger respondents (18–24 at 18% vs 11% quota) and slight underrepresentation in several mid-age bands (35–44 each ~ 8% vs 11% quota); older groups 70–79 run somewhat above quota (6% and 5% vs 4% and 3%), with 80–84 at 2% and 85 + at 1% matching quotas. Overall, key gender and major race/ethnicity targets were met, with modest deviations in language mix and age distribution.

Even though this survey provides a valuable county-representative sample, there are some limitations. First, dual-frame RDD may still suffer from coverage errors: households without stable phone access, app-based/VoIP-only users, and recent movers may be underrepresented. Second, cellphone “local call boundaries” plus billing ZIP Codes may introduce a small misclassification error. Third, nonresponse and mode effects (CATI vs. text-to-web) may introduce selection and measurement biases—people with heavier housing burdens, limited data plans, or low digital literacy may respond differently or opt out. Finally, the cross-sectional window (March 11–April 4, 2025) captures conditions at one point in time, prohibiting causal attribution and making results sensitive to short-term shocks (e.g., rent spikes, policy changes).

Following Burgard (5) and Murdoch et al. (47), the instrument incorporates components that measure housing instability around three latent constructs—lack of affordability, lack of stable occupancy, and lack of safety/decency—each measured by clusters of observed indicators (see Table 1). Affordability captures acute and ongoing financial strain related to housing alongside broader household constraints. Stable occupancy reflects residential precarity through formal risks and events, mobility disruptions, and extreme displacement markers. Safety/decency gauges habitability and crowding, physical and environmental defects, essential infrastructure, and contextual safety perceptions. Together, these dimensions provide a comprehensive, multi-domain profile of housing instability spanning affordability pressures, tenure security, and the quality and safety of the living environment.

Table 1
Housing Instability Index Latent and Observed Constructs

| **Lack of Affordability** | **Obs.** | **Mean** | **Std. dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| ***Stress*** | | | | | |
| Past Stress Pay Mortgage/Rent (1 = Always…5 = Never) | 640 | 3.63 | 1.38 | 1 | 5 |
| Current Stress Pay Mortgage/Rent (1 = Very worried…4 = Not at all) | 397 | 2.86 | 1.11 | 1 | 4 |
| **Financial Hardship** | | | | | |
| Food (1 = Yes… 0 = No) | 850 | 0.19 | 0.39 | 0 | 1 |
| Medical Bills (1 = Yes… 0 = No) | 847 | 0.23 | 0.42 | 0 | 1 |
| Transportation (1 = Yes… 0 = No) | 848 | 0.22 | 0.42 | 0 | 1 |
| Debt (1 = Yes… 0 = No) | 850 | 0.26 | 0.44 | 0 | 1 |
| Savings (1 = Yes… 0 = No) | 847 | 0.51 | 0.50 | 0 | 1 |
| Healthcare (1 = Yes… 0 = No) | 850 | 0.24 | 0.43 | 0 | 1 |
| Utilities (1 = Yes… 0 = No) | 844 | 0.21 | 0.41 | 0 | 1 |
| **Mortgage/Rent Payment Hardship** | | | | | |
| Afford Payment | 606 | 3.23 | 0.93 | 1 | 4 |
| Mortgage/Rent Half Income (1 = Yes… 0 = No) | 628 | 0.31 | 0.46 | 0 | 1 |
| Household Income (1 < $25k…6>$150k) | 705 | 3.32 | 1.77 | 1 | 6 |
| **Behind Payment (1 = Yes… 0 = No)** | 638 | 0.20 | 0.40 | 0 | 1 |
| **Lack of Stable Occupancy** | | | | | |
| **Risk** | | | | | |
| Eviction Risk (1 = Not at all…4 = V.likely) | 848 | 1.31 | 0.68 | 1 | 4 |
| Current Eviction/Foreclosure (1 = Never worried…7 = Always) | 850 | 1.42 | 1.12 | 1 | 7 |
| Past Eviction/Foreclosure (1 = Yes… 0 = No) | 627 | 0.04 | 0.20 | 0 | 1 |
| **Instability** | | | | | |
| Forced Move (1 = Yes… 0 = No) | 108 | 0.09 | 0.29 | 0 | 1 |
| Number of Moves | 844 | 0.89 | 1.18 | 0 | 10 |
| Homeless Ratio (%) | 846 | 0.03 | 0.13 | 0 | 1 |

| Lack of Affordability | Obs. | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| *Stress* | | | | | |
| **Nowhere to Go Ratio (%)** | 845 | 0.06 | 0.19 | 0 | 1 |
| **Lack of Safety and Decency** | | | | | |
| **Overcrowding** | | | | | |
| Number of Subfamilies | 829 | 0.59 | 1.24 | 0 | 9 |
| Persons per Room | 847 | 1.23 | 0.77 | 0 | 9 |
| **Quality** | | | | | |
| Inside Leak (1 = Never…5 = Daily) | 845 | 1.35 | 0.76 | 1 | 5 |
| Outside Leak (1 = Never…5 = Daily) | 848 | 1.26 | 0.64 | 1 | 5 |
| Wall crack (1 = Yes… 0 = No) | 850 | 0.14 | 0.35 | 0 | 1 |
| Musty (1 = Never…5 = Daily) | 848 | 1.38 | 0.87 | 1 | 5 |
| Working Toilet (1 = Never…5 = Daily) | 850 | 1.31 | 0.66 | 1 | 5 |
| Running Water (1 = Never…5 = Daily) | 850 | 1.18 | 0.52 | 1 | 5 |
| Neighborhood Search (1 = Not a problem…4 = Serious problem) | 842 | 1.82 | 1.05 | 1 | 4 |
| Perceived Home Safety (1 = Not at all safe… 4 = Very safe) | 849 | 3.69 | 0.55 | 1 | 4 |

Additionally, we include a range of demographic variables in the survey, such as gender, race, and ethnicity, as well as socioeconomic factors like income and education, which may all affect mental health outcomes. We also incorporate indicators that measure quality of life, such as quality-of-life perceptions and the EuroQol-5 dimensions questionnaire, which serves as the basis for our HQoL measurement. The HQoL is a standardized patient-reported outcome measure designed for clinical evaluation, economic appraisal, and population health surveys to capture current health (48).

We also include questions related to mental health assessments: the Perceived Stress Scale (PSS-4), the Generalized Anxiety Disorder scale (GAD-7), and the Patient Health Questionnaire (PHQ-9). Although GAD-7 and PHQ-9 offer some clinical cut points, there are no noticeable changes between the original scale and these cut points (49), however, the PSS-4 scale was not designed to be used with cut points (38), so these variables were kept in their original scales. These items help us assess the broader health and well-being implications associated with housing instability and HQoL. We create indices based on these measures to create three distinct dependent variables that measure different aspects of mental health. Table 2 summarizes the data.

Table 2
Summary Statistics.

| Variable | Obs. | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Stress Scale PSS-4 (very low = 1… high = 14) | 837 | 5.30 | 3.23 | 0 | 14 |
| Depression Scale PHQ9 (Minimal = 1…Severe = 27) | 836 | 4.46 | 5.34 | 0 | 27 |
| Anxiety Scale GAD7 (Minimal = 1…Severe = 21) | 837 | 4.50 | 5.17 | 0 | 21 |
| Housing Instability Index (lower values = < instability) | 850 | 0.00 | 1.00 | (0.8) | 6.23 |
| Sex (1 = Female / 0 = Male) | 841 | 0.52 | 0.50 | 0 | 1 |
| Latino (1 = Latino / 0 = non-Latino) | 850 | 0.28 | 0.45 | 0 | 1 |
| Race (1 = non-Caucasian /0 = Caucasian) | 850 | 0.57 | 0.50 | 0 | 1 |
| Speaks another Language at Home (1 = yes, 0 = no) | 850 | 0.38 | 0.48 | 0 | 1 |
| Education (1 = some HS….6 = Graduate degree) | 831 | 3.88 | 1.56 | 1 | 6 |
| Income (1 < $25,000…6 >= $150,000) | 705 | 3.32 | 1.77 | 1 | 6 |
| HQoL (5 = excellent health to 25 worst health) | 848 | 7.27 | 2.73 | 5 | 23 |
| Rate Quality of Life (1 = very poor…5 = very good) | 848 | 4.10 | 0.91 | 1 | 5 |
| Rate Physical Environment (1 = not at all…5 = extreme amount) | 849 | 3.85 | 0.97 | 1 | 5 |
| ZIP Code | 612 | -- | -- | -- | -- |

We also account for geographic variation by including respondents' ZIP Codes, which will allow us to control for potential individual-level disparities attributable to place-based differences. The following maps illustrate the bivariate relationships between housing instability and average PHQ-9 depression scores, average perceived stress, average GAD-7 anxiety scores, and Health-Related Quality of life; as well as where these relationships coincide spatially.

Across our Housing Instability Index and our mental health measures—our respective independent and dependent variables—there are four combined conditions. The 1) white condition indicates places in which there is low housing instability and low prevalence of mental health conditions; 2) light gray means high housing instability and low prevalence of mental health conditions 3) dark gray means low housing instability and high prevalence of mental health conditions; 4) and black means high housing instability and high prevalence of mental health conditions.

The most geographically salient patterns are those associated with the black cluster areas where housing instability and adverse mental health indicators are highly concentrated. Descriptively, these spatial patterns align with our hypothesized relationship between housing instability and mental health.

In these places, residents experience greater instability in addition to mental health conditions. The distribution of these patterns also suggests that there is variation in how housing instability and the prevalence of mental health conditions are experienced geographically. The variation underscores the importance of geographic context for understanding where risks concentrate and where policy interventions may be the most effective.

# 3.3. Methods

Using Stata ver. 19/SE, we create our overall housing instability index following Murdoch (47), which outlines a comprehensive methodology using Confirmatory Factor Analysis (CFA) via structural equation modeling (SEM). This technique is used to examine how observed variables (i.e., survey responses) relate to unobserved or latent constructs (i.e., housing affordability, stable occupancy, and safety and decency) (50). A central strength of this method is its ability to estimate multiple equations simultaneously while accounting for measurement error. We applied CFA to the three domains of housing instability—lack of affordability, lack of stable occupancy, and lack of safety/decency—estimating a separate measurement model for each. In every model, the domain was specified as a higher-order latent factor, reflected in several subdimensions, each derived from our survey items. This design allowed us to quantify each domain as an overall construct while preserving its constituent subdimensions.

Finally, to build the housing instability index, we apply principal component factor analysis (PCF), which serves a different but complementary purpose than CFA. PCF is used to simplify data by identifying combinations of indicators that maximize variance. It does not create a measurement model or differentiate between unique and error variance, unlike CFA, which is used to confirm hypotheses, in this case, to confirm the latent structure of housing instability.

To test the impact of housing instability and its interaction with HQoL on mental health outcomes—perceived stress (PSS-4), depression (PHQ-9), and anxiety (GAD-7)—we use Gradient Boosting Regression (GBR) via the H2O machine learning platform. Machine learning—particularly GBR—offers several methodological advantages. GBR flexibly captures nonlinear relationships and higher-order interactions, often yielding stronger out-of-sample performance than linear models. Its hyperparameters (learning rate, tree depth, number of trees, and early stopping) act as built-in regularization, limiting overfitting, which is valuable with many, potentially correlated predictors. GBR also handles mixed data types (e.g., binary, ordinal, continuous) with minimal preprocessing, and there is no need to standardize predictors on different scales, as tree splits depend on the order of values, not their absolute magnitudes. GBR is also relatively robust to scaling and outliers, thanks to tree-based splits, and provides interpretable diagnostics that reveal which predictors matter and how their effects vary across the range of the predictor space. In short, GBR performs better than linear regression by uncovering complex patterns while maintaining conservative validation and interpretability.

GBR builds predictive models by sequentially correcting errors through decision trees, enabling the flexible and accurate estimation of complex relationships. Each model includes housing instability,

demographic controls (e.g., sex, race, language used at home other than English), socioeconomic indicators (income, education), HQoL, and perceived quality of life factors. We estimate each model using a deliberately conservative specification to limit overfitting. Hyperparameters are tuned via grid search over a shallow depth range (maxdepth = 3–6) and moderate tree counts (ntrees = 50–300) with a small learning rate (≈ 0.05), selecting the configuration that minimizes MSE on a hold-out validation frame (80/20). Together, shallow trees, a small step size, and validation-guided tuning provide a robust conservative guardrail that promotes generalizable estimates given the sample size.

# 4. Results

## 4.1. Index Construction

As indicated by Table 1, three subdimensions represent our first housing instability component: affordability. The three subdimensions capture stress about paying rent or a mortgage (past and present), financial hardship in meeting basic expenses such as food, transportation, and healthcare, and difficulty making housing payments. A final observed indicator adds the number of times households fell behind on payments in the past year. This model shows a strong fit (CFI = .962, TLI = .953, RMSEA = .056) despite the expected significance of the chi-square test ($\chi^2_{62}$ = 224.78, p < .001) due to sample size. The high coefficient of determination (CD = .98) indicates the model captures nearly all relevant variance.

The second component measures the lack of occupancy stability, including both the risk of eviction or foreclosure and actual instances of forced, frequent moves. It also includes the presence of unhoused individuals in the household. This model also performs well statistically, with CFI = .966, TLI = .940, RMSEA = .063, and a CD of .961.

The third component addresses safety and decency. It includes overcrowding, structural issues such as leaks and mold, lack of essential utilities, and barriers to finding affordable housing in safe neighborhoods with basic amenities. Residents' sense of personal safety is also taken into account. This component achieves once again a good model fit (CFI = .978, TLI = .965, RMSEA = .041), with a CD of .921.

Finally, to create a unified housing instability index, a principal component factor (PCF) analysis was conducted using each latent standardized construct. The results show that a single factor effectively represents the three latent constructs. This factor accounts for two-thirds of the total variance, with strong loadings on affordability (0.80), occupancy (0.84), and safety (-0.81). More lack of affordability, lack of stable occupancy, and less safety and decency increase housing instability. The high eigenvalue (1.98) and significant likelihood ratio test $\chi^2(3) = 574.41$, $p < 0.001$ support the validity of this approach. Overall, the results confirm that a combined index reliably captures housing instability by integrating affordability, occupancy, and safety dimensions, consistent with Murdoch et al. (47).

## 4.2. Mental Health Outcomes

The PSS-4 is a brief measure of perceived stress. The total score is determined by adding together the scores of each of the four survey items, with some responses flipped to maintain directional consistency (i.e., question 2 and question 3), to obtain a minimum total score of zero (least perceived stress) to a maximum total score of 16 (highest perceived stress) (38, 51).

The Patient Health Questionnaire-9 (PHQ-9) is a 9-item scale used to assess the severity of depression. Each item reflects one of the DSM-IV criteria for major depressive disorder. Each of the nine items is scored from 0 to 3, based on how often the respondent experienced each symptom over the past two weeks (0 = Not at all, 1 = Several days, 2 = More than half the days, 3 = Nearly every day), with a total range from 0 to 27 (49).

The GAD-7 is a 7-item screening tool developed to identify probable cases of generalized anxiety disorder and assess symptom severity. The scale is the product of adding each item based on how often the respondent experienced symptoms over the past two weeks (0 = Not at all, 1 = Several days, 2 = More than half the days, 3 = Nearly every day), with a possible score range from 0 to 21 (52).

# 4.3. Predicting Mental Health

Our next step is to ask how much housing instability, HQoL, and their interaction impact mental health outcomes in the form of perceived stress (PSS-4), depression (PHQ-9), and anxiety (GAD-7). We assess the predictive power of our housing instability index alongside HQoL, demographic, socioeconomic, and health-related factors: sex, Latino ethnicity, race, home language, education, income, perceived quality of life, environmental health perceptions, and ZIP Code. We fit a series of Gradient Boosting Regression models, designed to balance flexibility and generalizability, to better understand the contribution of housing instability, HQoL, and their interaction on mental health outcomes.

# 4.3.1. Perceived Stress (PSS-4)

The GBR predicting PSS-4 performs strongly on the validation set (RMSE ≈ 1.16, MAE ≈ 0.91, $R^2$ ≈ 0.88), with errors under 1 point, and a validation fit slightly better than training (RMSE 1.16 vs 1.20), suggesting no obvious overfitting on this split. The tuner selected the largest tested capacity—300 trees, with a maximum depth of 6 and a learning rate of 0.05—indicating that the model continued to gain from more trees at shallow depths. The specification appears well-regularized and accurate.

Overall, quality-of-life rating is the strongest predictor of perceived stress, followed closely by the interaction between housing instability and HQoL (HI×HQoL), indicating that the stress–QoL rating is amplified when housing is unstable. HQoL alone ranks next, then socioeconomic markers—income and education—and the housing instability index itself, all with comparable mid-tier influence. ZIP Code and perceived physical environment contribute modestly, while basic demographics (sex and race) add relatively little. Interpreted cautiously, the pattern suggests stress is most tightly tied to perceived QoL—especially its health dimension—and that housing instability meaningfully conditions that relationship (see Fig. 5a).

The SHAP (Shapley Additive Explanations) summary indicates that high overall QoL rating values (red points) mostly reduce predicted stress (negative SHAP), while low QoL rating (blue) increases it. The HI×HQoL term displays a complementary pattern: when housing instability is high, and HQoL is low, contributions skew positive—amplifying stress—whereas better HQoL under instability dampens it. Better-rated physical environments also lower stress, and a higher Housing Instability Index tends to increase stress (red points tend to have negative SHAP values). Income and education exert modest, generally stress-reducing effects at higher values, while ZIP Code exhibits mixed, place-specific impacts. Demographics (race, Latino, sex, other-language vs English) cluster tightly around zero, indicating relatively small, context-dependent contributions compared with QoL rating and housing factors (see Fig. 5b).

# 4.3.2. Depression (PHQ-9)

The GBR for depression shows good predictive accuracy on the validation set (RMSE ≈ 1.39, MAE ≈ 1.03, $R^2$ ≈ 0.93) with performance slightly better on validation than training (RMSE 1.39 vs 1.53), again indicating no obvious overfitting with a small error about 5% of the scale—suggesting the model captures much of the depression severity signal from quality-of-life, housing instability, and socioeconomic predictors.

The depression variable-importance profile is dominated by HQoL, which contributes roughly twice as much as any other predictor, indicating that perceived HQoL status is the primary driver of depressive symptoms in this model. Perceived quality of life ranks next, followed by housing instability and the HI×HQoL interaction, suggesting both a direct effect of unstable housing and an amplifying/moderating role when HQoL is poor. Education and income add a minor but nontrivial contribution, while ZIP Code and perceived physical environment contribute modestly, once again suggesting significant place variation. Language and race have minimal influence (see Fig. 6a).

The SHAP summary indicates that HQoL is the dominant driver: low HQoL values (blue, low HQoL indicates better health) push predicted depression down, while high HQoL (red) increases it. Overall quality of life shows the same pattern (i.e., low QoL perception increases symptoms), and the HI×HQoL term reveals that housing instability amplifies the impact of poor health-related QoL (more positive SHAP when HQoL is low under higher HI). The Housing Instability Index itself contributes mainly positive SHAP at higher values—i.e., greater instability elevates predicted PHQ-9. Education and income exhibit modest, generally protective effects (higher values skew negative SHAP), whereas ZIP Code and physical environment have mixed, place-specific but smaller influences. Demographic and language indicators (sex, race, Latino, other-language vs English) cluster near zero, suggesting limited incremental contribution relative to QoL and housing conditions (see Fig. 6b).

# 4.3.3. Anxiety (GAD-7)

The GBR predicting GAD-7 achieves good out-of-sample accuracy: validation RMSE ≈ 1.50 and MAE ≈ 1.07 (errors are ~ 5–7% of the range), with a very high $R^2$ ≈ 0.92 and slightly better validation than

training performance (RMSE 1.50 vs 1.61), suggesting no obvious overfit.

The anxiety-importance profile is dominated by HQoL and perceived quality of life, which outweigh other predictors, indicating that health-related quality of life and its perception are the primary drivers of anxiety severity in the model. Housing Instability (HI) and the HI×HQoL interaction are the next most influential, suggesting both a direct effect of instability and an amplifying role when HQoL is poor. Overall, education and income provide smaller contributions. ZIP Code shows modest place-based influence, and race, physical environment ratings, and other-language vs. English contribute little (see Fig. 7a).

The GAD-7 SHAP summary shows HQoL as the dominant driver: low HQoL values (blue, low HQoL indicates better health) pushes predicted anxiety down, while high HQoL (red) increases it. The HI × HQoL term indicates that housing instability intensifies the impact of poor health—when instability is higher and HQoL is bad, SHAP contributions skew positive. HI itself adds mostly positive contributions at higher values, whereas higher overall QoL tends to reduce anxiety. Socioeconomic factors (income, education) provide modest, generally protective effects; ZIP Code shows mixed, place-specific influence. Demographics and language (race, sex, Latino, other-language vs English) cluster near zero, indicating relatively small incremental contributions compared with HQoL and housing conditions (see Fig. 7b).

# 5. Discussion

This study examined how housing instability, HQoL, and their interaction relate to perceived stress, depression, and anxiety. Across the gradient boosting regressions, three consistent patterns emerged. First, perceived QoL and HQoL are the strongest correlates of mental health symptoms.

Second, HI has a chiefly *conditional* association: the HI×HQoL interaction robustly predicts higher stress, anxiety, and depression, but at different magnitudes, implying that when health is poor, instability magnifies distress. The interaction for depression seems to suggest symptom-specific pathways: anxiety and stress are more reactive to acute uncertainty and threat appraisals—conditions plausibly intensified by unstable housing—whereas depression may be more tightly tied to chronic health burden and cumulative adversity irrespective of contemporaneous instability. Moreover, stress and anxiety as emotional responses commonly manifest together, while depression centers on mood and motivation, not just arousal or worry (53). Third, sociodemographic covariates contribute comparatively little once perceived quality of life, HQoL, and HI are accounted for; education is modestly protective, and perceived physical environment reduces stress. These results converge across the high out-of-sample fit in GBR ($R^2 \approx .88–.93$), supporting the credibility of the signal while also indicating room for unmeasured factors.

These patterns sit comfortably within stress-process and social-determinants frameworks. Instability represents a cluster of stressors (insecure occupancy, affordability strain, safety/decency deficits) that heighten vigilance, uncertainty, and perceived uncontrollability—key levers of stress and anxiety (9, 54, 55).

The interaction with HQoL may both reflect and exacerbate these stressors (e.g., pain, functional limitations), creating conditions where instability has greater affective “leverage.” The modest incremental value of basic demographics after HQoL and HI aligns with evidence that proximal living conditions and health states often overshadow static traits in explaining near-term psychological symptoms (56). The protective role of education, and the specific buffering from better-rated physical environments on stress, echoes work showing that cognitive/financial resources and supportive neighborhoods attenuate stress reactivity (57, 58).

# 6. Conclusions

This analysis offers compelling evidence that structural conditions—particularly housing instability—and subjective and health-related quality of life, as well as spatial variation, are central to understanding mental health outcomes. The high explanatory power of the models and their consistency across multiple outcomes support the reliability of these conclusions. From a population health perspective, screening for HI alongside HQoL in primary care and community clinics can identify patients at higher risk for stress and anxiety. A dual-flag approach (poor HQoL and instability) should prompt more intensive care coordination, such as referrals to housing navigators and eviction prevention services. Integrating these “housing vital signs” (59) into care pathways is likely to be more beneficial than targeting health or housing in isolation.

This project contributes to a broader understanding of the systemic issues surrounding housing instability and mental health by combining local knowledge with advanced ML techniques. This approach is essential for developing comprehensive policy recommendations and advocacy strategies to address housing instability at its roots. Our results support stability-first strategies like short-term rental assistance, eviction prevention, arrears relief, and code enforcement to ensure safety. Improvements in physical environments (e.g., lighting and noise control) can provide stress relief even without immediate income changes. Educational programs that enhance financial and problem-solving skills can be especially valuable for households managing chronic health issues in tight housing markets.

From a spatial perspective, across the bivariate maps and the GBR models, the central story is that housing instability clusters with multiple forms of health burden—mental health symptoms and broader health-related functioning—yet the mechanisms differ by place. The most consistent “stacked-risk” signal remains the southwestern Fort Bend footprint (Needville–Fairchilds–Rosenberg/Richmond), which repeatedly appears as high housing instability co-located with higher depression (PHQ-9), higher perceived stress, higher anxiety (GAD-7), and—on the HQoL map—higher health (worse overall health/functioning). Southwestern Fort Bend is the clearest case for a bundled, place-based response. In this part of the county, upstream housing stabilization (eviction diversion, rental/utility relief, repairs, legal/navigation supports) paired with accessible mental health screening for depression, anxiety, and stress may help alleviate the housing and health burdens face in this area of the county as the evidence suggests these burdens occur in the same place.

At the same time, the results of this paper identify mismatched geographies that should shape targeting. The northeast/Houston–Sugar Land–Missouri City border more often shows elevated symptom burden and/or worse whole-person health even where housing instability is not uniformly high, implying a stronger role for non-housing drivers (commute/time strain, job and caregiving stress, social isolation, chronic pain/disability, access barriers). These tracts call for access-focused behavioral health and support, not a housing-only strategy. Finally, areas with high instability but lower symptom/health-utility burden represent the county's prevention window: intervening early on housing instability in these locations is the most direct way to prevent escalation into higher depression/anxiety/stress and deterioration in overall functioning.

For example, with information on areas of the county that may be suffering from greater housing instability, the FBC HHS can introduce targeted interventions, such as in the case of North Carolina's Healthy Opportunities Pilot Program (60) the use of Medicaid Section 1115 waivers to support those experiencing homelessness (61), a program similar to Colorado's Housing First program (62) or Food Is Medicine interventions (28). In other words, our contributions not only support the Fort Bend County HHS but also serve as a model for other communities facing similar forms of housing instability.

These dynamics are likely not unique to Fort Bend County, or the U.S., for that matter. Similar development pressures are playing out in urban and suburban areas globally, where rapid growth commonly collides with limited governmental resources and uneven governance capacity (63–65). In many international contexts, rapid development is accompanied by informal housing markets, inadequate infrastructure, and fragile safety nets, which exacerbate equal access to health, education, and basic services (66, 67). The experiences of these communities, therefore, speak to broader global debates on how to manage growth, balance competing demands for land and services, and ensure that mental health across these global communities does not deteriorate in the process.

Future research should focus on causation rather than association by using longitudinal cohorts alongside natural experiments, such as changes in eviction policies, to determine timing and effects. It should also explore the link between respondents and neighborhood factors, such as eviction filings and crime, and assess how these factors interact to influence risk. Additionally, measurement should improve by combining surveys with administrative records to identify non-linear responses and cost barriers to scaling interventions.

Other work may also address how development, gentrification, and demographic trends contribute to health inequities at the county level (62, 68). Policies related to housing, such as zoning and small business development, can shape access to resources such as affordable housing, healthcare facilities, and public spaces such as parks and trails—all of which are important social determinants of health (69, 70). Examining these relationships can offer valuable insights into social determinants of health and help design effective health interventions to improve the overall health of the community.

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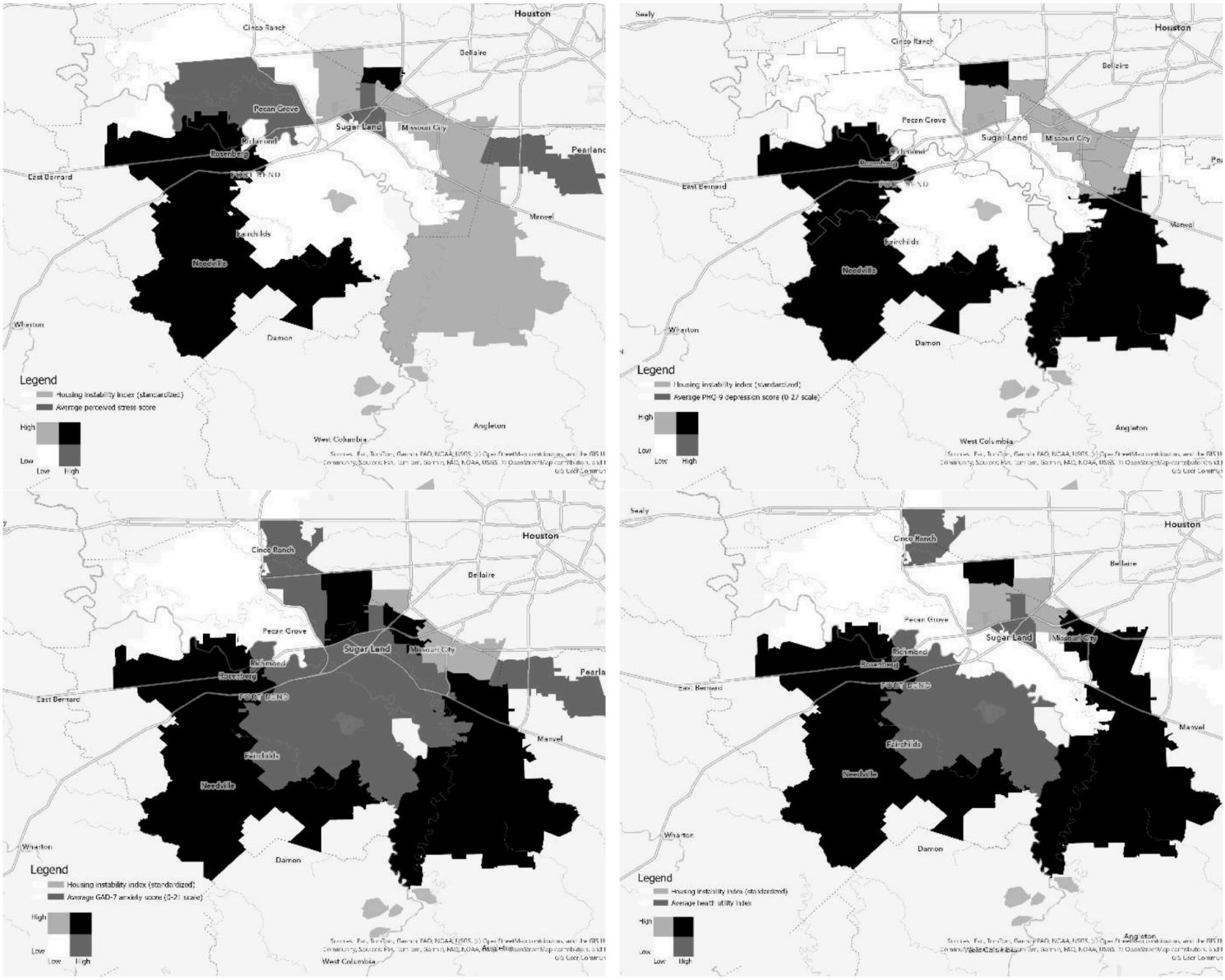
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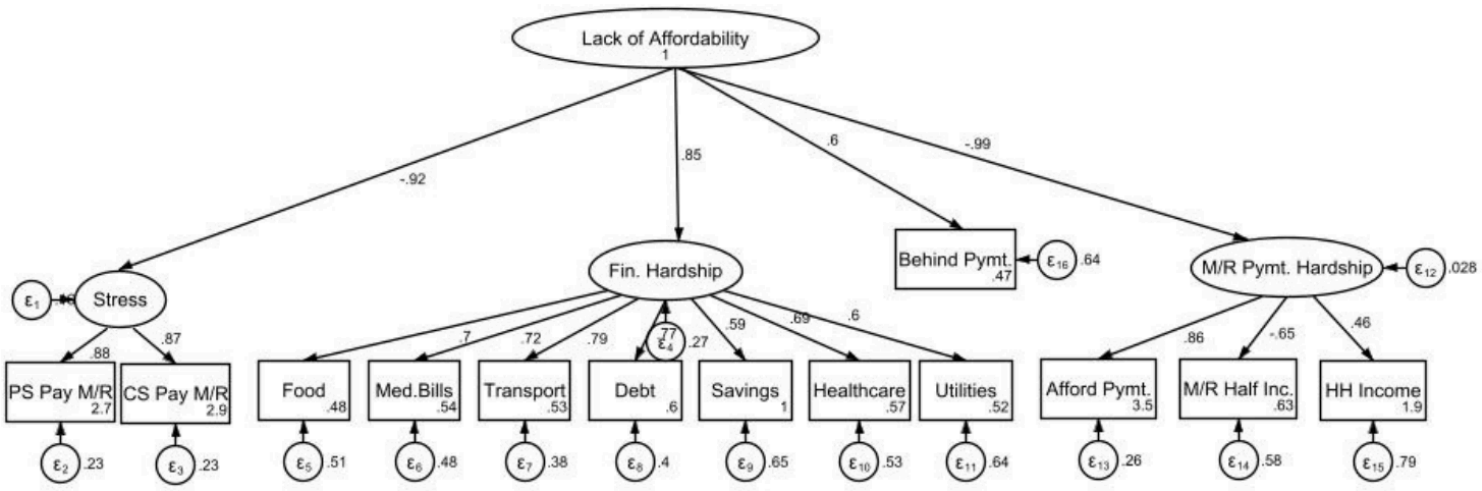
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# Figures



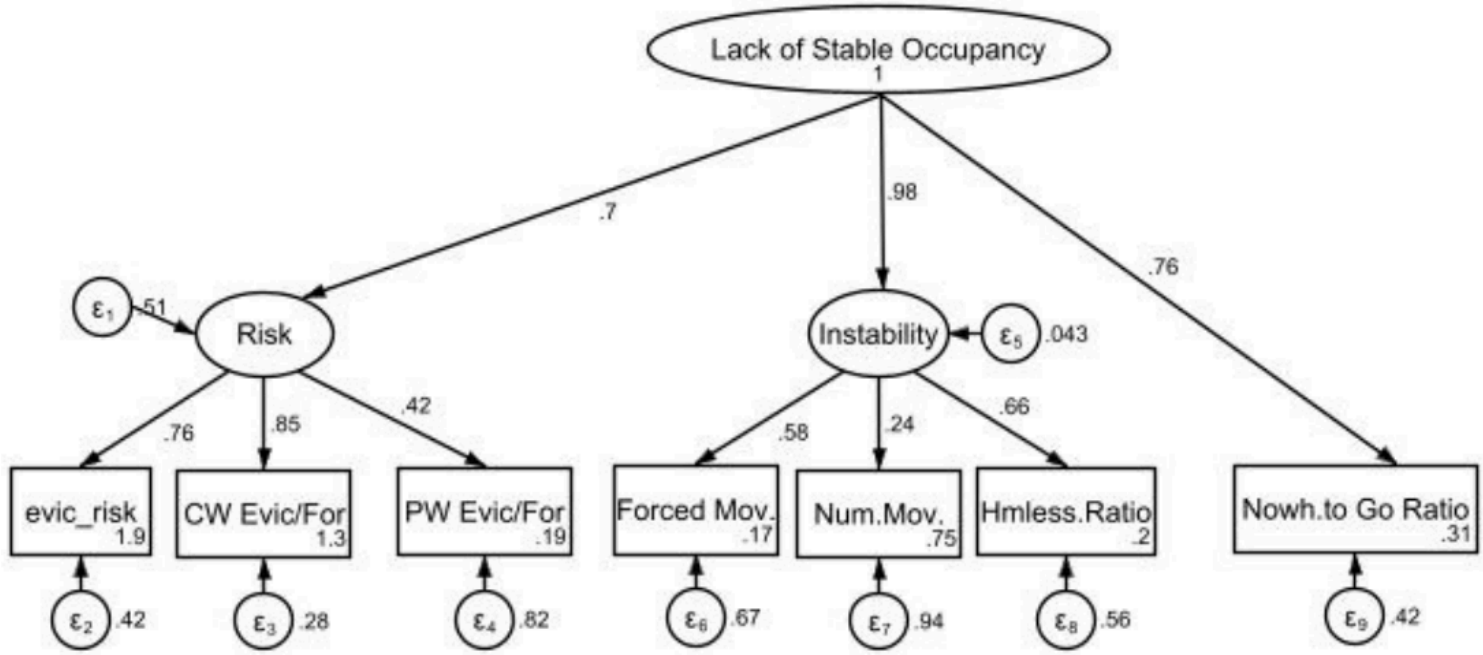

## Figure 1

Co-Location of Housing Instability with Mental Health Symptoms and HQoL Limitations (PHQ-9, Stress, GAD-7, and Health Related Quality of Life)



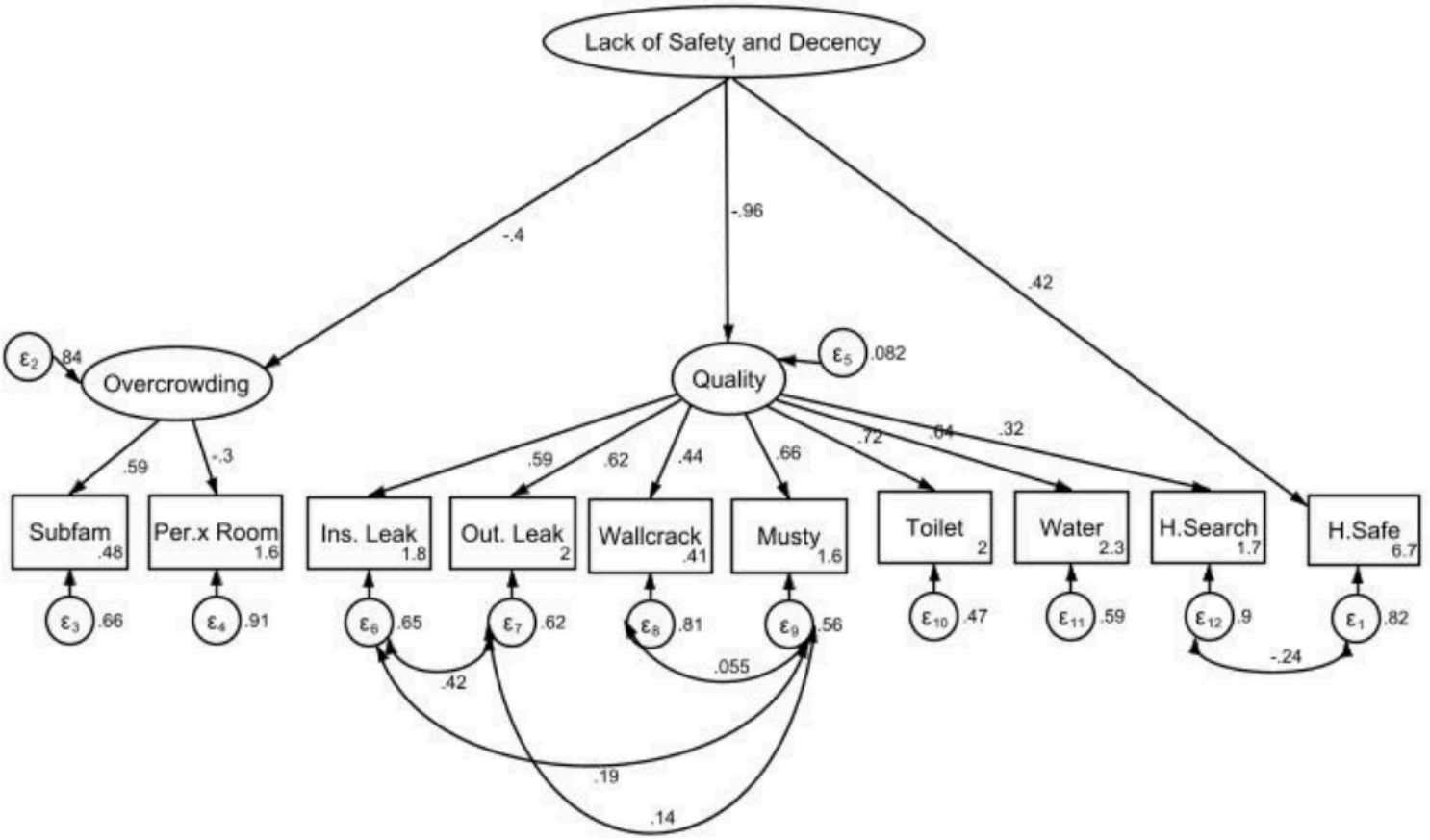

## Figure 2

Lack of Affordability SEM: Worry/stress about being able to pay mortgage/rent, financial hardship, mortgage/rent hardship (Standardized Loadings).



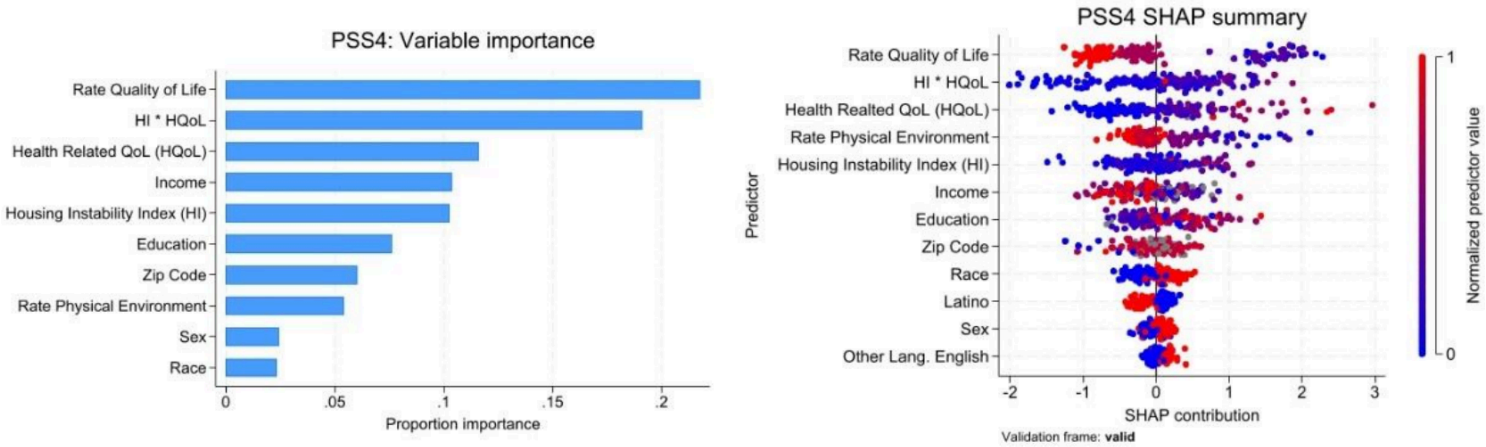

## Figure 3

Lack of Stable Occupancy SEM: Eviction/Foreclosure Risk, Instability, and Nowhere to go to spend the night (Standardized Loadings)




## Figure 4

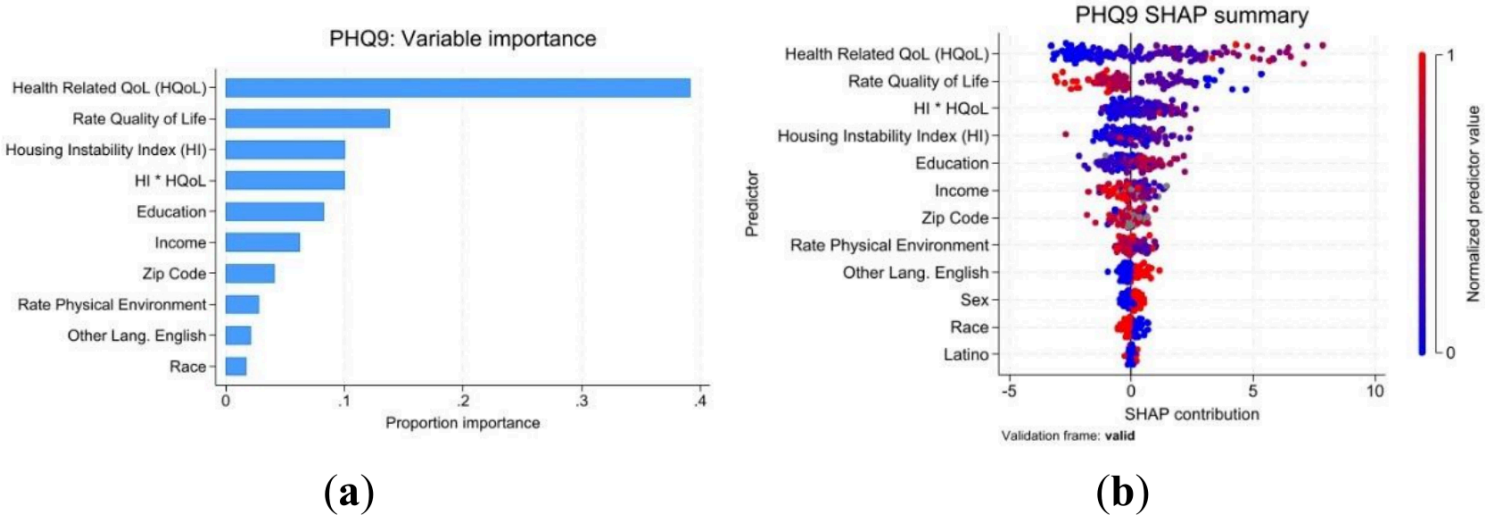
Lack of Safety & Decency SEM: Housing Quality, Overcrowding, and Safety (Standardized Loadings)




(a) (b)

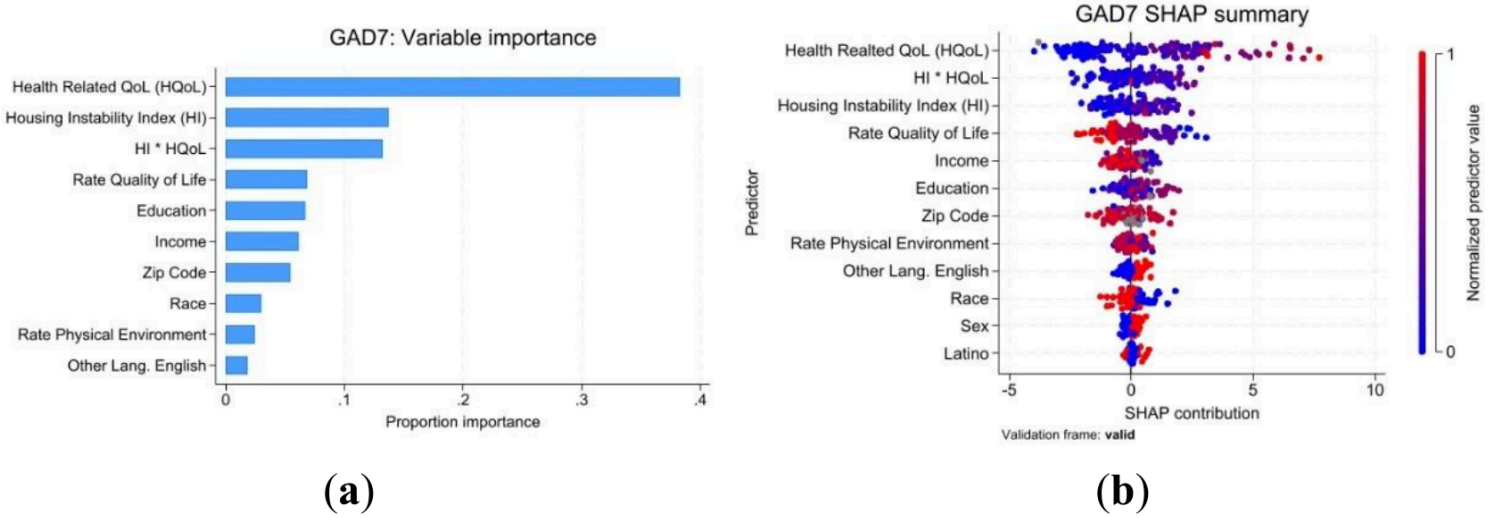
## Figure 5

Summary plots for housing instability and perceived stress: (a) variable importance graph depicting how much each predictor contributes to the predicted power of the model; variables with higher importance scores have a stronger impact on the model's predictions; (b) Shapley Additive Explanations graph highlighting predictors' impact, direction, and magnitude on individual perceived stress predictions.




## Figure 6

Summary plots for housing instability and depression: (a) Variable importance graph depicting how much each predictor contributes to the predicted power of the model; variables with higher importance scores have a stronger impact on the model's predictions; (b) Shapley Additive Explanations graph highlighting predictors' impact, direction, and magnitude on individual depression predictions.




## Figure 7

Summary plots for housing instability and anxiety: (a) variable importance graph depicting how much each predictor contributes to the predicted power of the model; variables with higher importance scores have a stronger impact on the model's predictions; (b) Shapley Additive Explanations graph highlighting predictors' impact, direction, and magnitude on individual anxiety predictions.