HOUSING INSTABILITY AND MENTAL HEALTH

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Research Team

This report examines housing instability as a core non-medical determinant of health, and shows how affordability pressures, unstable occupancy, and substandard or unsafe conditions jointly shape mental health in Fort Bend County. Working in partnership with the Fort Bend County Department of Health and Human Services and PolicyMap, our team fielded a representative countywide survey and analyzed the results using both linear regression and machine-learning methods. Across models, housing instability consistently predicts higher stress, depression, and anxiety—and the effects are tightly linked to residents' health-related quality of life (HQoL) and self-rated quality of life. Together, these findings reinforce the value of data-driven, place-based strategies that improve housing stability and strengthen quality of life as a pathway to better mental health and community well-being.

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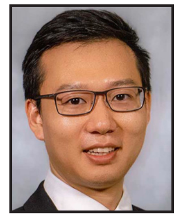

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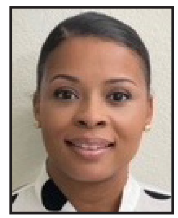

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Background

Researchers have increasingly shown that health is shaped not only by medical care but also by social and economic conditions—such as income, education, neighborhood environments, and housing, among others. These non-medical determinants of health influence the opportunities people have to live safely, stay connected, and thrive. Housing is central because it structures daily routines, safety, and financial security, and it is closely tied to quality of life. When housing is stable, affordable, and decent, it supports health and well-being; when it is unstable, it erodes quality of life and increases risk for poor physical and mental health.

Housing instability—frequent moves, displacement risk, eviction threats, doubling up, or living in unsafe conditions—creates financial strain, disrupts employment and childcare arrangements, and generates persistent uncertainty. That instability can weaken social networks and community belonging, which are key ingredients of quality of life. For children, repeated school changes can undermine academic progress and peer relationships; for adults, relocation can sever ties to neighbors, teachers, faith communities, and other informal supports. Over time, these disruptions elevate the risk of anxiety, depression, and chronic stress.

Housing instability also affects physical health in ways that reinforce mental health burdens. Substandard conditions—mold, overcrowding, poor ventilation, inadequate heating or cooling, and structural hazards—can contribute to chronic illness (e.g., asthma or cardiovascular strain). Frequent moves can interrupt continuity of care, while high housing costs may force households to trade off rent against food, medications, or preventive care—further reducing health-related quality of life. In combination, financial hardship, disrupted social support, and compromised living conditions connect housing instability to lower quality of life and worse mental health outcomes, making housing stability a central lever for improving community well-being.

To learn more about this project and explore the data, please visit:
https://www.policymap.com/newmaps/e/uhfbcunstablehousing

Research Design

To assess how housing conditions shape mental health, the research team partnered with Fort Bend County Health & Human Services (HHS) to design a survey and sampling approach that captures multiple dimensions of housing instability. The instrument asked about frequent moves, cost-driven relocations, temporary doubling up due to financial hardship, homelessness, eviction, foreclosure, and related housing disruptions. Responses were combined into a Housing Instability Index, our primary exposure measure. The survey also collected key demographic characteristics (e.g., age, sex, race/ethnicity, language spoken at home) and socioeconomic indicators (e.g., income, education, employment) to contextualize risk and quality-of-life differences across residents.

To capture well-being alongside mental health, the survey included the EQ-5D health-related quality of life instrument, a self-rated quality of life measure, and three widely used mental health scales: the Perceived Stress Scale (PSS-4), the Generalized Anxiety Disorder scale (GAD-7), and the Patient Health Questionnaire (PHQ-9). The instrument also collected ZIP Code information to examine geographic variation in housing instability, quality of life, and mental health.

The research team fielded the survey using a random sample of adults living in Fort Bend County. The sampling frame included both landline numbers (selected via random digit dialing) and cellphone numbers (identified through local call areas and billing ZIP Codes), recognizing that mobile numbers do not always align with current residence. This dual-frame design ensures coverage of adults without landlines and strengthens the representativeness of our quality-of-life and mental health estimates.

To align results with the county's adult population, responses were weighted to U.S. Census American Community Survey benchmarks using raking adjustments for age, race, ethnicity, and language spoken at home. This weighting approach improves precision and representativeness, providing a reliable foundation for estimating how housing instability relates to mental health—and how that relationship is conditioned by health-related and self-rated quality of life across Fort Bend County.

MULTI
DIMENSIONAL
REPRESENTATIVE
SURVEY

Housing Measures

The research team constructed a comprehensive measure of housing instability following Murdoch et al. (2022) by combining affordability strain, occupancy stability, and safety/decency into a single index using structural equation modeling (SEM). SEM links observed survey responses to broader latent concepts while accounting for measurement error—an important step when measuring complex lived experiences that directly influence well-being and quality of life.

1. LACK OF AFFORDABILITY
2. LACK OF STABLE OCCUPANCY
3. LACK OF SAFETY AND DECENCY

SEM includes a measurement model (which connects survey indicators to latent housing constructs) and a structural model (which specifies relationships among constructs). This framework allows us to evaluate model fit and ensure that our Housing Instability Index is statistically sound, interpretable, and useful for identifying where housing conditions may be undermining quality of life and mental health.

To estimate how housing instability relates to mental health, we modeled associations with perceived stress (PSS-4), depression (PHQ-9), and anxiety (GAD-7) using both linear regression and Gradient Boosting Regression (GBR) implemented through the H2O machine-learning platform. GBR improves predictive accuracy by iteratively fitting decision trees, enabling flexible estimation of non-linear and interaction effects that often characterize how housing conditions and quality of life shape mental health.

All models included housing instability along with demographic characteristics (sex, race/ethnicity, language spoken at home), socioeconomic indicators (income, education), and measures of health-related quality of life and self-rated quality of life. This specification allows us to separate the direct contribution of housing instability from broader well-being and resource constraints, and to highlight how quality of life amplifies or buffers mental health risk.

Lack of Affordability

Affordability reflects whether households can meet housing costs without sacrificing other essentials that sustain quality of life—food, healthcare, transportation, and basic utilities. Our affordability component draws on stress about paying rent or a mortgage; current and past difficulty meeting basic needs; trouble making housing payments; and the frequency of falling behind over the past year. The model shows a strong fit and captures the central affordability pressures that erode quality of life and contribute to mental health risk.

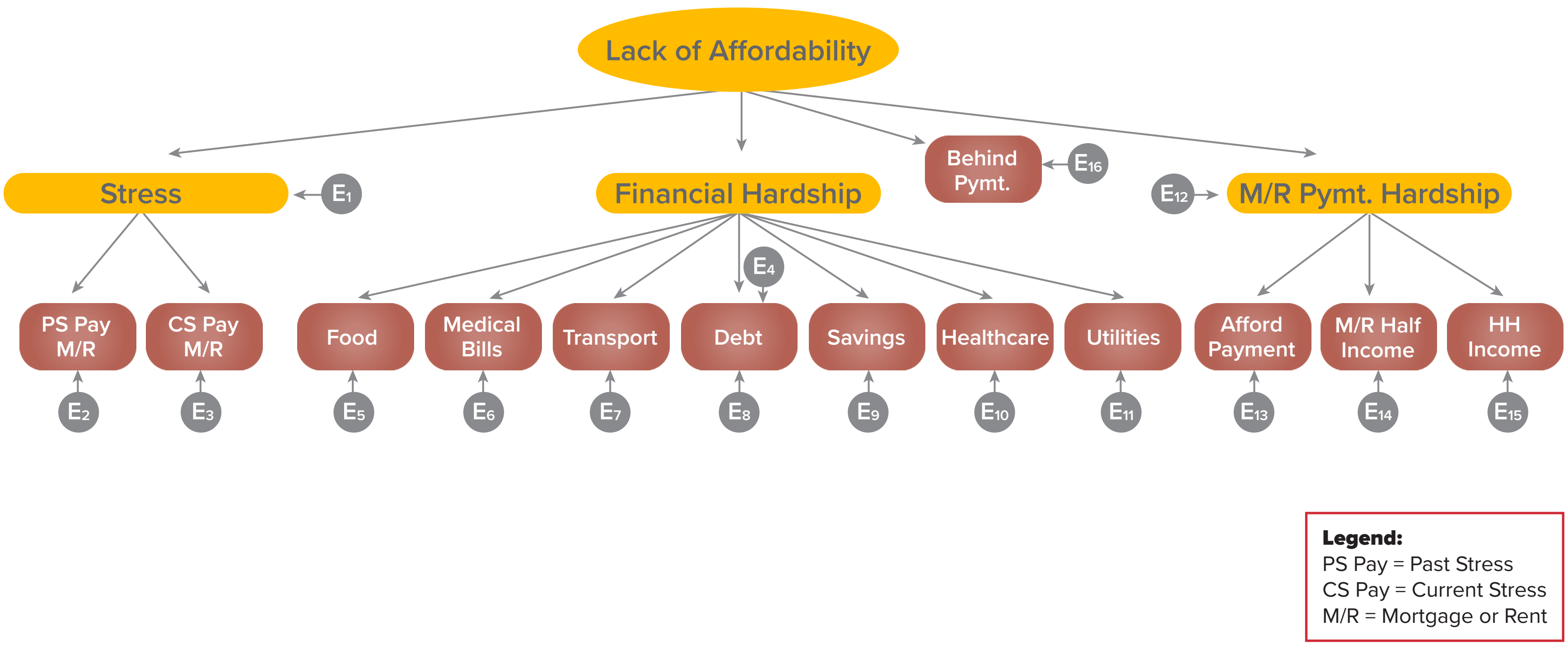
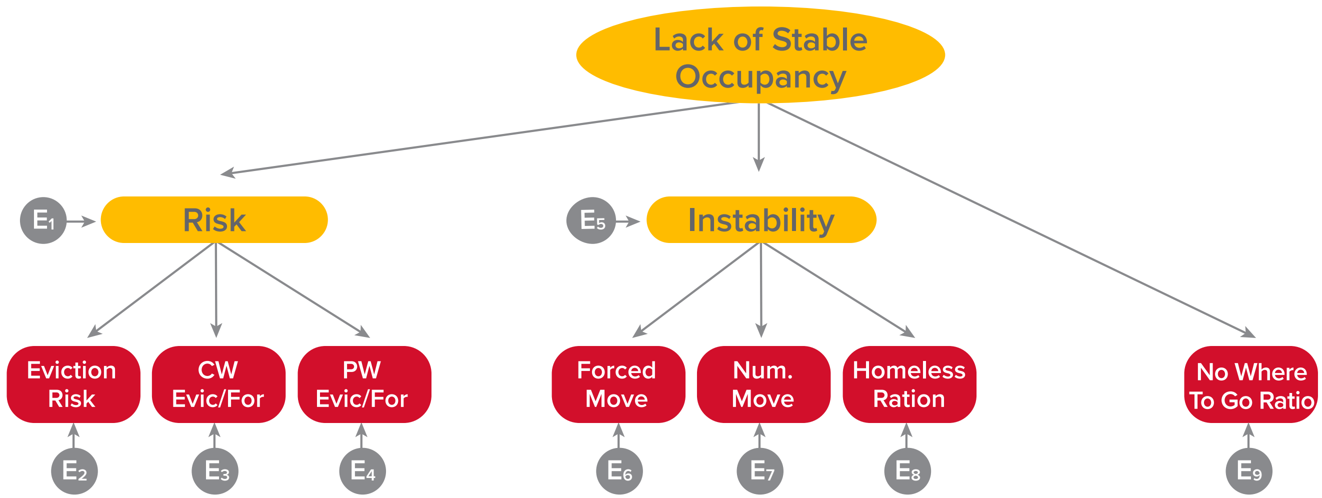


Figure 1. *Lack of Affordability SEM: Worry/stress about being able to pay mortgage/rent, financial hardship, mortgage/rent hardship.*

Lack of Stable Occupancy

The stable-occupancy component captures housing churn and displacement risk, including eviction or foreclosure threats, forced moves, frequent relocations, and living with unhoused individuals in the household. The model fits the data well and reliably identifies patterns of instability that disrupt routines, weaken social support, and reduce quality of life.



Legend:
CW= Current Worry
PW = Past Worry
Evic/For = Eviction/Foreclosure

Figure 2. *Lack of Stable Occupancy SEM: Eviction/Foreclosure Risk, Instability, and Nowhere to go to spend the night.*

Lack of Safety and Decency

The safety and decency component measures whether housing conditions support health, security, and everyday life. It includes overcrowding; structural problems such as leaks or mold; missing essential utilities; barriers to finding affordable housing in safe areas with needed services; and residents' perceptions of safety at home. The model fits the data well, indicating that it accurately captures housing conditions that can directly constrain health-related quality of life and elevate stress, anxiety, and depressive symptoms.

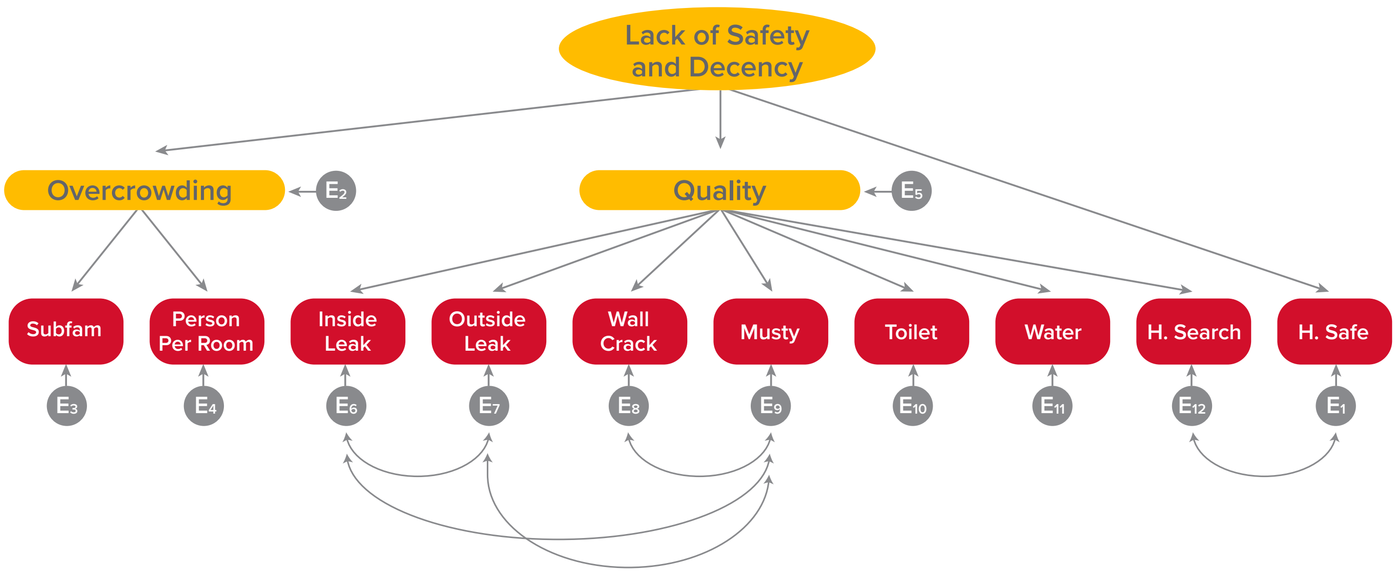


Figure 4. *Lack of Safety & Decency SEM: Housing Quality, Overcrowding, and Safety.*

To produce a single Housing Instability Index, we combined affordability, stable occupancy, and safety/decency through principal components analysis. Results indicate that these domains load onto one underlying factor that explains about two-thirds of the variation observed in the data. Each component contributes strongly (affordability = 0.80; occupancy = 0.84; safety = -0.81), with a high eigenvalue (1.98) and a highly significant test statistic. In practical terms, this yields a reliable, interpretable score that captures whether housing is affordable, stable, and safe—providing a powerful way to identify residents and places where housing conditions are most likely to undermine quality of life and mental health, consistent with the approach in Murdoch et al. (2022).

Mental Health Measures

1. Perceived Stress

We use the Perceived Stress Scale (PSS-4) to measure the degree to which individuals perceive their lives as stressful. Higher scores indicate greater perceived stress, reflecting feelings of being overwhelmed or out of control in the past month—an important dimension of day-to-day quality of life.

33%
EXPERIENCED MODERATE PERCEIVED STRESS

2. Depression

We measure depression using the Patient Health Questionnaire (PHQ-9), which assesses depressive symptoms consistent with Diagnostic and Statistical Manual criteria. Higher scores indicate more severe symptoms and reflect sustained impairment in functioning and quality of life.

17%
EXPERIENCED MILD TO MODERATE DEPRESSION

3. Anxiety

We measure anxiety with the Generalized Anxiety Disorder scale (GAD-7), a standard instrument for assessing symptoms of generalized anxiety. Higher scores indicate greater anxiety severity and capture the extent to which worry and tension interfere with daily life and quality of life.

60%
EXPERIENCED MILD ANXIETY

Perceived Stress

The Gradient Boosted Regression (GBR) model predicting PSS-4 scores demonstrated strong predictive performance on the validation set (RMSE ≈ 1.16, MAE ≈ 0.91, $R^2 \approx 0.88$), with no evidence of overfitting, as validation error was marginally lower than training error. Feature importance analysis identified overall quality-of-life rating as the strongest predictor of perceived stress, followed by the interaction between housing instability and health-related quality of life (HI×HQoL), suggesting that housing instability amplifies the relationship between health-related QoL and stress. Socioeconomic factors—including income and education—and the housing instability index itself demonstrated moderate influence, while geographic indicators (ZIP Code and perceived physical environment) contributed modestly. Shapley Additive Explanations (SHAP) confirmed these patterns, showing that higher HQoL ratings generally reduce predicted stress, while low HQoL combined with housing instability amplifies it; conversely, demographic variables such as race, sex, and language status clustered near zero, indicating comparatively limited and context-dependent contributions to perceived stress outcomes.

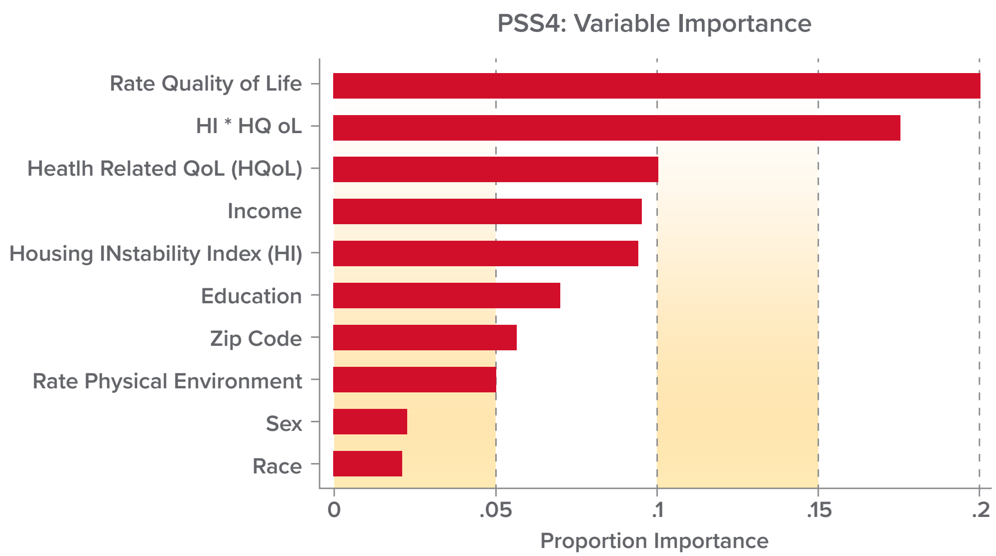


Figure 5. *Summary plots for housing instability and perceived stress: variable importance graph depicting how much each predictor contributes to the predicted power of the model; variables with higher importance scores have a stronger impact on the model's predictions.*

Depression

The machine learning model predicting depression scores performed well, accurately capturing depression severity with minimal error and no signs of overfitting (RMSE ≈ 1.39, MAE ≈ 1.03, $R^2 \approx 0.93$). The most important factor driving predicted depression was HQoL—contributing roughly twice as much as any other variable—meaning that how a person perceives their own health is strongly tied to their level of depressive symptoms. Overall quality of life was the next most influential factor, followed by housing instability and its interaction with HQoL, indicating that unstable housing both directly raises depression risk and worsens the impact of poor health perception. Education and income played a smaller but still meaningful protective role, where higher levels of both tended to be associated with lower predicted depression. Geographic factors such as ZIP Code and perceived physical environment contributed modestly, pointing to some place-based variation in depression outcomes. Demographic characteristics such as race, sex, and language had very little influence on predictions compared to the health and housing-related factors.

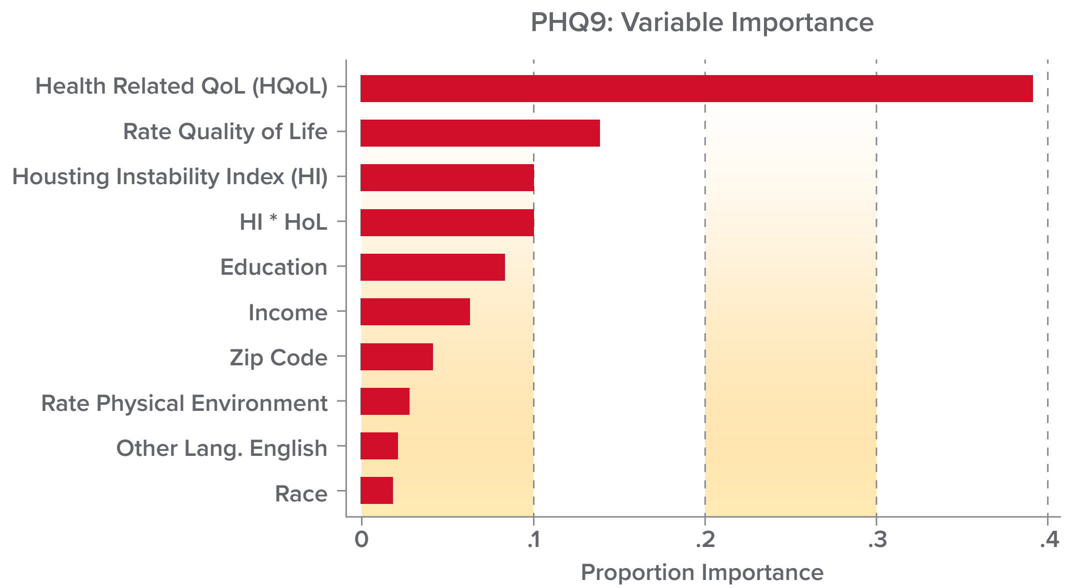


Figure 6. *Summary plots for housing instability and depression: variable importance graph depicting how much each predictor contributes to the predicted power of the model; variables with higher importance scores have a stronger impact on the model's predictions.*

Anxiety

The machine learning model predicting anxiety scores (GAD-7) performed very well, explaining approximately 92% of the variation in anxiety severity with small prediction errors of around 1 to 1.5 points, and showed no signs of overfitting. Similar to the depression model, health-related quality of life (HQoL) and overall perceived quality of life were the strongest predictors of anxiety, meaning that how a person feels about their health and life overall is most closely tied to their anxiety levels. Housing instability was the next most influential factor, both directly increasing anxiety and amplifying the negative effects of poor health-related quality of life—that is, when someone is experiencing housing instability and poor HQoL simultaneously, their predicted anxiety is pushed even higher. Education and income contributed modestly, with higher levels of both generally associated with lower anxiety. Geographic location (ZIP Code) showed some place-based variation in anxiety outcomes, while race, perceived physical environment, and language had very little impact on predictions.

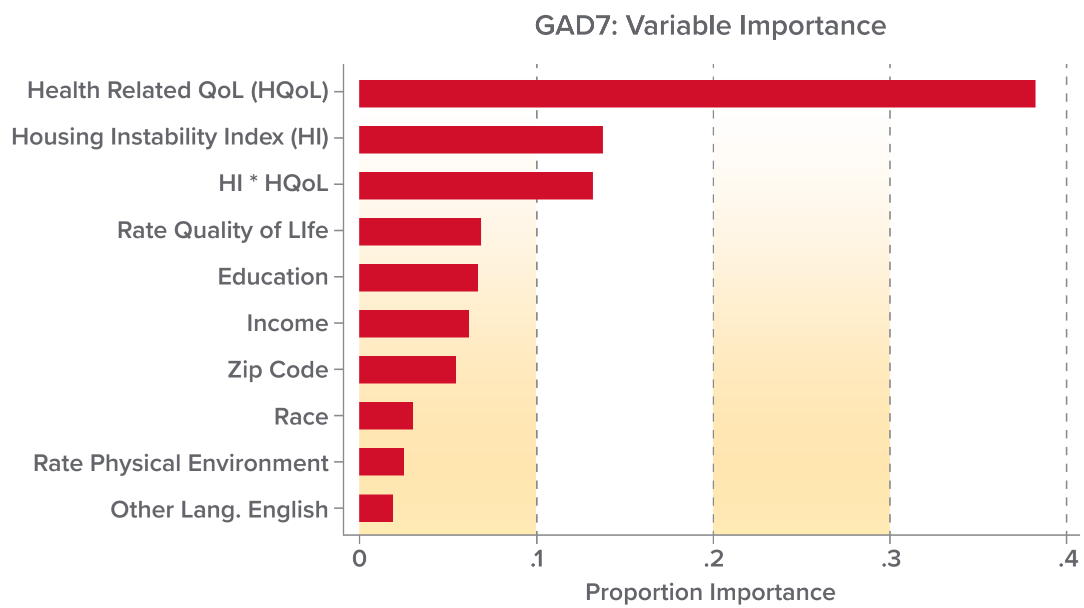


Figure 7. *Summary plots for housing instability and anxiety: variable importance graph depicting how much each predictor contributes to the predicted power of the model; variables with higher importance scores have a stronger impact on the model's predictions.*

Summary

Across outcomes, our results show that housing instability and health-related quality of life are the two most influential predictors of mental health—stress, depression, and anxiety—among Fort Bend County residents.

Quality of life is not a secondary consideration in these models; it is a central pathway. Health-related quality of life and self-rated quality of life consistently predict mental health outcomes and, in many cases, show effects that are as large as or larger than housing instability itself.

Income, education, and financial stability also contribute, typically ranking just below housing instability and quality of life in importance. Demographic characteristics such as sex, race/ethnicity, and language spoken at home have more limited predictive value once differences in housing conditions and quality of life are accounted for.

Geographic variation also plays a very important role. Housing instability and mental health challenges overlap geographically, the research team grouped ZIP Code areas into four easy-to-read categories: (1) white = low housing instability and low levels of mental health symptoms; (2) light gray = high housing instability but low mental health symptoms; (3) dark gray = low housing instability but high mental health symptoms; and (4) black = high housing instability and high mental health symptoms.

From a policy standpoint, the black areas matter most. These are the places where housing instability and poor mental health are concentrated at the same time—and where residents are also more likely to face limits on health-related quality of life. Overall, the map patterns line up with the results of this project: when housing is unstable and quality of life is strained, mental health risks tend to rise. The key point is that this risk isn't spread evenly across the county; it clusters in specific ZIP Codes where multiple challenges stack on top of each other. Seeing the issue spatially helps clarify where targeted action—stabilizing housing, improving conditions, and strengthening quality-of-life supports—can do the most good.

In short, improving mental health in Fort Bend County requires attention to both housing stability and the quality-of-life conditions that make stability meaningful—safe, decent housing; predictable occupancy; affordability that does not force trade-offs; and the supports that allow residents to live healthy, connected lives.

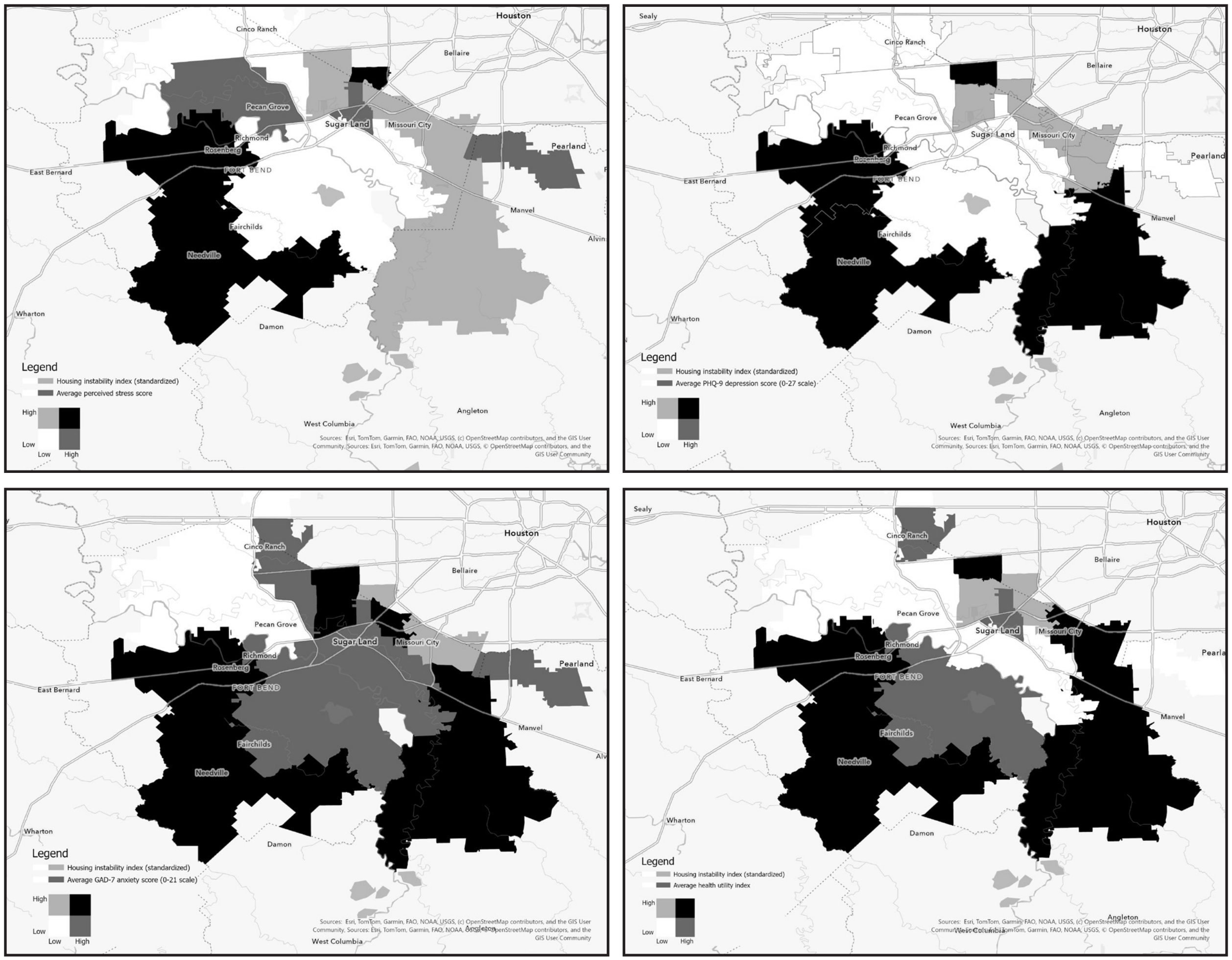


Figure 8. *Co-Location of Housing Instability with Mental Health Symptoms and HQoL Limitations (PHQ-9, Stress, GAD-7, and Health Related Quality of Life).*

References

Murdoch J, Brahmachari M, Okyere D, Moumen F, Streiff S. Measuring Housing Insecurity: Index Development Using American Housing Survey Data. Washington, DC; 2022.

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