

The Homelessness Prevention Unit:

A Proactive Approach to Preventing Homelessness in Los Angeles County



**BRIAN BLACKWELL, COLIN CAPRARA, JANEY ROUNTREE,
ROBERT SANTILLANO, DANA VANDERFORD, CLAIRE BATTIS**

NOVEMBER 2024



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The California Policy Lab generates research insights for government impact. We are an independent, nonpartisan research institute at the University of California with sites at the Berkeley and Los Angeles campuses.

This research publication reflects the views of the authors and not necessarily the views of our funders, our staff, the California Policy Lab Advisory Board, the Homelessness Prevention Unit the Los Angeles Department of Health Services (DHS), the Los Angeles County Chief Information Office, the Los Angeles Department of Mental Health (DMH), or the Regents of the University of California.

Executive Summary

Homelessness continues to be a major problem in California, and new approaches to addressing it are urgently needed. This report brings to light an innovative predictive model for homelessness prevention that is showing promising results.

“It came in a time of crisis when I didn’t expect the help.”¹

The data reveals that this approach — being used for the first time in California and the United States — reaches individuals who are outside of the usual preventive safety net at critical junctures in their lives. Timing is everything — and the Homelessness Prevention Unit connects at-risk people to crucial services and support that could help them avoid homelessness.

Consider the scope of the problem: more than 75,000 people experience homelessness in Los Angeles County on any given night in 2024. This represents a 9% increase since 2022 and a 43% increase since 2018.² Clearly, long-term solutions to homelessness require not just housing people experiencing homelessness but also preventing homelessness before it occurs.

A statewide survey in California revealed that most people experiencing homelessness believe that a one-time payment of \$5,000 to \$10,000 would have resolved their rapidly escalating financial crises and prevented them from experiencing homelessness.³ Existing homelessness prevention programs typically include one-time cash assistance ranging on average between \$1,000 to \$5,000 and short-term direct services such as legal assistance. Several studies have found this approach to be effective at reducing homelessness.⁴ Yet research also highlights how difficult it is to ensure that scarce prevention resources primarily reach people who will experience homelessness if they do not receive this help.⁵ In partnership with Los Angeles County, the California Policy Lab (CPL) is researching strategies to address this challenge, including developing a data-driven predictive model that can proactively identify people at highest risk of experiencing homelessness.

- 1 Unattributed quotes throughout this report were collected by the LA County Homelessness Prevention Unit (HPU) from surveys of those who completed the HPU program. HPU staff conducted these exit surveys as part of their standard program operations for their internal benefit.
- 2 Los Angeles Homeless Services Authority, 2024. 2024 Greater Los Angeles Homeless Count: Data Summary. <https://www.lahsa.org/documents?id=8170-los-angeles-county-hc2024-data-summary> [Accessed: 4 September 2024].
- 3 Benioff Homelessness and Housing Initiative, 2023. California Statewide Study of People Experiencing Homelessness. <https://homelessness.ucsf.edu/our-impact/our-studies/california-statewide-study-people-experiencing-homelessness> [Accessed: 4 September 2024].
- 4 Rolston, H., Geyer, J., Locke, G., Metraux, S. and Treglia, D., 2013. Evaluation of the homebase community prevention program. *Final Report, Abt Associates Inc*, 6, p.2013; Evans, W.N., Sullivan, J.X. and Wallskog, M., 2016. The impact of homelessness prevention programs on homelessness. *Science*, 353(6300), pp.694–699; Phillips, D.C. and Sullivan, J.X., 2023. Do homelessness prevention programs prevent homelessness? Evidence from a randomized controlled trial. *Review of Economics and Statistics*, pp.1–30.
- 5 Shinn, M., Baumohl, J. and Hopper, K., 2001. The prevention of homelessness revisited. *Analyses of Social Issues and Public Policy*, 1(1), pp.95–127.; Evans, W.N., Sullivan, J.X. and Wallskog, M., 2016. The impact of homelessness prevention programs on homelessness. *Science*, 353(6300), pp.694–699.; Phillips, D.C. and Sullivan, J.X., 2023. Do homelessness prevention programs prevent homelessness? Evidence from a randomized controlled trial. *Review of Economics and Statistics*, pp.1–30.

In many prevention programs, participants self-identify as being at risk of homelessness and are then screened into programs based on eligibility criteria or surveys that ask questions about risk factors. CPL's predictive model, however, analyzes de-identified data to proactively identify people at high risk of homelessness. Our research finds that people identified by the predictive model are not connected to typical prevention programs, indicating that both approaches are valuable and reach different people.

“It was perfect timing. I just didn't know where I was going to go.”⁶

To test whether this model could be used to better target prevention resources, in 2020, Los Angeles County created the Homelessness Prevention Unit (HPU) operating out of the Housing for Health division of the Department of Health Services (DHS) in close collaboration with the Chief Information Office (CIO) and Department of Mental Health (DMH). A County seed funding investment in the HPU made it possible to pilot an innovative approach to homelessness prevention that offers flexible cash assistance and tailored case management to individuals and families predicted by CPL's model to be at the highest risk of experiencing homelessness.

Because the HPU is located within the Los Angeles County health system, CPL's model is focused on people who recently received DHS or DMH services and who are observed as stably housed in County administrative data. This group includes nearly 100,000 people over the course of a year (the “eligible population”). CPL uses the model to produce lists multiple times a year of people with the highest risk of homelessness. The lists are anonymized and rank-ordered from highest to lowest risk of homelessness.

CPL sends the high-risk lists to the CIO, where County staff match each person's anonymized record to a County medical record ID. The CIO then transfers the lists to the HPU so that they can identify names, addresses, and contact info of the patients listed. HPU staff then screen out some people on the risk lists that other data sources indicate are currently experiencing homelessness and are therefore ineligible. For eligible individuals, HPU staff attempt to contact them, and, if they are willing, enroll them in the intervention. The HPU serves between 400 to 600 people per year. The intervention includes rapidly delivered, flexible cash assistance, tailored case management, and referrals to other services, such as mental health care, workforce development, and legal services.

This policy report provides an overview of: (1) CPL's predictive model, including data sources and engineering; (2) the equity of the predictive model; (3) outreach and enrollment in the HPU; (4) the HPU's design and service model; and (5) how CPL will evaluate the impact of the HPU program in a randomized control trial.

⁶ Unattributed quotes throughout this report were collected by the LA County Homelessness Prevention Unit (HPU) from surveys of those who completed the HPU program. HPU staff conducted these exit surveys as part of their standard program operations for their internal benefit.

Key findings

The predictive model identifies people at high risk of experiencing homelessness and does it in an equitable manner.

- **The predictive model identifies people at high risk of experiencing homelessness.** Individuals on the high-risk list experience homelessness at a rate that is nearly 3.5 times higher than the rate of homelessness among the eligible population. In addition, all individuals on the high-risk list — whether they experienced homelessness or not — experience other adverse events, such as hospitalizations, mental health crisis holds, criminal legal involvement, and death, at a higher rate than the overall eligible population.
- **The model is equitable in the way it predicts risk of homelessness.** We evaluated whether the model performs similarly for people from different races, ethnicities, and genders. This is important because if the model is less effective at predicting a person's risk of homelessness because of their race, ethnicity, or gender, it could lead to a program that underserves people from that group. We found that the model was slightly better at predicting Black people who were at risk of homelessness. Because Black people are historically at greater risk of homelessness as a result of discrimination and systemic racism, we did not adjust the model to select fewer Black people for the program. Otherwise, we found no differences in the model's performance across race, ethnicity, and gender.

The Homelessness Prevention Unit identifies high-risk individuals who are not accessing other prevention services and responds to their complex needs.

- **The predictive model identifies and the HPU serves individuals who are otherwise not accessing other homelessness prevention services.** There is minimal overlap between the HPU high-risk list and people enrolled in current prevention programs in LA County. There may be multiple reasons for this finding. The HPU model requires recent LA County service activity to be considered eligible, whereas current prevention programs are open to people without any County service history. The HPU model also excludes individuals with recent enrollments in homelessness services, while most other prevention programs do not.
- **HPU participants have more intense service needs than those in other homelessness prevention programs.** The HPU is serving a population with significantly higher service needs, including higher rates of service use indicating serious mental illness, substance use, risk of mortality, and prior involvement with the criminal legal system.

- **The HPU intervention model is more intense than most prevention programs (which typically offer cash assistance without customized case management) and is designed to serve participants with complex needs.** The HPU provides an average of 6 months of case management catered to participants' unique service needs; a 15 to 1 ratio of participants to case managers; an average of \$6,469 of financial assistance used in a variety of ways to foster housing stability or return to work; and direct connections to other County supportive services like job training or mental health treatment.

While enrolling people is very challenging, 92% of people who chose to enroll ended up completing the program.

- **Proactive outreach is very challenging and warrants further research.** Between May 2, 2022, and October 11, 2023 (the “study period”), the HPU attempted to contact 2,271 individuals, and of this group, about 1 in 5 people (472 individuals) enrolled. While the HPU is meeting its enrollment goals, if the County were to expand the HPU's capacity, it would likely also need to strengthen outreach efforts. Outreach to single adults was more difficult than for families, with enrollment rates of 16% and 29% respectively. A significant barrier to contact was incorrect or non-functional contact information or unreturned voicemails, emails, and letters, and 55% of single adults and 45% of families were unreachable. Although proactive outreach presents challenges, it is critical to reach highly acute individuals and families who are otherwise unlikely to connect to prevention resources.
- **The HPU enrolled 472 participants during the study period.** It served slightly more single adult households (52%) than families (48%). It served more women than men (64% vs. 36%), with a participant demographic mainly comprising Black (43%) and Hispanic/Latino (35%) individuals. Most individuals served were between the ages of 25 and 54 (82%) and the largest geographic concentration of participants came from Service Planning Area 6 (25%), which serves South Los Angeles.
- **HPU participants received a variety of services during enrollment.** On average, participants were enrolled for 6 months, received at least one successful service referral, and \$6,469 was spent to support their household.
- **HPU participants have a high level of program completion.** Of the participants who have been discharged from HPU's program, 92% completed the program, 5% lost contact with the program, and the remaining 3% left the program early for various reasons.⁷

⁷ Completing the program means that HPU staff discharged participants after they received their allotted financial assistance and they did not leave the program early like the other 8% (due to losing contact, incarceration, moving out of the county or state, declining to move forward with services, or becoming institutionalized). In the early stages of the program, discharge decisions were made on a case-by-case basis, and specific to each participant's financial assistance budget, housing stability, and other needs as they approached four months with the program. However, since the beginning of 2024, the HPU has tried to standardize and enforce a more consistent discharge policy which expects case managers to discharge participants at the four-month mark with exceptions based on participant need or if they are currently moving. These exceptions allow case managers to extend the enrollment for an additional 2 months.

Evaluation of the Homelessness Prevention Unit

- **The evaluation of the HPU's impact on homelessness is ongoing.** Because there are more people identified as being at high risk of homelessness by the model than the program can serve, it is appropriate for us to randomly select people for the HPU. This allows CPL to evaluate the HPU program's impact with a randomized control trial. Randomization began in February of 2023. CPL plans to analyze the program's outcomes once enough participants have completed the program to estimate its impact, which it projects will be in 2027.

The [Los Angeles Times](#) captured Marshawn Cross wiping away tears after visiting with HPU's Dana Vanderford and Kourtni Gouché. Cross has been in and out of the emergency room and barely getting by on \$200 a month in disability aid plus whatever she could make finding and recycling used cans and bottles. In this meeting, Kourtni Gouché (her HPU caseworker) started the process to get Cross a new bed to soothe her back pain, basic household supplies to help her save money, and to connect Cross with services to ease her depression and addiction to cigarettes, something she told them she long wanted but struggled to do on her own.



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1. Background: A New Approach to Preventing Homelessness in Los Angeles

“...you lose hope. MediCal dropped me, [prior provider] hung up on me. I sat there thinking, ‘Who’s going to help me now?’ And then [case manager] called about a week later and she helped me so much.”⁸

In January 2024, just over 75,000 people were experiencing homelessness in Los Angeles County, and 70% of those were living on the street or in vehicles.⁹ During the Point-in-Time (PIT) Count, researchers survey a representative sample of people to ask more detailed questions about their experiences of homelessness. In the 2024 survey, two out of three surveyed individuals (68%) reported that this was the first time they had ever experienced homelessness. Roughly 30% of respondents experiencing homelessness for the first time are estimated to have been homeless for less than a year.¹⁰ At the same time, the County reported providing nearly 28,000 total housing placements in 2023.¹¹ Taken together, these statistics underscore the importance of responding to and reducing the number of people each year who experience homelessness for the first time. In recognition of this dynamic, the policy response in Los Angeles includes not only increasing housing resources and using those resources more efficiently, but also preventing more people from experiencing homelessness.

Existing homelessness prevention programs typically serve people who are currently housed but at imminent risk of experiencing homelessness. They offer one-time cash assistance ranging between \$1,000 to \$5,000 on average and short-term direct services such as legal assistance. Enrollment may depend on meeting eligibility criteria or risk factors, such as having a low income, receiving a three-day notice to pay rent or vacate, recently having health or behavioral health crises, having a history with the foster care system, or having recent contacts with the criminal legal system.

Several studies have found this approach to be effective at reducing homelessness.¹² While studies in New York City, Chicago, and Santa Clara County found that prevention programs reduce homelessness, these studies also highlight how difficult it is to ensure that scarce prevention resources are targeted to people who would

8 Unattributed quotes throughout this report were collected by the LA County Homelessness Prevention Unit (HPU) from surveys of those who completed the HPU program. HPU staff conducted these exit surveys as part of their standard program operations for their internal benefit.

9 Los Angeles Homeless Services Authority, 2024. 2024 Greater Los Angeles Homeless Count: Data Summary. <https://www.lahsa.org/documents?id=8170-los-angeles-county-hc2024-data-summary> [Accessed: 4 September 2024].

10 Henwood, B., Hickey, S., Kwack, S., Landrian-Gonzalez, A., Stein, A., Kuhn, R. and Petering, R., 2024. *2024 Los Angeles Continuum of Care Homeless Count methodology report*, Suzanne Dworak-Peck School of Social Work, University of Southern California.

11 Los Angeles Homeless Services Authority, 2024. 2024 Greater Los Angeles Homeless Count: Infographics. <https://www.lahsa.org/documents?id=8174-2024-greater-los-angeles-homeless-count-infographics.pdf> [Accessed: 4 September 2024].

12 Rolston, H., Geyer, J., Locke, G., Metraux, S. and Treglia, D., 2013. Evaluation of the Homebase Community Prevention Program. *Final Report, Abt Associates Inc*, 6, p.2013; Evans, W.N., Sullivan, J.X. and Wallskog, M., 2016. The impact of homelessness prevention programs on homelessness. *Science*, 353(6300), pp.694–699; Phillips, D.C. and Sullivan, J.X., 2023. Do homelessness prevention programs prevent homelessness? Evidence from a randomized controlled trial. *Review of Economics and Statistics*, pp.1–30.

otherwise experience homelessness if they did not receive help.¹³ For example, a study on the effectiveness of referring individuals to financial assistance in Chicago found that only 2.1% of families that applied for assistance but did not receive it actually ended up enrolling in an emergency shelter within 6 months of applying for assistance.¹⁴ In a Santa Clara County study, 4.1% of the control group experienced homelessness within 6 months, compared to only 0.9% in the treatment group.¹⁵ Even with the screening conducted in both studies, it's challenging to accurately assess risk of homelessness in advance and, therefore, challenging to target scarce resources to those who need them most.

In 2018, CPL began collaborating with the LA County Chief Information Office (CIO) to explore whether predictive analytics could address this challenge by helping target homelessness prevention services in Los Angeles. In September 2019, CPL and research partners at the University of Chicago Lab for Economic Inclusion published a report on [Predicting and Preventing Homelessness in Los Angeles](#), which used County data on multi-system service use to successfully predict homelessness among single adults receiving mainstream County services. This report provided a sufficient proof of concept for using predictive modeling to predict homelessness among people who were already receiving County services.

In response, the Los Angeles Board of Supervisors approved funding in 2020 for the newly created Homelessness Prevention Unit (HPU), based out of the Housing for Health division of the Los Angeles County Department of Health Services (DHS).¹⁶ The HPU is designed to serve single adults and families who recently received County health services and are predicted to be at high risk of future homelessness by CPL's model.¹⁷ Because available resources are insufficient to serve all eligible individuals identified as being at high risk, individuals are randomly selected for program outreach after an initial eligibility screening. HPU staff then call these individuals and send letters in an attempt to enroll them into the prevention program. Once enrolled, individuals receive 4 to 6 months of ongoing case management, flexible cash assistance to cover such expenses as housing or transportation costs, and referrals to other services that participants might benefit from, such as mental health services, housing navigation, or job-training programs. While these services are tailored to each individual's situation, the goal is the same, which is to help stabilize their situation so they can retain their housing.

13 Shinn, M., Baumohl, J. and Hopper, K., 2001. The prevention of homelessness revisited. *Analyses of Social Issues and Public Policy*, 1(1), pp.95–127; Evans, W.N., Sullivan, J.X. and Wallskog, M., 2016. The impact of homelessness prevention programs on homelessness. *Science*, 353(6300), pp.694–699; Phillips, D.C. and Sullivan, J.X., 2023. Do homelessness prevention programs prevent homelessness? Evidence from a randomized controlled trial. *Review of Economics and Statistics*, pp.1–30.

14 Evans, W.N., Sullivan, J.X. and Wallskog, M., 2016. The impact of homelessness prevention programs on homelessness. *Science*, 353(6300), pp.694–699.

15 Phillips, D.C. and Sullivan, J.X., 2023. Do homelessness prevention programs prevent homelessness? Evidence from a randomized controlled trial. *Review of Economics and Statistics*, pp.1–30.

16 The Board initially approved \$1.5m in Measure H funding, but the HPU later received \$26m in American Rescue Plan Act (ARPA) funds.

17 See section 4 for detailed eligibility criteria.

2. Building the Predictive Model and Testing for Equity

This section provides an overview for a general audience of CPL's approach to building and testing the HPU predictive model. For a more detailed description, please refer to the Technical Appendix.

Data sources

To build and test the HPU predictive model, we used an individual-level linked administrative dataset from the LA County CIO, referred to as the "Information Hub." The Information Hub started in 2006 as an effort by the CIO to link health services and benefits data for adults in LA County. In subsequent years, the CIO and County agencies have worked hard to forge legal agreements and build data-engineering pipelines to link administrative data from 11 County agencies into a secure, regularly-updated data environment. The Information Hub is a critical piece of data infrastructure for both analytical and operational use cases in LA County. It includes health, mental health, social service benefits, arrests, probation, and homelessness service records for millions of individuals from 2010 onwards.^{18, 19}

Building the predictive model

Predictive modeling refers to the use of statistical methods to discover patterns and relationships in data that can be used to predict future outcomes. In this case, the model is designed to predict the future risk of homelessness among individuals who recently engaged with DHS or DMH services. The model looks at historical relationships across hundreds of variables in de-identified data drawn from individuals' prior encounters with health services, safety-net programs, homelessness services, and the criminal legal system. The research team assessed the accuracy of the model by testing its predictions during a defined time period in the past when the outcome was already known and could be checked against the model's predictions. In this case, the model produces a risk score from 0 to 100% for every individual, which represents the estimated probability that they will experience homelessness in the next 18 months. Those risk scores are then compared to actual outcomes to assess the accuracy of the model. If the model is sufficiently accurate, it can be used to predict the same outcome in the future.

18 Social service benefits include programs like CalFresh, MediCal, CalWORKs, and General Relief.

19 See Table 1 for a comprehensive list of the Information Hub data elements used in the predictive model.

Predictive modeling is useful in situations where an estimate of the future likelihood of an outcome can improve decision making. For example, when prevention resources are scarce, predictive modeling may help identify the group of individuals who are most in need of these resources based on the likelihood that they will experience homelessness.²⁰

Predictive Models Do Not Identify Risk Factors or Causes of Homelessness

Because the model can predict homelessness, people assume the model can also identify risk factors for homelessness, but that is not the case. Despite their technical sophistication, the output of predictive models is extremely simple: they produce risk scores from 0 to 100%, representing the predicted probability of an outcome such as future homelessness. They do not explain *why* someone is at risk of future homelessness. Many potential risk factors for homelessness — such as amount of income, notice of eviction, job loss, or significant debt — are not observed in the data because they are not in data sources owned by LA County and are not available for this project. Instead, the goal of the predictive model is to analyze data that is available to make an accurate prediction. For example, one model could identify specific variables that are efficient at predicting the outcome, and a different model could select completely different variables and perform just as well. In such a case, both models are good at prediction but neither offer generalizable information about risk factors for homelessness.

Predictive models also do not identify the underlying causes of homelessness. For example, if you want to know if criminal legal involvement causes homelessness, reverse engineering a predictive model cannot, in itself, give you a credible answer to this question — even if the model predicts homelessness with a high degree of accuracy.²¹ Doing so requires a different research design using specialized causal inference methods in order to separate out genuine causes from spurious or confounding factors. These methods are related to, but distinct from, the techniques used to build predictive models to generate risk scores.²² For these reasons, we do not use predictive models to identify risk factors or causes of an outcome.

20 It is important to note that in this case, we are not predicting the likelihood that people benefit from a prevention program, which would require that we predict the relative impact of the program. Instead, we predict people's risk of homelessness.

21 One important reason is that there may be unobserved “confounding” factors that are not included in the model. For example, after reverse engineering a predictive model, you might find, counterintuitively, that criminal legal involvement *reduces* homelessness according to the model's features or coefficients. However, this might be because your local homelessness service provider runs an in-reach program which helps people exiting jail find stable housing. By implicitly taking into account the jail in-reach program as a protective factor, the predictive model is doing the best possible job of predicting future homelessness in your context. However, it provides misleading information about whether criminal legal involvement increases risk of homelessness.

22 See Westreich and Greenland (2013) “The Table 2 Fallacy” for an explanation of why the full set of coefficients in a model cannot be interpreted causally, even when the main exposure is causally identified.

We started the process of developing a predictive model by defining a relevant population and the target outcome to predict. In this instance, the relevant population consists of stably housed people who had recently used County health services in calendar years 2018 and 2019.²³ The target outcome we predicted is whether these individuals are flagged as experiencing homelessness in any County data system — including homelessness services, health services, and safety-net programs — over a subsequent 18-month period.²⁴

We next selected the “features” used to make the prediction. Features are measures of an individual’s characteristics or their situation at a given point in time that are used to create relationships with a future event. Ideally, we would have included features that we believe are important in determining future outcomes. However, we are often limited to the administrative data that is available. For this study, we rely on a rich set of data elements from the Information Hub. This includes an individual’s characteristics as well as engagement with six county agencies, including health, behavioral health, and safety-net programs, among others. [Table 1](#) gives a high-level description of the features included in the predictive model.

TABLE 1. Features Included in the California Policy Lab’s Predictive Model

CATEGORY	HIGH-LEVEL DESCRIPTION OF FEATURES INCLUDED
Demographics and Geography	Age, Gender, Service Provision Area (SPA), Area Deprivation Index (ADI) of last known ZIP code
Department of Health Services (DHS)	Admission and discharge dates; Emergency/Inpatient/Outpatient; Diagnosis and Procedure Codes; Facility Information
Department of Mental Health (DMH)	Admission and discharge dates; Outpatient/Inpatient/Psychiatric Hold; Diagnosis and Procedure Codes; Facility Information
Department of Public and Social Services (DPSS)	History of benefit receipt (CalFresh, MediCal, CalWORKs, General Relief, and other programs); History of housing and homelessness; Other self-reported characteristics (disabilities, substance abuse, education)
Sheriff	Arrest, booking, and discharge dates; arrest and release codes; arresting agency
Probation	Dates of probation spells; facility information
LA Homeless Services Authority (LAHSA)	Dates of enrollment and exit in homelessness services; service details (interim housing, street outreach, permanent housing)
Dimensions	Time (last 6 months vs. earlier); number and duration of services

²³ See section 3 for a full description of the eligibility criteria for the predictive model. Years 2018 and 2019 were chosen because they provided the required coverage for feature and outcome variables in the Information Hub data at the time of model development.

²⁴ We restrict homelessness services, as observed in the Homeless Management Information System (HMIS) data from the LA Homeless Services Authority (LAHSA), to enrollments in Interim Housing or Street Outreach because enrollment in these programs are most likely to represent experiences of homelessness.

We next select a specific strategy for building or “training” the predictive model. There are various strategies that can be used to model the relationship between features and the target outcome. We assess the performance of each strategy by calculating a measure of its accuracy and then select the final model based on the strategy with the highest accuracy. When doing this, it is important not to test the accuracy of the model using the same population that was used to train the model, otherwise, the accuracy of the models may be overly optimistic. Instead, we create two study populations when identifying the final model: (1) a population of individuals that is used to create the models; and (2) a non-overlapping population of individuals to measure the accuracy of the models and select the final approach.

Measuring the model’s accuracy

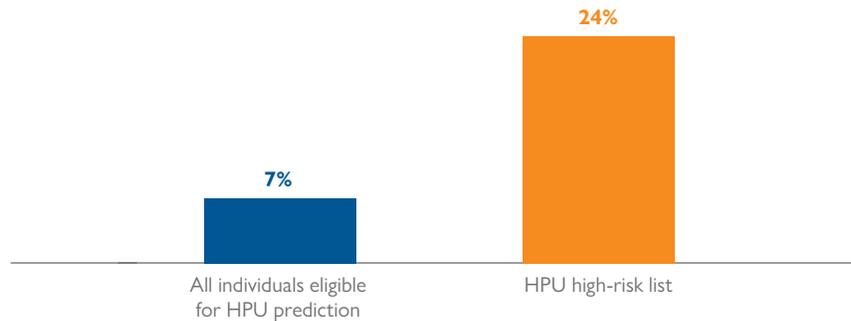
It is essential to measure the accuracy of the predictive model’s approach so that we can assess its value. The measure of accuracy we use is called *Precision*, which is the percentage of individuals who experience the outcome among the high-risk group identified by the model.²⁵ This measure gives a general sense of how much better a model is at predicting an outcome for a group of people as compared to randomly selecting individuals who might experience that outcome. The size of the high-risk group identified by the model is just over 10,000 people over a 12-month period.²⁶ That number accommodates the need for a comparison group in the evaluation, the projected success rate of HPU staff in contacting and enrolling people, and program capacity to serve participants. [Figure 1](#) shows the precision of the model calculated on a test sample of 47,582 individuals. The high-risk group, which is a subset of the overall sample, was almost 3.5 times more likely to experience homelessness (24%) than the overall sample (7%).²⁷

25 Precision for a risk list of just over 10,000 people is the most policy-relevant metric for understanding how the model will perform during the HPU pilot, because the capacity of the pilot is fixed. However, when selecting the specific algorithm used for the predictive model, we found that multiple algorithms yielded similar precision metrics. In order to choose between them, we used the Average Precision Score metric which averages precision across all high-risk group sizes, and thus gives a general sense of how precision might change in the future as the program changes. In general, a smaller risk list size will result in higher precision. See the Technical Appendix for more information.

26 See the Technical Appendix for the formula which determines the size of the risk list.

27 Additional accuracy metrics, including Average Precision Score and Area Under the Receiver Operating Curve (AUROC), are presented in the Technical Appendix.

FIGURE 1. Precision: the prevalence of homelessness within 18 months among people eligible for prediction versus people on the high-risk list



Note: This figure uses 2019 test data to evaluate the precision of the model so that 18 months of outcome data is available. It compares the prevalence of homelessness for the 47,582 individuals eligible for HPU prediction in 2019 to the 10,714 individuals on the HPU high-risk list during the same time period.

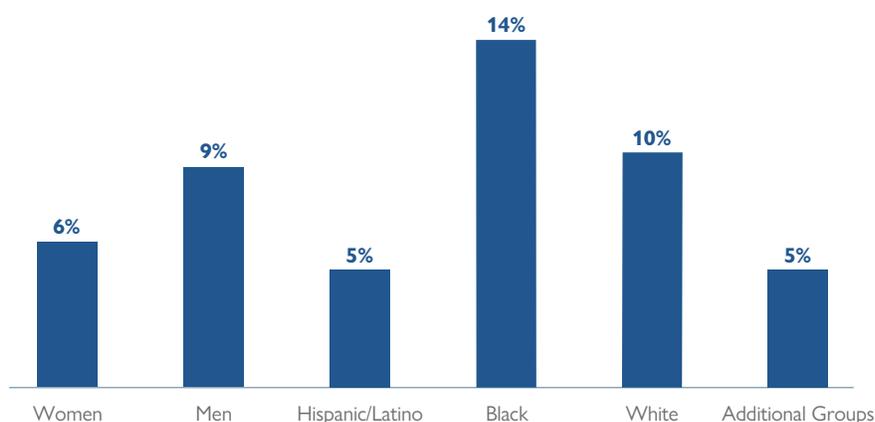
Evaluating the model for equity and fairness

The final step in assessing a predictive analytics model is to assess its equity and fairness. The use of predictive models, a rudimentary form of artificial intelligence fueled by data collected in various settings and human interactions, understandably raises questions about equity, racial bias, and fairness.²⁸ Models can make different mistakes (or errors) for different groups of people — particularly people in different demographic groups. Because of this, transparency around these errors is critical for decision makers and the public to know whether a selected predictive analytics model would create or contribute to inequities across groups. If there is evidence that it would introduce or worsen inequities, then the decision maker could ask for the model to be adjusted or choose to not use it at all. If the model is adjusted, it may become less accurate, but the trade-off may be worthwhile to the decision maker.

28 For an overview, see: Mitchell, S., Potash, E., Barocas, S., D'Amour, A. and Lum, K., 2021. Algorithmic fairness: Choices, assumptions, and definitions. *Annual Review of Statistics and Its Application*, 8(1), pp.141–163.

The context in which the predictive model and the program are being deployed is an important, and often overlooked, dimension of equity. In the U.S., people of certain racial or ethnic groups, particularly Black individuals, are at much higher risk of experiencing homelessness due to discrimination and structural racism in the labor and housing markets and in the criminal legal system. As a result, 30% of those experiencing homelessness in LA County are Black even though Black Angelenos only make up 10% of the overall population.²⁹ When we narrow our scope to only the group of people the model predicts homelessness for, we see again that Black people are more likely to experience homelessness (Figure 2).

FIGURE 2. Prevalence of homelessness within 18 months among people eligible for prediction, by gender, race, and ethnicity



Note: This figure shows rates of future homelessness in an 18 month outcome period for the 47,582 individuals in the 2019 test data used to evaluate the model. Also, people who identified as “Asian American,” “American Indian or Alaska Native,” “Native Hawaiian and Pacific Islander,” “Multiracial,” or “Other” are included in the “Additional Groups” category because they could not be meaningfully analyzed due to small sample sizes..

A key policy goal of homelessness prevention is to address these disparities by helping people at high risk of homelessness avoid that outcome. In addition, this predictive model identifies people who are otherwise disconnected from homelessness prevention programs, including people with higher rates of criminal legal involvement, serious mental illness, and substance use. The HPU is expanding the reach of County resources to people who are historically underserved, which could help address long-standing racial disparities in who experiences homelessness and who has access to services. That said, the predictive models must be monitored for fairness and equity so new biases are not unintentionally introduced. The following section describes how we tested the models for equity and the results of those tests.

²⁹ L.A. County Anti-racism Diversity and Inclusion (ARDI) Initiative, 2022. *State of Black Los Angeles County*. <https://storymaps.arcgis.com/collections/cc7914ce627845448d235549b353f411?item=1> [Accessed 26 September 2024].

HPU client Sandricka Henderson shared with [CalMatters](#) that she was diagnosed with lupus at the start of the COVID-19 pandemic, forcing her to leave her physically demanding warehouse job. Disability benefits only provided about \$1,000 a month, roughly 25% of her former income, leaving her about \$400 short on bills each month. Just before Christmas, her HPU case manager reached out to Henderson and provided a grocery gift card. She also helped her avoid eviction and catch up on car payments.

“I just really needed the help,” Henderson said. Used to working hard and taking care of herself, she added that she never would have asked for it on her own. “It really did change my whole circumstances,” she said. “My son had a Christmas I didn’t think I’d be able to give him.”

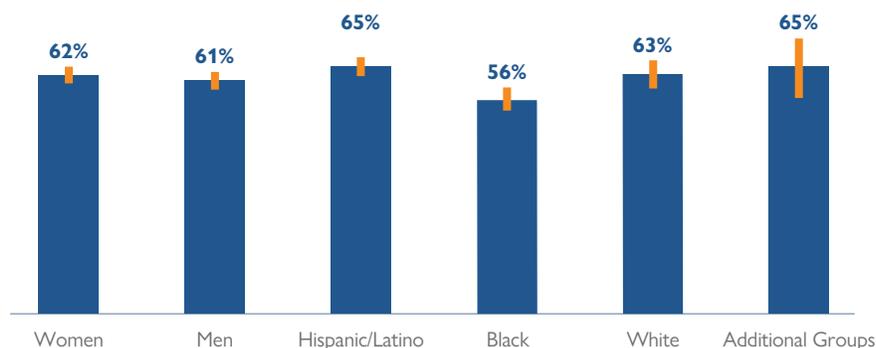


Photo: Jules Hertz

The specific metric we use to evaluate the model’s equity is the false negative rate, sometimes referred to as a “miss rate.” Here, the false negative rate is the percentage of people who were not assigned to HPU outreach, among those who experienced homelessness. Note that because the analysis is concerned with equitable opportunities to enroll in HPU, we define false negatives to include both people who were not selected on the high-risk list, as well as those who were selected on the high-risk list but randomly assigned into the group which does not receive HPU outreach. Because the HPU’s program is a pilot that can only serve a small percentage of eligible people, we expect the false negative rate to be fairly high because it represents the percentage of people who will experience homelessness but did not get access to the limited resources of the HPU. The overall false negative rate is 62%, which means that of about 3,300 people in the 2019 test sample who went on to experience homelessness, 62% (a little more than 2,000) were not predicted by the model as high risk and then assigned to HPU outreach. From an equity perspective, however, the overall false negative rate is less important than differences in false negative rates between groups, which could indicate that some groups are being systematically underserved by the model and the program. An equity analysis is intended to ensure that is not the case.

In our equity analysis of false negative rates by gender, race, and ethnicity, we do not find evidence that the predictive model introduces inequities in identifying individuals who are at high risk of homelessness (Figure 3).³⁰ The only statistically significant difference is for Black individuals, whose false negative rate is five percentage points lower than the overall false negative rate.³¹ This means that the model is more likely to identify Black people who are at risk of homelessness and then assign them to HPU outreach. This may reflect the fact that Black people are at significantly higher risk of experiencing homelessness due to discrimination and systemic racism in the housing and labor market and criminal legal system (see Figure 2). A lower false negative rate also likely reflects indications in the administrative data that Black individuals are at higher risk of homelessness. In the judgment of the research team and the leadership of the HPU, this difference in false negative rates does not warrant making an adjustment to the model, since doing so would involve taking explicit steps to reduce the representation of Black individuals on the HPU high-risk list.³²

FIGURE 3. False Negative Rates: the percentage of people who were not assigned to HPU among those who experienced homelessness, broken down by gender, race, and ethnicity



Note: This figure uses test data on 47,582 individuals in the prediction eligible population (see section 4 for a comprehensive list of “prediction eligible” criteria) from 2019 so that 18 months of outcome data is available to evaluate the equity of the model. Yellow bars represent 95% confidence intervals. Also, people who identified as “Asian American,” “American Indian or Alaska Native,” “Native Hawaiian and Pacific Islander,” “Multiracial,” or “Other” are included in the “Additional Groups” category because they could not be meaningfully analyzed due to small sample sizes.

30 Note that the overall false negative rate (62%) is primarily explained by limited program capacity for the pilot, with only 11% of prediction-eligible individuals in the test data being who would have been assigned to outreach if the HPU was operating at that time. Tests of statistical significance were conducted using 1,000 bootstrap iterations, with selection into the high-risk list and treatment randomization performed within each bootstrap iteration. For race and ethnicity, comparisons are made with White false negative rate as baseline. For gender, comparisons are made with Male false negative rate as baseline.

31 False positives — defined as people who did not experience homelessness but were assigned to HPU outreach — are less important from an equity perspective because they do not represent a harm to the individual. For example, even if someone who would not have experienced homelessness is assigned to HPU outreach, the program may have positive effects on other outcomes such as health and criminal legal involvement. Analogous to the false negative rate results, the only statistically significant difference in false positive rates is for Black individuals, whose false positive rate is higher (more favorable) than for other race and ethnicity groups.

32 The implication that, in practice, equalizing false negative rates entails reducing Black representation in the HPU high-risk list was verified empirically by applying the preprocessing adjustment (“massaging”) described in Kamiran and Calders (2012), where outcome variables in the training data are altered in order to equalize equity metrics in the test data. After applying this adjustment to the model, the statistically significant difference between Black false negative rates and those for other race and ethnicity groups was eliminated. However, Black representation on the high-risk list was reduced from 34% (HPU production model) to 25%.

3. Reaching People with Complex Needs that are Disconnected from Other Prevention Programs

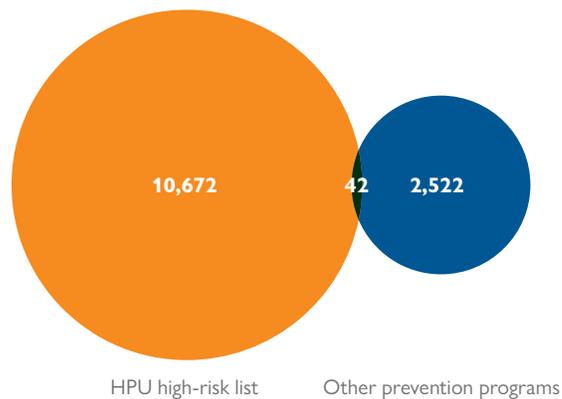
“[The most helpful thing was] helping me pay my rent, helping me get a medical bed that I need for my operation because I have cancer. You guys came at a time when I really needed the help.”³³

After the model was tested for precision and equity, it was put into use. CPL uses the model multiple times a year to produce risk lists totaling 10,000 people per year. The lists are anonymized and rank-ordered from highest to lowest risk of homelessness. The data reviewed in this section reveals that people on these risk lists are much less likely to be served by other prevention programs and have more serious and complex service needs.

Broadening the reach of prevention services

First, the model appears to identify people who are otherwise disconnected from other homelessness prevention programs. **Figure 4** compares people identified by the model using 2019 test data to participants in other homelessness prevention programs in LA County in 2019 that followed a more traditional approach to program enrollment where individuals seek out assistance (i.e., Measure H prevention and problem-solving programs, together referred to as “other prevention programs”).³⁴ In 2019, there was almost no overlap between these two groups.

FIGURE 4. In 2019, only 42 people overlap between the Homelessness Prevention Unit’s high-risk list and other prevention programs



Note: This figure shows the HPU high-risk list from 2019 model validation data, as described in section 3. Other prevention enrollments are from 2019 HMIS data in the Information Hub, for people aged 25 and older in order to correspond with HPU eligibility criteria.

³³ Unattributed quotes throughout this report were collected by the LA County Homelessness Prevention Unit (HPU) from surveys of those who completed the HPU program. HPU staff conducted these exit surveys as part of their standard program operations for their internal benefit.

³⁴ The Los Angeles County Board of Supervisors launched the Homeless Initiative on August 17, 2015 to address the County’s homelessness crisis. The initiative recommended multiple strategies to reduce homelessness, including Strategy A1 for family homelessness prevention and Strategy A5 for individual homelessness prevention. To better fund these strategies, Los Angeles County voters approved Measure H in March 2017, raising taxes to allocate approximately \$355 million annually for homelessness services. To date, “Measure H prevention and problem-solving” represents the County’s primary approaches to homelessness prevention.

While we lack an empirical explanation for why these groups do not overlap, we can make the following educated guesses:

1. **The HPU was designed to reach people with specific service histories not required by other prevention programs.** The predictive model used by the HPU identifies only people who recently received County services. The HPU model also excludes individuals with enrollments in homelessness services in the last two years as observed in the HMIS data. The model uses this as a proxy for housing stability at the time of intervention because the goal of the HPU is to keep people housed. In contrast, other prevention programs do not use prior service history as an eligibility criteria.
2. **Because the HPU uses proactive outreach, it may reach people who are unlikely to seek services.** In a recent statewide survey, only 36% of those experiencing homelessness reached out for help prior to losing their housing, and most of them asked friends and family for support instead of seeking help at a prevention provider or government agency.³⁵ While other prevention programs rely on referrals, HPU's proactive outreach may connect a group that is otherwise not applying for help.
3. **The HPU does not require the same screening and documentation, such as proof of eviction proceedings, as other prevention programs.** Providers for other prevention programs screen applicants and often require them to submit proof of imminent risk of homelessness, including proof of eviction proceedings. They may also require that applicants provide evidence that they have the necessary income to remain stably housed after the prevention assistance ends. The HPU bypasses this additional screening and documentation by removing ineligible participants before outreach and relying on the predictive model — instead of documentation — to identify those at risk.
4. **Some other prevention programs require applicants to be leaseholders or identify a landlord to whom payments can be made.** In practice, this may exclude those with non-leaseholding arrangements who make up a significant share of inflow into homelessness. Nearly half of those entering homelessness in California are leaving doubled-up living situations where they are not formally on the lease.³⁶ In contrast, the HPU can serve people in doubled-up living situations.

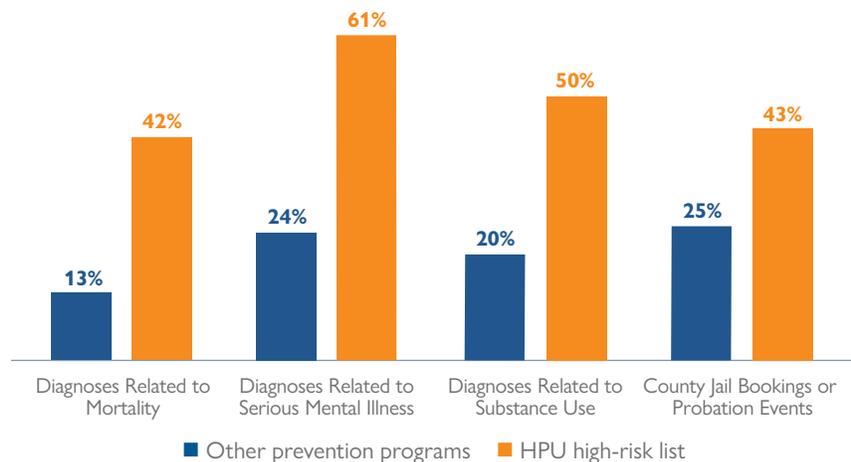
35 Benioff Homelessness and Housing Initiative, 2023. California Statewide Study of People Experiencing Homelessness. <https://homelessness.ucsf.edu/our-impact/our-studies/california-statewide-study-people-experiencing-homelessness> [Accessed: 4 September 2024].

36 Benioff Homelessness and Housing Initiative, 2023. California Statewide Study of People Experiencing Homelessness. <https://homelessness.ucsf.edu/our-impact/our-studies/california-statewide-study-people-experiencing-homelessness> [Accessed: 4 September 2024].

Contacting and serving people with complex needs

In addition to being otherwise disconnected from prevention resources, on average the people on the HPU high-risk lists have more intense service needs. Individuals referred to the HPU from May 2, 2022 to October 11, 2023 had much higher rates of diagnoses related to mortality, serious mental illness, and substance use, as well as higher rates of prior involvement with the criminal legal system when compared to people enrolled in other prevention programs during the same time period (Figure 5).^{37, 38} The fact that individuals on the risk list had higher needs prompted HPU leadership to design a program with more intensive support. The HPU program model is described in more detail in section 4.

FIGURE 5. People identified as high risk by the Homelessness Prevention Unit model are more likely to have prior diagnoses related to mortality, serious mental illness, or substance use and have prior involvement with the criminal legal system than people enrolled in other prevention programs³⁹



Note: This figure compares the 4,559 individuals enrolled in other prevention programs from 5/2/2022 and 10/11/2023 to the 1,614 individuals on the HPU high-risk list during the same time period.

37 Diagnosis codes come from contact with County health and mental health facilities, and are therefore likely to represent an undercount. Diagnoses related to mortality are identified through a combined indicator derived from the Charlson and Elixhauser indices of ICD10 codes. Diagnoses related to serious mental illness and substance use were classified by subject matter experts from UCLA medical school.

38 Measured through County Sheriff bookings and probation data.

39 Date range was chosen to align with the period used to analyze HPU enrollments in section 5. "Diagnoses Related to Mortality" refers to diagnoses in LA County health facilities with an ICD10 diagnosis code having a non-zero value on either the Elixhauser or Charlson comorbidity indices which are frequently used to predict in-hospital mortality (Elixhauser et al., 1998; Charlson et al., 1987). "Diagnoses Related to Serious Mental Illness" refers to diagnoses in LA County health or mental health facilities with an ICD10 code categorized as Serious Mental Illness according to an index provided by the UCLA medical school. "Diagnoses Related to Substance Use" refers to diagnoses in LA County health or mental health facilities with an ICD10 code related to substance use, or admission into LA County Department of Public Health (DPH) substance abuse treatment programs. "Criminal Legal Involvement" refers to bookings into County jails or probation spells.

HPU participants Dulce Volantin (left), Valarie Zayas, and their dog Zoey met with [NPR](#) in their new apartment. Volantin had experienced severe episodes of mental illness that led to hospitalization, while Valarie worked temporary jobs to supplement Dulce disability benefits. The couple, who met in prison years earlier, had been living in their car before losing it. They resorted to selling clothes and donating blood plasma to afford motel rooms. Their HPU case manager helped them secure a subsidized apartment with on-site support for Dulce’s mental health needs. When asked what the program has meant for them, Dulce became emotional and said, “The world, the world.”



Photo: Grace Widyatmadja/NPR

“I started to reach out to local churches or places that said they offered rent assistance...But a lot of them wanted me to have active eviction notices in order to give me assistance. I felt like I was running out of options. I’d reached out to pretty much everyone I could possibly think of with no luck.”

— Courtney Peterson⁴⁰

40 Rogers, K., 2024. Los Angeles is using AI in a pilot program to try to predict homelessness and allocate aid. CNBC, April 19, 2024. <https://www.cnbc.com/2024/04/19/los-angeles-is-using-an-ai-pilot-program-to-try-to-predict-homelessness.html> [Accessed 21 October 2024].

4. Prevention Unit

Due to the unique characteristics of those identified as being at high risk of homelessness by CPL’s model, the HPU needed to design a novel program specifically suited to their needs. The HPU gives case managers flexibility and discretion for how to spend financial assistance and how quickly it can be used. In collaboration with participants, case managers develop customized service and housing plans due to variation in needs among households served. HPU also implemented program design elements that are critical for the impact evaluation to test if the program is working as intended. The following section describes the sequence of events that led to the creation of the HPU and how the program operates.

“[The most helpful thing was] getting financial help to pay my rent. I had just lost my job so this came at a good time”⁴¹

In 2020, the County initially funded the HPU with \$1.5 million to design and implement its new pilot program. With this funding, the HPU adopted a participant-centered homelessness prevention model, where participants help determine the intervention components that will best meet their specific needs. Case managers work closely with participants to identify their highest priorities for flexible cash assistance, connect them to other County services and benefits, and tailor housing retention or housing navigation plans to each household’s needs. Case manager caseloads are kept intentionally low at 15 participants per case manager so that they can provide high-quality, responsive support for the duration of their program enrollment.

In December of 2021, the HPU received an additional \$26 million in funding under the American Rescue Plan Act, which helped the HPU scale up and make meaningful changes to the program model. The HPU expanded eligibility to include families, hired additional data specialists, case managers, and program managers to account for increased enrollment, and hired specialized staff for outreach and housing navigation. The program’s key components are described in the following section, including how the prediction to enrollment workflow operates in practice as well as the staffing structure and services provided during enrollment.

FIGURE 6. Homelessness Prevention Unit program timeline

2019	2020	2021	2022	2023
California Policy Lab and its partners publish proof-of-concept report on predicting homelessness for prevention	County approves pilot funding for HPU to design and implement new program	CPL builds and tests prediction pipeline HPU begins outreach and enrollment for pilot HPU receives \$26 million in additional funding from the American Rescue Plan	HPU continues scaling up with additional funds: <ul style="list-style-type: none"> expands to families hires more case and program managers hires specialized staff for outreach and housing navigation 	Evaluation begins with randomized treatment

41 Unattributed quotes throughout this report were collected by the LA County Homelessness Prevention Unit (HPU) from surveys of those who completed the HPU program. HPU staff conducted these exit surveys as part of their standard program operations for their internal benefit.

Workflow from prediction to enrollment

Implementing predictive analytics within a new program operating out of a government agency required careful planning, design, and implementation. The process and stages took about a year to design and implement and are described below.

1. **Identify eligible people:** Using LA County’s linked administrative data environment (called the Information Hub),⁴² people are identified who meet the eligibility criteria for receiving a prediction, or risk score, from the predictive model. In summary, HPU program participants must:
 - a. Be 25 years or older⁴³;
 - b. Have used County health services in Department of Health Services (DHS) or Department of Mental Health (DMH) facilities in the last six months;
 - c. Have an active Department of Public and Social Services (DPSS) benefit receipt record without a homelessness flag in the month of the prediction date;
 - d. Have no records in HMIS in the two years prior to the prediction date;
 - e. Have no history of placement in Permanent Supportive Housing; and
 - f. Have no prior CES triage tool assessment scores of 8 and above.

Criteria (c) through (f) are primarily intended to ensure that people referred to the HPU are stably housed and not already experiencing homelessness. Because stable housing status at any given time is not directly observable in the Information Hub data, we used a range of proxy measures to approximate it. These criteria were developed in collaboration with HPU staff and were verified by inspection of internal administrative data systems unavailable in the Information Hub. There were 95,308 individuals meeting the above eligibility criteria in the 2019 test data used to validate the model. The number of eligible people will vary over time with changes in inflows into County health facilities and social service benefits programs.

FIGURE 7. Stages of identification and enrollment of Homelessness Prevention Unit program participants



42 See section 2 for a description of the data used for the HPU model.

43 The pilot program was originally intended to only serve adults, and so this requirement screened out Transition-aged Youth (TAY) aged between 18 and 24 as well as unaccompanied minors under the age of 18. For more information about programs that serve TAY, please see CPL’s recent report: [Aging Out of Foster Care in Los Angeles: Opportunities to Prevent Homelessness Among Transition-Aged Youth](#). The HPU expanded eligibility to include families in 2022, but this age requirement remained in place to continue to serve adult heads of households.

2. **Produce high-risk list:** The predictive model is used to generate risk scores (predicted probabilities of future homelessness between 0 and 100%) for the people identified in stage (1). Individuals with the highest risk scores are added to the “high-risk list.” The number of people on the high-risk list is determined by the anticipated number of enrollments in the program. Because not everyone referred to the HPU is contactable or ends up enrolling in the program, and because people are randomly selected for outreach as described in stage (4), the size of the high-risk list is larger than the number of anticipated enrollments in the program. Based on expected enrollment and manual screening rates, and taking into account the size of the randomized comparison group, we estimated that approximately 10,000 people would need to be referred to the HPU over a 12-month period to meet program capacity of 450 single adults and 300 families as anticipated during the program design phase in 2021.⁴⁴
3. **Re-identification and additional eligibility screening:** CPL sends the high-risk list multiple times a year to the CIO where they match the anonymized records with County medical record IDs so that HPU staff can identify the names, addresses, and contact info of individuals listed. Then HPU staff perform an additional eligibility screening process, checking that referred participants still meet the eligibility criteria according to internal County medical records and case management data which are unavailable for use in the predictive model. This screening is required because participants’ stable housing status and other eligibility criteria may have changed in the time that elapses between the participants’ data being loaded into the Information Hub and the date of referral to the HPU, and also because there are eligibility indicators, such as homelessness status in County mental health facilities, that are not currently in the Information Hub.

⁴⁴ The number referred to the HPU is much larger than the number eventually enrolled because many people are screened ineligible, are unable to be contacted or choose not to enroll during outreach, or are randomized into the comparison group for the causal evaluation. See the Technical Appendix for the formula which determines the size of the risk list referred to the HPU.

4. **Random selection:** Among the remaining eligible individuals, half are randomly selected for proactive outreach. The HPU uses random selection because there are more eligible individuals than the program can currently serve, and it also enables CPL to evaluate the causal impact of the program by comparing outcomes of those who were selected for proactive outreach with the remainder of eligible individuals.⁴⁵
5. **Proactive outreach:** The people randomly selected in stage (4) are assigned to HPU case managers for proactive outreach. HPU case managers and outreach coordinators receive new lists for outreach monthly, and the number of assignments varies based on caseload capacity. Each potential participant receives an outreach letter mailed to every address gathered during the additional eligibility screening process described above and three phone calls to every available phone number over the span of three weeks. If an email address is available, HPU will also use that. An example of the script that outreach staff use once they establish contact with a new potential participant is available in [Appendix Figure A1](#). These outreach attempts are logged in workbooks that document various outreach outcomes. The team notes when people are not successfully contacted or choose to not enroll in the program.
6. **Program enrollment:** People who agree to participate in the program are asked to complete consent forms that are either emailed, mailed, or signed in person. After returning their consent forms, participants are assigned a case manager and outreach staff complete a warm handoff to the case manager. The HPU requires that case managers schedule and complete the assessment with their participants (which typically takes about 1 hour) prior to the participant receiving their financial assistance budget cap. This is required because the assessment may show that some participants were actually a different household type (single adults vs. family) or not eligible. Additionally, information collected during the assessment is used to complete profile creation and enrollment in the County's internal medical database. If a participant is experiencing a crisis or needs financial assistance before they can complete the assessment then a case manager can do a partial assessment to collect consents as well as verify the household type and eligibility, and then finish the full intake assessment later. Only after case managers complete this consent, assessment, and enrollment process can participants begin to receive services, including case management, flexible financial assistance, and referrals to other resources.

⁴⁵ See section 6 for details on the randomized evaluation.

HPU Program design

To accomplish the above workflow, DHS developed an organizational structure broken into four major teams: (1) Case Management, (2) Data, (3) Support, and (4) Budget. The Case Management team consists of about 20 case managers (ten for single adults and ten for families) who are responsible for the overall care coordination of HPU program participants. The Data team is made up of two program managers and four data specialists in charge of analyzing internal County data systems to verify eligibility and service needs of people referred to the HPU by the risk list. The Support Team includes a housing navigator, linkage navigator, and the outreach team (one program manager and four outreach specialists). The housing navigator helps participants that need to find new housing identify opportunities and apply, while the linkage navigator identifies County services and resources that participants might be eligible for and helps get them connected. The outreach team is focused solely on reaching out to eligible potential participants to get them enrolled in the program. Finally, the Budget team — one manager and one budget specialist — coordinates and reconciles the provision of financial assistance within assigned budget caps in a close working relationship with the service provider contracted to provide financial assistance, Brilliant Corners.⁴⁶

Once enrolled, the HPU provides participants with (1) specialized case management, (2) flexible financial assistance, and (3) connections to supportive services to help them stabilize and sustain their housing situation.

1. **Case management:** HPU case management includes regular check-ins with a HPU case manager, over the phone or in-person, with a focus on tailoring housing retention or navigation plans to households needs. Case management also includes problem solving support, such as mediation between landlords, tenants, and other third parties, or advocacy on behalf of the participant for securing housing, preventing eviction, or applying for other benefits.
2. **Financial assistance:** HPU program participants are allocated a financial assistance budget that ranges from \$4,000 to over \$10,000 depending on household size and the program arm they are assigned.^{47, 48} When possible, this is provided to third parties such as landlords or vendors in order to avoid directly impacting participants' eligibility for means-tested programs. This flexible assistance can be spent on a wide range of housing needs identified with case managers as part of their housing plan, but it often includes rental assistance and assistance with rental

⁴⁶ Brilliant Corners is a nonprofit organization that provides supportive housing solutions, combining affordable housing with supportive services to help vulnerable individuals and families achieve housing stability. The HPU partners with the Brilliant Corners to administer financial assistance to speed up the process.

⁴⁷ The HPU designed the program with two different types of financial assistance, or “program arms,” to see if the amount of financial assistance has a significant impact on effectiveness. See section 5 for more information about the two types of financial assistance offered to participants.

⁴⁸ See section 5 for preliminary analyses of financial assistance actually received by HPU participants.

arrears, utility payments or utility arrears, transportation assistance (vehicle repairs, DMV support, Transit Access Pass Cards for public transportation, etc.), medical expenses, debt resolution, food support, and home furnishing support.

“At the time when I got the phone call, I had a lot of issues with my car, my job, a lot of things. At that moment it helped me be able to pay rent, drive a car so I can look for a job”⁴⁹

3. **Connections to additional services:** Case managers also make referrals to other providers and resources in an effort to connect participants with long-term community support that would extend beyond their time in the program. The most frequently documented County referral categories include employment services, housing navigation, other housing support, and mental health services. The HPU team has pointed out that this is an especially challenging part of their work. While many participants acknowledge the potential benefits of focusing on longer-term services, they are often reluctant when the opportunity arises. Case managers report that participants are often overwhelmed, which makes prioritizing longer-term services difficult. Instead, participants are focused on more immediate issues that can be resolved with financial assistance. Moreover, the program’s short duration makes it difficult for case managers to follow up on pending referrals or ensure continued engagement after participants leave the program. Despite these challenges, the HPU team would like to expand and prioritize this part of their program as it continues to grow and evolve.

After receiving all or some combination of the above services, participants are discharged from the program. They are usually enrolled for around 4 months unless an extension is granted which can extend their service duration to 6 months. At the time of discharge, all participants are asked to complete an exit survey which provides the HPU with self-reported data on the overall experience of their time in the program and how they feel about their housing stability and prospects at the time of leaving the program.⁵⁰

49 Unattributed quotes throughout this report were collected by the LA County Homelessness Prevention Unit (HPU) from surveys of those who completed the HPU program. HPU staff conducted these exit surveys as part of their standard program operations for their internal benefit.

50 See section 5 for preliminary analyses of exit survey data for HPU participants who have completed the program to date. It should be noted, these surveys were not conducted by the CPL research team but rather by the HPU for the purpose of program improvement.

5. Outreach, Enrollment, and Services Provided

Outreach and the challenge of establishing contact

“We have clients who have understandable mistrust of systems... They’ve experienced generational trauma. Our clients are extremely unlikely to reach out for help.”⁵²

— Dana Vanderford,
Associate Director of
Homelessness Prevention
at Housing for Health

Outreach data reveal that establishing initial contact with a prospective participant is the biggest challenge to enrollment. Reliable contact information is not always available to the HPU. When it is, households often do not answer the phone. From May 2, 2022 through October 11, 2023, the HPU reached out to 2,271 people: 1,499 single adults and 772 families.⁵¹ Only 21% of people the HPU attempted to reach ultimately enrolled in the program (472 individuals).

Figure 8 illustrates that outreach and enrollment of single adults was more challenging than families, with only 16% of single adults enrolling compared to 29% of families. Over half (55%) of single adults and a little less than half (45%) of families that the HPU attempted to reach were unable to be contacted, due to either non-working or wrong phone numbers or unreturned voicemails, emails, and letters.

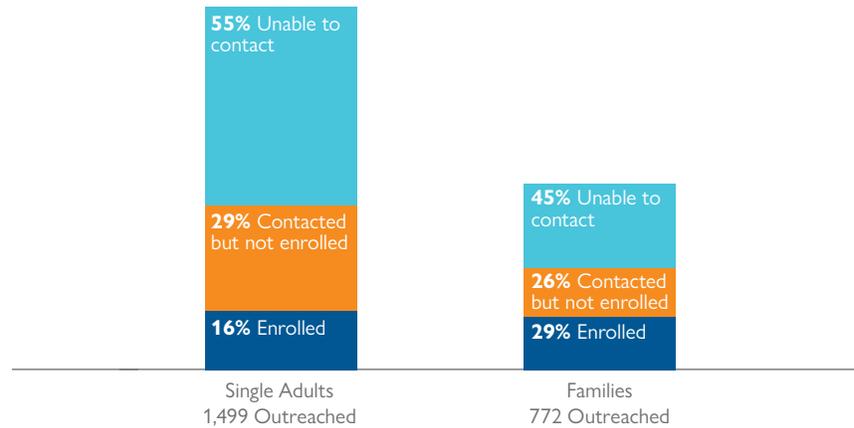
However, getting into contact is not the only barrier to enrollment. Of those assigned to outreach, 29% of single adults and 26% of families were reached by HPU staff but they ended up declining to enroll or stopped responding to the outreach specialist. Due to the nature of the proactive outreach process, HPU staff find that people are often skeptical about the legitimacy of the program, and rightfully so given that receiving an unsolicited phone call with an offer of substantial rental assistance might seem too good to be true. The Federal Trade Commission reported that the most common type of fraud victimizing people in the US in 2023 was “imposter fraud” where people pretend to be offering assistance from a government agency, a bank, technical support, or a well-known business.⁵³ However, HPU outreach specialists, some of whom are multilingual, are trained on how best to approach this reticence by offering to follow up via email with additional information to build trust. If they can establish this trust and convince individuals that the program is real, outreach specialists find that people are more likely to enroll.

51 These dates represent when the HPU began collecting data on participants (May 2022), and the end of the sample period used in the study (October 2023). People are referred to the HPU on an as-needed basis depending on program capacity at any given time. These numbers are lower than the anticipated 10,000 per year due to the additional time required to develop and scale the intervention in the pre-evaluation and early evaluation phases.

52 Ludden, J., 2023. Los Angeles is using AI to predict who might become homeless and help before they do. NPR, October 4, 2023. <https://www.npr.org/2023/10/04/1202374047/los-angeles-is-using-ai-to-predict-who-might-become-homeless-and-help-before-they-do> [Accessed 21 October 2024].

53 Federal Trade Commission (FTC), 2024. Think you know what the top scam of 2023 was? Take a guess. <https://consumer.ftc.gov/consumer-alerts/2024/02/think-you-know-what-top-scam-2023-was-take-guess> [Accessed: 4 September 2024].

FIGURE 8. Homelessness Prevention Unit outreach outcomes by household type



Note: This figure uses data from the 2,271 people HPU conducted outreach to from 5/2/2022 to 10/11/2023; 472 people from this group subsequently enrolled in the HPU.

Characteristics of enrolled participants

This section analyzes preliminary data on who enrolled in the HPU. [Table 2](#) provides demographic data for the 472 participants that enrolled in the HPU from May 2, 2022 through October 11, 2023. It shows that overall, the HPU served more women than men, a majority of participants were either Black (43%) or Hispanic/Latino (35%), and most participants were between the ages of 25 and 54 (82%) with only 18% of participants 62 years or older. Participants came from across the county, but roughly 1 in 4 were in South Los Angeles (SPA 6) while fewer than 1 in 10 were in West Los Angeles (SPA 5).

Fifty-two percent of households served by the HPU were single adults and 48% were families. Single adults enrolled in the HPU were primarily Black (37%) and Hispanic/Latino (34%), with slightly more men (55%) than women. For families, HPU participants were much more likely to be women (86%) and disproportionately Black (50%). Single adult participants were also slightly older. Twenty-seven percent were fifty-five years of age or older compared to only 8% of family participants.

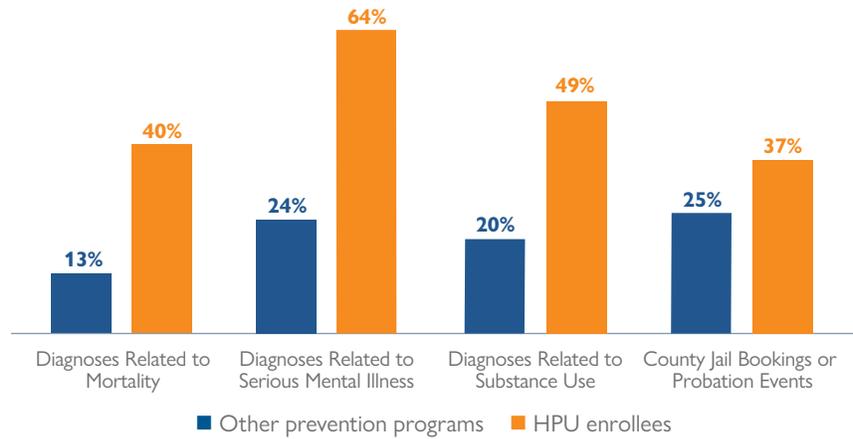
TABLE 2. Demographics of Homelessness Prevention Unit enrollees

	ALL(%)	SINGLE ADULTS (%)	FAMILIES (%)
Gender			
Male	36	55	14
Female	64	43	86
Race and/or Ethnicity			
Black	43	37	50
Hispanic/Latino	35	34	36
White	12	18	6
Asian	2	—	—
Native Hawaiian or Other Pacific Islander	—	—	—
American Indian or Alaska Native	—	—	—
Multiracial	—	—	—
Other	—	—	—
Age			
25–34	35	30	40
35–54	47	43	52
55+	18	27	8
Geography			
SPA 1 (Antelope Valley)	14	10	17
SPA 2 (San Fernando Valley)	12	13	10
SPA 3 (San Gabriel Valley)	8	8	8
SPA 4 (Central Los Angeles)	13	14	12
SPA 5 (West Los Angeles)	—	—	—
SPA 6 (South Los Angeles)	25	23	27
SPA 7 (South Bay / Harbor)	10	10	9
SPA 8 (East Los Angeles)	18	20	15
Total (#)	472	246	226

Note: This table uses data from 472 people enrolled in the HPU from 5/2/2022 and 10/11/2023. Here data for “families” refers to the individual serving as the HPU’s point of contact. Table values denoted with “—” are suppressed due to cell sizes below 10. The Los Angeles Coordinated Entry System (CES) for homeless services is organized into eight geographic regions called Service Planning Areas (SPAs). For more information, see <https://www.lahsa.org/ces/home/accessingces/>

Because people identified by the high-risk lists had higher rates of services related to risk of mortality, serious mental illness, substance use, and criminal legal involvement compared to people enrolled in other prevention programs, it's not surprising that those enrolled in the HPU did as well. In the 5 years prior to their referral to the HPU, 64% percent of HPU enrollees received services related to serious mental illness, 49% received services related to substance use, 40% received services indicating a diagnosis related to mortality, and 37% had contact with the County jail or probation (see Figure 9).

FIGURE 9. People enrolled in the Homelessness Prevention Unit are more likely to have prior diagnoses related to mortality, serious mental illness, or substance use and have prior involvement with the criminal legal system than people enrolled in other prevention programs^{54, 55}



Note: This figure compares the 4,559 individuals enrolled in other prevention programs from 5/2/2022 and 10/11/2023 to the 472 individuals enrolled in the HPU during the same time period.

Services provided

There is meaningful variation in experiences for those enrolled in the HPU's prevention program. The following data uses a smaller subset of the above sample to look at variations in service duration and financial assistance. The smaller sample is limited to individuals who had at least 6 months of data to observe these outcomes. Table 3 shows that between May 2, 2022 and April 1, 2023, the HPU program enrolled 306 participants who were in the program for

54 "Diagnoses Related to Mortality" refers to diagnoses in LA County health facilities with an ICD10 diagnosis code having a non-zero value on either the Elixhauser or Charlson comorbidity indices which are frequently used to predict in-hospital mortality (Elixhauser et al., 1998; Charlson et al., 1987).

"Diagnoses Related to Serious Mental Illness" refers to diagnoses in LA County health or mental health facilities with an ICD10 code categorized as Serious Mental Illness according to an index provided by the UCLA medical school. "Diagnoses Related to Substance Use" refers to diagnoses in LA County health or mental health facilities with an ICD10 code related to substance use, or admission into LA County Department of Public Health (DPH) substance abuse treatment programs. "Criminal Legal Involvement" refers to bookings into County jails or probation spells.

55 Similar to Figure 6, this figure looks at diagnoses and criminal legal involvement, but instead of comparing these risk factors for those enrolled in other prevention programs to the HPU high-risk list, it compares them to those actually enrolled in the HPU program. This is done to show that not only does the model identify a higher risk group of individuals than other prevention programs, but that the HPU also enrolls and serves those with more complex service needs.

“I have a clear head. I don’t have to worry about where our next meal is going to come from.”⁵⁶

— Valarie Zayas

an average of about 6 months (182 days), which is 2 months longer than the 4 month duration the HPU originally intended for the program. HPU staff found it increasingly difficult to discharge participants after only 4 months because it felt too short for many case managers to fully resolve all of a participant’s needs and establish stability. HPU staff also reported that delayed payment processes (e.g., waiting on a final check to get to a landlord or a furniture order to get delivered) and unspent budgets led to extended program durations. Case managers often needed more time to spend down budgets not because they couldn’t identify a need but instead because of payment delays or sudden changes in housing plans (e.g., case managers saved up funds for a move that didn’t happen in 4 months, so then funds had to be redirected to a different need).

TABLE 3. Number of days over 6 months Homelessness Prevention Unit participants were enrolled

	N	MEAN	CENTILES				
			MIN	25TH	MEDIAN	75TH	MAX
All	306	182	31	126	177	210	489
Single Adults	163	184	36	126	181	217	489
Families	143	179	31	126	176	208	388

Note: This table uses data from 306 people enrolled in the HPU from 5/2/2022 to 4/1/2023.

During the same time period, participants received an average of \$6,469 per household in financial assistance (Table 4). The HPU assigns budget caps based on household size, and single adults on average received \$4,215 less than family households. However, family households were also more likely (by 16 percentage points) to receive more than \$50 over those predetermined budget caps. The HPU also designed the program with two different types of financial assistance available to see if the amount of financial assistance has a significant impact on effectiveness. As expected, single adults assigned to the expanded financial assistance version of the program received on average \$1,711 more than those assigned to the base financial assistance, while families assigned to expanded financial assistance received \$2,126 more on average. Interestingly, regardless of whether a household was assigned to the base or expanded financial assistance, HPU staff were less likely to adhere to the budget cap for families than single adults. The HPU reports that a majority of this total funding was spent on rental assistance and overdue rent, but most participants also received financial assistance for basic needs items (clothing, hygiene, department store gift cards), transportation, and food.

⁵⁶ Los Angeles is using AI to predict who might become homeless and help before they do. NPR. <https://www.npr.org/2023/10/04/1202374047/los-angeles-is-using-ai-to-predict-who-might-become-homeless-and-help-before-the> [Accessed 21 October 2024].

TABLE 4. Financial assistance received over 6 months for Homelessness Prevention Unit participants

	N	MEAN	MIN	25TH	MEDIAN	75TH	MAX	OVER CAP (%)
All	306	6,469	0	4,036	6,000	8,134	17,530	25
Single Adults	163	4,499	0	3,900	4,467	5,977	8,134	18
Base Financial Assistance	77	3,597	0	3,817	3,925	4,025	7,894	19
Expanded Financial Assistance	86	5,308	0	5,746	5,952	6,002	8,134	17
Families	143	8,714	0	7,523	8,650	10,025	17,530	34
Base Financial Assistance	74	7,688	0	6,255	7,587	8,866	12,650	32
Expanded Financial Assistance	69	9,814	0	8,267	9,925	11,097	17,530	35

Note: This table uses data from 306 people enrolled in the HPU from 5/2/2022 to 4/1/2023. “Over Cap” provides the share of households in that row whose total financial assistance exceeded their budget cap by more than \$50. HPU staff advised us to use a \$50 buffer so as to prevent small gift cards from registering as exceeding the cap.

In addition to financial assistance, case managers also attempt to link participants with other County programs and resources specialized to their needs. On average, case workers documented 2.2 attempted referrals and one “successful” referral (i.e., a referral resulting in a participant enrolling in a new program or receiving a new resource) for each participant. The most common linkages were employment, housing navigation, and mental health services. The HPU assigned 160 participants to work with their internal housing navigator, who assisted them with finding new housing if determined feasible and appropriate. Of the participants who received housing navigation services, 22 used their financial assistance to move into new housing while in the program.

Preliminary results point to a positive response

For households that enrolled in the program, preliminary results from exit surveys and administrative data on exit destinations seem promising. According to exit surveys completed with the 170 participants discharged since August 2022, 64% of respondents were “not concerned” about having a stable place to live in the next six months, and about half reported no concerns about paying for housing or utilities. All respondents rated the financial assistance from the program as helpful and a majority reported that, as a result of the program, their housing situation improved (88%) and they were better able to take care of their needs (96%).

“I feel like I’ve got a friend right here.”⁵⁷

— Mashawn Cross

57 Alpert, R., 2022. A computer model predicts who will become homeless in L.A. Then these workers step in. Los Angeles Times, June 12, 2022. <https://www.latimes.com/california/story/2022-06-12/homeless-prevention-unit> [Accessed 21 October 2024].

“We connect to clients at critical junctures in their lives. Clients share with us in very early conversations that they have just recently lost a job, received a verbal warning of eviction from their landlord, or exited the hospital. Clients often report that they have recently had the experience of several doors closing when they attempted to connect to help and that the HPU proactively connecting with them was much-needed relief... We consistently hear from clients that the assistance that they needed came at just the right time from the HPU.”⁵⁸

— Dana Vanderford, Associate Director of Homelessness Prevention at Housing for Health

According to administrative data on exit destinations provided by the HPU, out of the 456 participants discharged from the HPU, 92% completed the program while 5% lost contact with the program and the remaining 3% ended the program early for various reasons (e.g., incarceration, moving out of the county or state, declining to move forward with services, or becoming institutionalized).⁵⁹ A majority of participants (86%) reported living in a permanent housing situation upon discharge, such as rentals, with friends or family long-term, or housing owned by the participant.⁶⁰ The remaining 14% reported living in temporary housing (e.g., staying with friends and family temporarily), incarceration, or their data was missing.

⁵⁸ HPU leadership provided this quote about the timing of the HPU intervention to respond to a request from the CPL research team.

⁵⁹ Completing the program means that HPU staff discharged participants after they received their allotted financial assistance, and they did not leave the program early like the other 8%. In the early stages of the program, discharge decisions were made on a case-by-case basis, and specific to each participant's financial assistance budget, housing stability, and needs as they approached four months with the program. However, since the beginning of 2024, the HPU has tried to standardize and enforce a more consistent discharge policy which expects case managers to discharge participants at the four-month mark with exceptions based on participant need or if they are currently moving. These exceptions allow case managers to extend the enrollment up to 2 more months.

⁶⁰ Living in a “permanent housing situation upon discharge” means that the participant maintained or moved into one of the following situations: (1) Housing owned by participant with or without an ongoing housing subsidy (paying mortgage with no time limit), (2) Housing rented by participant with or without an ongoing rental subsidy (includes shared housing, public housing, or housing with family or friends if participant is paying some portion of rent), (3) Permanent housing or permanent supportive housing for people formerly experiencing homelessness, (4) Nursing or long-term medical care facility, (5) Staying or living with family or friends permanently (cannot be temporary arrangement), or (6) Residential project or halfway house with no homelessness eligibility criteria.

6. Ongoing Evaluation of the HPU Program

At the request of the County, CPL designed an evaluation of the HPU program. Because there are more high-risk individuals than available resources, the HPU program randomly selects individuals on the high-risk list to offer the program. This makes it well suited for a randomized control trial design, which is considered the gold standard for evaluating interventions. The following section describes how CPL plans to evaluate the HPU program.

HPU client Ricky Brown shared his story with [NPR](#). After injuring his back in his 40s, Brown went on disability and lived in a one-bedroom apartment, getting by on Social Security income and occasional odd jobs. When his ex-wife passed away, he became the primary caregiver for his three grandsons. Although he had some savings, it quickly ran out while caring for them. At the time of the NPR interview, Brown's HPU case manager was helping him search for a larger home, likely requiring a housing voucher. They were also working on boosting Brown's income through cash aid and re-enrolling his grandsons in CalFresh. Brown is photographed here with one of his three grandsons.

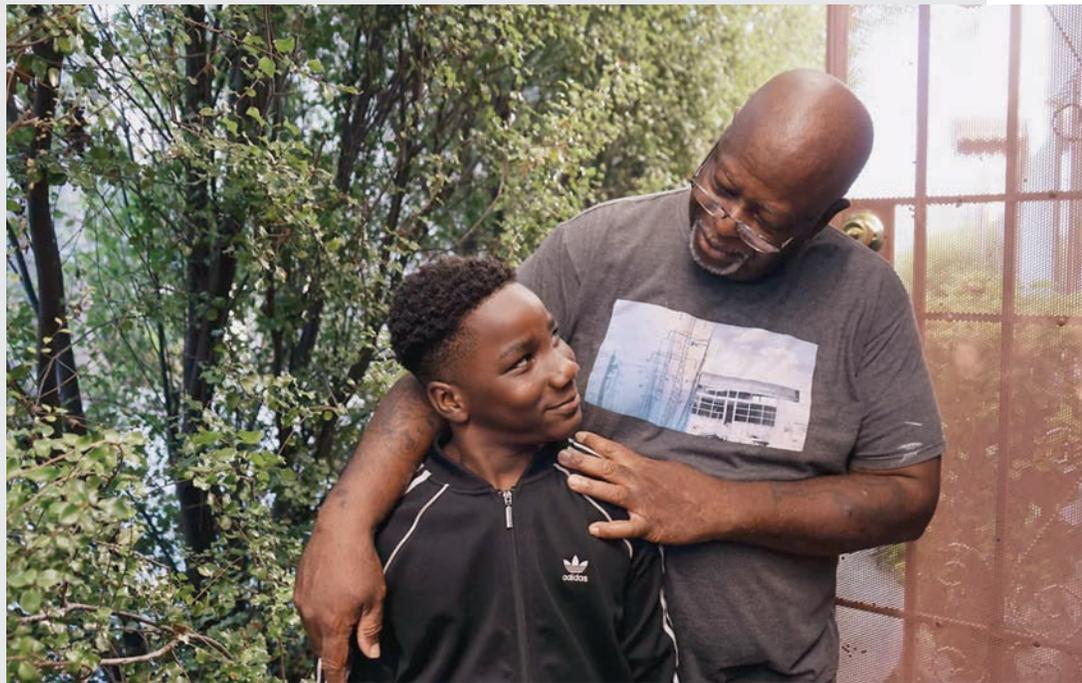


Photo: Grace Widyatmadja/NPR

A randomized control trial is an evaluation design that enables researchers to measure the impact of an intervention on an outcome. In a randomized control trial, participants are randomly selected for different groups. For example, one group may be outreached to and offered enrollment in the HPU program (the treatment group), while a second group (the comparison group) is not considered for outreach. For the HPU program, the comparison group is considered a “pure control” in that HPU staff do not reach out to those who are assigned to the comparison group and thus they receive no contact or treatment from the program. Because random assignment was used, any differences observed between the groups are likely due to the HPU program and not other factors. By comparing outcomes between the intervention and comparison groups, researchers can draw conclusions about the causal effects of the treatment being tested.

In addition to comparing those who receive HPU services to those who do not, Los Angeles County was also interested in measuring if different designs of the program would have different impacts. Specifically, they identified two distinct versions of the program related to the amount of financial assistance being provided. This was important to the HPU because it could inform decisions on future program costs and scaling of the program. To help the HPU learn about this, a second level of randomization was used for program participants. Specifically, those who enrolled in the program were randomly assigned to receive one of two different types of treatment: (1) a base level of financial assistance starting at \$4,000 and increasing based on household size or (2) an expanded level of financial assistance starting at \$6,000 and increasing based on household size.

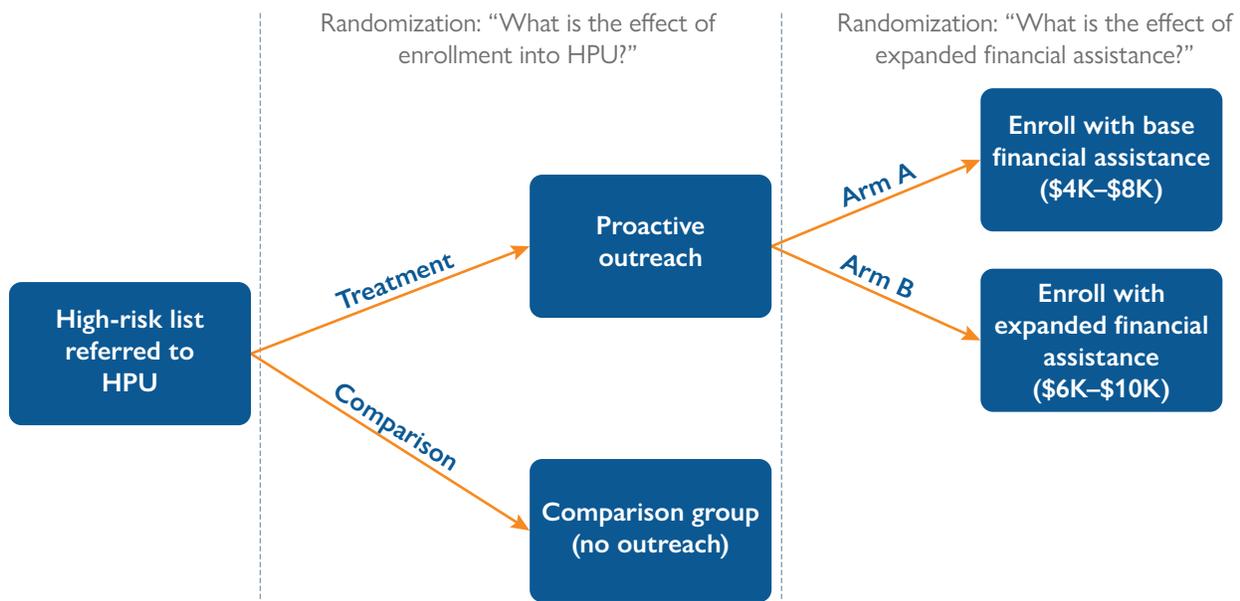
“That’s our main goal, to make sure they are able to take care of themselves after we’re done.”⁶¹

— Fred Theus,
County Case Manager

The evaluation will estimate differences in both program experiences and whether or not individuals experience homelessness after assignment. Differences in program experiences include whether participants remain engaged for four months, the total financial assistance they receive, and whether or not they enrolled in a new program or received a new County resource (e.g., mental health services or job training programs). Outcomes related to the experience of homelessness include enrollment in street outreach or interim housing services through the Coordinated Entry System, being flagged as experiencing homelessness either through the Coordinated Entry System, or in County service data (DPSS, DHS, or DMH indicators for experiencing homelessness), and adverse events such as ER visits, DMH crisis stabilization, arrests, or death. This design, illustrated in [Figure 10](#), allows the HPU to estimate not only the impact of enrolling in the HPU but also the impact of expanded financial assistance.

⁶¹ To provide external, expert review of the evaluation design and predictive modeling, the CPL convened a Technical Advisory Board, including Dr. Rediet Abebe (Harvard University), Dr. Beth Shinn (Vanderbilt University), Dr. Daniel Gubits (Abt Associates), and Dr. Dana Rotz (Mathematica Policy Research). Board members reviewed and offered feedback on the research design, which was pre-registered with Open Science Framework (OSF) on February 23, 2023.

FIGURE 10. California Policy Lab’s randomized control trial design for the Homelessness Prevention Unit⁶²



Random assignment for the evaluation began in February of 2023. The research team originally intended for the enrollment period for the evaluation to end in June 2024 or once a total of 1,080 individuals or families enrolled in the program. Based on the current rate at which the HPU enrolls participants, the enrollment period needs to extend well beyond June of 2024 in order to reach a sample size large enough to make statistically meaningful impact estimates. Moreover, once the enrollment period is over, the study will need an additional 18 months from the final randomization assignment in order to observe outcomes. We anticipate results from the evaluation will be available in 2027.⁶³

⁶² As per Figure 8, there is an additional manual eligibility screening process that occurs prior to the initial randomization into treatment and control. Also, the treatment arm randomization occurs after participants have agreed to enroll in the program.

⁶³ Due to the length of time required to obtain a sufficient sample size, we plan to document and understand any significant changes to the intervention that occur over this time period in the final program evaluation.

Conclusion

Given the scale of the homelessness crisis in Los Angeles and the number of people each year who experience homelessness for the first time, a long-term solution will require a range of strategies. With the HPU, LA County is testing an innovative approach to homelessness prevention, and the HPU's approach brings many potential benefits that are worth testing. The predictive model can help the County identify people at high risk of homelessness, and proactive outreach enables the HPU to reach high-needs populations who would not otherwise have been connected to prevention services. The services provided through the HPU are flexible, customized to participants' needs, and offered in a more intense manner than many other programs. Through our evaluation, we will be able to show whether this three-pronged approach is effective at preventing homelessness in Los Angeles. Individuals served by the HPU tend to have more complex needs, and so the program uses a more tailored and intense approach, and we're excited to test how effective this approach is in preventing homelessness.

It is also important to recognize that the predictive model, and the way that it is used, can be adjusted in the future in order to meet evolving policy goals. For example, the size of the high-risk list referred to the HPU — currently 10,000 people per year — could be reduced once a randomized control group is no longer required, which could improve the precision of the high-risk list. Also, despite the real risk of racial and other forms of bias being introduced by predictive modeling, if equity is built into the process of building and testing the model — as was the case with the HPU — there can be a much more intentional and transparent focus on equity goals than is typically the case with government programs.

This approach is not without its challenges. Due to imperfect data sources, manual screening is still required to determine eligibility. Proactive outreach involves cold-calling, which can make it difficult to reach people and enroll them in the program. Predictive modeling also relies on individuals having prior contact with government agencies, meaning that not everyone at risk of homelessness can be identified. Additionally, the high level of need among HPU participants requires an intensive, tailored intervention program. For these reasons, the HPU approach should be viewed as a complement to—rather than a replacement for—existing prevention services that rely on people self-identifying as at risk. Responding fully to this crisis requires a wide range of preventative efforts, and the HPU is a key part of this response, helping reach more people and providing the support they need so they can remain stably housed.

Acknowledgments

We would like to express our gratitude to CPL's Homelessness Prevention Community Advisory Board, who enriched and informed our work. The insights of people with lived expertise of homelessness and people with direct experience providing or receiving homelessness prevention services in Los Angeles were critical to this project.

We also appreciate the oversight provided by CPL's Technical Advisory Board, which is composed of experts on homelessness prevention and predictive analytics who provided us with independent review of the predictive model and evaluation design. The Board included the following members: Dr. Rediet Abebe (Harvard University), Dr. Beth Shinn (Vanderbilt University), Dr. Dana Rotz (Mathematica Policy Research), and Dr. Daniel Gubits (Abt. Associates).

We also want to thank the leadership and staff of the Homelessness Prevention Unit, including Dana Vanderford, Associate Director of Homelessness Prevention at Housing for Health, Claire Battis, Lead Data Program Manager, and all of their case managers, outreach specialists, and other staff who contributed knowledge, feedback, and passion to this work. We also appreciate our partners at the Housing for Health division of Los Angeles County's Department of Health Services and the Los Angeles County Department of Mental Health. We are also grateful to our partners at the Los Angeles County Chief Information Office, including Max Stevens and Andy Perry, for their work in building and maintaining the legal and data infrastructure for the Information Hub linked administrative dataset.

This research was made possible through support from Conrad N. Hilton Foundation. We also thank other supporters of the California Policy Lab including the James Irvine Foundation, the University of California Office of the President Multicampus Research Programs and Initiatives, M21PR3278, and the Woven Foundation. This publication reflects the views of the authors and not necessarily the views of our funders. All opinions and errors should be attributed entirely to the authors.

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Technical Appendix

Data sources

To build and test the HPU predictive model, CPL used an individual-level linked administrative dataset from LA County's Chief Information Office (CIO), referred to as the "Information Hub." The Information Hub started in 2006 as an effort by the CIO to link health services and benefits data for adults in LA County. In subsequent years, the CIO and County agencies have worked hard to forge legal agreements and build data-engineering pipelines to link administrative data from 11 County agencies into a regularly-updated data environment. The Information Hub is a critical piece of data infrastructure for both analytical and operational use cases in LA County. It includes health, mental health, social service benefits, arrests, probation, and homelessness service records for millions of individuals from 2010 onwards.⁶⁴ Under a data-sharing agreement with the CIO, CPL periodically receives a full de-identified mirror of the Information Hub for training the predictive model and for generating high-risk lists of people to be referred to the HPU.

Predictive Modeling approach

Structuring the source data

The Information Hub data primarily consists of tables which represent service encounters between people and LA County agencies. In addition, there are tables representing the demographic characteristics of people in the dataset. In order to train the predictive model, the data must be transformed into a modeling dataset containing numerical variables for model features and a binary indicator for the target outcome.

In structuring the data into a modeling dataset, we attempted to represent the actual workflow of the HPU pilot as closely as possible. We divide the data into quarterly "prediction dates" representing the dates on which a high-risk list is delivered to the HPU. The first step in the process to generate the modeling dataset is to determine a set of individuals who meet the eligibility criteria as-of a given prediction date. Once that is determined, we then generate features derived from people's demographic characteristics and patterns of service utilization prior to the prediction date. Because there is about a three-month time lag in ingesting data into the Information Hub, in our modeling dataset we also lag the features 3 months behind the outcome window to simulate this delay.

⁶⁴ For a list of the Information Hub data elements used in the predictive model, see section 3, Table 1, "Features in the Predictive Model!"

Outcome measure

The prediction outcome is **Any Observed Homelessness**, a binary indicator for the occurrence of a homelessness flag in any County system (DPSS, HMIS, DHS, or DMH) in an 18-month outcome window from the prediction date.⁶⁵ We only consider HMIS enrollments in street outreach or interim housing projects (defined by the LA Homeless Services Authority as emergency shelter, transitional housing, day shelter, and safe haven projects). This is because the HPU may potentially refer participants to other CES projects as part of its program model, and such referrals should not count as negative outcomes. Although it is included in the **Any Observed Homelessness** definition, the DMH homelessness flag is not currently available in the Information Hub data at the time of writing (September 2024). We anticipate that this data will be made available for the causal impact study in 2026.

Feature engineering algorithm

Our primary approach to feature engineering was to use as much of the data's information content as possible given computational and storage constraints. The feature engineering process can be described at a high level as follows:

- Data elements representing service encounters with LA County agencies (for example, a visit to a DHS hospital or a booking by the County sheriff) are transformed into features representing:
 - Numerical variables representing number and duration of contact episodes;
 - Categorical variables for contact type (such as emergency or outpatient visits for County hospitals, or felony vs. misdemeanor charge code for Sheriff bookings);
 - Categorical variables for agency-specific codes (such as ICD10 procedure codes or California arrest codes); and
 - Categorical variables representing facility information (such as DHS hospitals or County jails).
- Categorical variables were encoded using binary encoding of most frequent levels, along with numerical proxies (historical rates of homelessness) for high-cardinality categorical variables such as ZIP codes or procedure codes.
- All features are interacted with a time indicator for “recent” service contacts within the last six months vs. “earlier” service contacts from six months to five years ago.

⁶⁵ Each County system uses a slightly different definition of homelessness. HMIS enrollments typically require that participants meet the federal Housing and Urban Development (HUD) definition of homelessness. DPSS's homelessness flag is more inclusive, as it also includes people who are in short-term doubled up situations. DHS's and DMH's homelessness flags are based on ICD10 and SNOMED homelessness diagnosis codes entered by clinicians. The outcome variable for the predictive model should therefore be seen as inclusive of all these definitions.

When applied to the Information Hub source data, the production feature engineering algorithm generates 580 numerical features. Since the algorithm, which we will call the “complex” feature engineering algorithm, maximizes the use of the data’s information content and results in the creation of many highly collinear features, the research team was interested in whether a simpler approach to feature engineering could yield comparable model accuracy results. The “simple” feature engineering algorithm attempts to minimize multicollinearity by creating a more limited set of binary indicators for major agency service contact types, such as emergency/inpatient/outpatient visits in County hospitals; misdemeanor/felony arrests; and crisis/non-crisis mental health treatment. Those binary indicators are interacted with a recent/earlier time indicator, resulting in 68 features. The performance of algorithms using the complex and simple feature sets was evaluated to select the final model, as described below.

Out-of-sample validation strategy

In order to simulate the real-world deployment scenario as much as possible given the data available at design time, we decided to apply an “out-of-sample, out-of-time” validation strategy. We structured the Information Hub data into *training* and *test* datasets. In order to reflect HPU operational workflows as closely as possible, these datasets were temporally structured as follows:

- Each year consists of four quarterly *prediction dates* in January, April, July, and October, representing the anticipated cadence of risk list deliveries to the HPU.
- Because people can have multiple visits to DHS or DMH facilities, they can meet the prediction eligibility criteria and thus be included in the data at multiple prediction dates each year. However, people can only be referred to the HPU on the risk list once.
- Features were constructed using data in the 5 years prior to the prediction date.⁶⁶
- Outcomes were constructed using data in the 18 months prior to the prediction date.⁶⁷

The training dataset comprised N=90,753 unique people observed at four quarterly prediction dates in 2018, resulting in N=220,109 observations at the person-date level. The test dataset comprised N=95,308 unique people observed at four quarterly prediction dates in 2019, resulting in N=225,409 observations at the person-date level. Because individuals can meet the prediction eligibility criteria

⁶⁶ This time range was determined by data coverage in the Information Hub.

⁶⁷ An 18-month window was chosen to allow for approximately 12 months’ follow-up from the anticipated program exit date, given that enrollment duration was anticipated to be 4 to 6 months.

multiple times by having repeated visits to DHS or DMH facilities, we ensured that the two datasets were disjoint by randomly splitting the pool of eligible people 50:50 across the two datasets. After restricting each dataset to the randomly partitioned individuals and deduplicating the datasets by selecting the first prediction date for each person, the training dataset comprises N=45,257 people and observations, and the test dataset comprises N=47,582 people and observations.

Model evaluation metrics

The metric used to validate the model is precision at top N, where N = 10,714. We came to this number based on the capacity requirements and constraints of the program. During the model design process in 2021–22, it was anticipated that the HPU would enroll 450 single adults and 300 families in the course of a 12-month pilot. Early pre-pilot participant screening and outreach in 2021 also indicated that approximately 30% of the high-risk list would be found ineligible through the manual screening process, and that 20% of the remaining eligible people would be successfully enrolled in the program. In addition, the study requires a 1:1 randomized comparison group. Using the following formula which incorporates these parameters, we determine that the high-risk list comprises 10,714 people who will need to be referred to the HPU during a 12-month pilot:

$$N_{\text{referred}} = (450 + 300) \times \frac{1}{0.7} \times \frac{1}{0.2} \times \frac{1}{0.5} = 10,714$$

We also only allow a person to be selected by the model once in a 12-month period.

Pilot precision is then defined as the percentage of the high-risk list who experienced the outcome in an 18-month period from the prediction date, and can be roughly interpreted as “what percentage of people referred to the HPU would have experienced homelessness?”

We also look at two other summary metrics: the Area Under the Receiver Operating Curve (AUROC), a measure of rank discrimination where 0.5 is no better than random guessing and 1.0 represents perfect predictions, and Average Precision Score (APS), a weighted average of precision at all probability thresholds.⁶⁸

68 See https://scikit-learn.org/stable/modules/generated/sklearn.metrics.average_precision_score.html for a technical definition.

Model performance

We evaluate out-of-sample model performance for Logistic Regression, Random Forest, and Boosted Trees (XGBoost) algorithms, applied to the “complex” and “simple” feature sets.⁶⁹ Table A1 gives performance metrics for the resulting six models. Performance is appreciably higher across all three metrics for the Random Forest and XGBoost algorithms as compared with the simpler, more interpretable model. Although the Random Forest and XGBoost algorithms have almost identical pilot precision, we chose XGBoost as the production model due to its higher Average Precision Score, which indicates how precision changes with the size of the high-risk group. For example, if the HPU decides to reach out to more (or fewer) people, the selected model is expected to be the best performing at other model thresholds.

TABLE A1. Model performance results

MODEL	AREA UNDER THE RECEIVER OPERATING CURVE (AUROC)	AVERAGE PRECISION SCORE (APS)	PILOT PRECISION
XGBoost, Complex Features (Production Model)	0.86	0.548	0.242
Random Forest, Complex Features	0.872	0.517	0.246
Random Forest, Simple Features	0.834	0.446	0.226
XGBoost, Simple Features	0.815	0.445	0.221
Logistic Regression, Complex Features	0.769	0.271	0.19
Logistic Regression, Simple Features	0.749	0.24	0.184

Evaluation for Equity

The specific metric we use to evaluate the model’s equity is the false negative rate, sometimes referred to as a “miss rate.” Here, the false negative rate is the percentage of people who went on to experience homelessness that were not selected for HPU outreach. Formally, False Negative Rate is defined as $P(D = 0 | Y = 1)$, where D is a binary variable which indicates that the person was referred to the HPU and randomized into the proactive outreach group, and Y is the outcome variable (any observed homelessness).

⁶⁹ Optimal hyperparameters for these algorithms were chosen through grid search on a separate dataset drawn from the Information Hub.

Adjustment to compensate for removal of race and ethnicity as a feature

The predictive model does not include race or ethnicity as a feature from the predictive models. We recognize that there is a lively academic and legal debate on this topic.⁷⁰ Nonetheless, we decided to act with caution and remove race and ethnicity as a feature before going ahead with the formal evaluation of the model.

When the decision was made, we compared the model performance and the demographic distribution of the high-risk list for a model using race and ethnicity as features to a model that does not. While the impact on performance was negligible, Black representation in the hypothetical 12-month pilot in 2019 test data was reduced from 37.1% using a model with race and ethnicity as features to 30.3% without. Further, the representation of Black individuals in the PIT Count was approximately 35%. HPU leadership requested that the model be adjusted to meet its equity goals, specifically to ensure the demographics of the high-risk list reflected the demographics of the PIT Count and that Black individuals were not underrepresented in the high-risk lists.

After testing a number of solutions, the research team found that the most effective approach was to weight the training data by geography: specifically, the rate of prior HMIS utilization among individuals in the Information Hub in each ZIP code.⁷¹ [Table A2](#) compares Average Precision Score and race and ethnicity distribution for three models: the original XGBoost model, an XGBoost model with race and ethnicity removed from the feature set, and an XGBoost model with race and ethnicity removed and the training data weighted by geography. The weighted model restores Black representation in the pilot to 34.0%, and also shifts the geographic distribution. The proposed adjustment was accepted by HPU leadership and was deployed as the final production model.

70 Basu, A., 2023. Use of race in clinical algorithms. *Science Advances*, 9(21), eadd2704. doi: 10.1126/sciadv.add2704. Epub 26 May 2023. PMID: 37235647; PMCID: PMC10219586.

71 We also tried two alternative approaches: (i) weighting the training data by the mean Area Deprivation Index (ADI) of individuals' ZIP codes; and (ii) including the rate of prior HMIS utilization in individuals' ZIP codes as a feature. Neither approach shifted the demographic distribution of the hypothetical pilot.

TABLE A2. Model performance and demographic distribution in pilot after removing race and ethnicity and after applying weighting adjustment. Production model highlighted in green

MODEL	AVERAGE PRECISION SCORE (APS)	PILOT PRECISION	HISPANIC/LATINO (%)	BLACK (%)	WHITE (%)	ADDITIONAL GROUPS (%)	FEMALE (%)	MALE (%)	CENTRAL SPAS (%)	VALLEY SPAS (%)	COASTAL SPAS (%)
Model Including Race (XGBoost)	0.578	0.248	34	37	20	4	54	46	37	32	22
Model Excluding Race (XGBoost)	0.566	0.247	41	30	19	5	54	46	37	32	22
Production Model Excluding Race (XGBoost, Weighted Training Data)	0.548	0.242	40	34	16	4	55	45	42	29	19

FIGURE A1. Homelessness Prevention Unit outreach script⁷²

1. Introduction

- *Hi there, this is _____ and I'm calling from LA County's Housing Stabilization Unit. How are you doing today?*
- *We're following up with folks who have received health services in LA County in the last year.*
- *We know that it's been a very challenging year for all residents of LA County and we're calling to find out if you're in need of any financial assistance or other types of support at this time. Our program can provide you with immediate assistance, like grocery or gas gift cards. We can also provide you with more long-term support, like rental and utility assistance.*
- *Is now a good time to talk?*
 1. If NO, schedule a follow-up call for next week
 - *"If now isn't a good time to talk, could we set up a time to contact you later? What day or time usually works best for you?"*
 2. If YES, proceed to Program Description
 - *"I'd love to tell you a little bit about our program and the kinds of assistance we offer..."*

2. Program Description

Note: Do not frame this conversation to clients as an assessment for eligibility, but use this space to collect information from clients to measure them against our Hard Stops and determine next steps.

- *The Housing Stabilization Unit is an initiative that the County's Department of Health Services is kicking off to support individuals after the difficult year we've all faced in light of COVID-19.*
- *We can provide housing assistance and other kinds of supports based on your needs.*
- *Can you tell me a little bit about your current living situation at this time? (Use this opportunity to continue to ask questions about where the client lives, what kind of housing they live in, who they live with, family composition)**
 1. If client does not appear to meet a Hard Stop
 - *"Thanks for sharing that. We're here to help with whatever you might need at this time. We can provide you with rental assistance or other housing-related supports, connections to legal assistance, medical care, help in exploring employment opportunities or options to increase your income."*
 2. If client does appear to meet a Hard Stop
 - Refer to 211 and [SPA Lead Homeless Services Providers](#)
 - Move to Phase Two Hard Stop list
 - If client inquires about gift cards after you refer them to a provider, emphasize that the provider you've referred them to can assist with those immediate needs

continued

⁷² This figure contains a sample of the script used by the HPU during proactive outreach. It does not include general guidelines or talking points that the HPU also provides outreach specialists.

3. Client Interventions (immediate + establish a goal for long-term)

- If client indicates housing needs + additional needs
 1. Offer Immediate Intervention
 - Gift card for groceries / food
 - Example: loss of job
 - a. *"I'm so sorry to hear about the loss of your job this year. I can't imagine how stressful that must've been for you. I really appreciate you sharing that with me -- and I'm wondering if a gift card for groceries might help alleviate some of the financial pressure you're currently facing."*
 2. Offer examples of tailored long-term assistance
 - Example: loss of job
 - a. *"I'd love to learn more about your employment goals and how we can help support you in getting back into the workforce..." - maybe for a later conversation?*

4. Explore next steps

- If client is open to continuing the conversation
 1. Schedule follow-up conversation for next week with the goal of enrolling client in HPU
- If client isn't open to continuing the conversation
 1. *"I know you've got a lot going on, so I don't want to take up too much of your time today."*
 2. *"Would you be open to setting up another time to chat next week so that I can learn more about your goals and how we can help?"*
 3. Give contact information and availability