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Very Low Food Security in US Households Is Predicted by Complex Patterns of Health, Economics, and Service Participation

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Abstract

Background: Very low food security (VLFS) happens at the intersection of nuanced and complex patterns of risk characteristics across multiple domains. Little is known about the idiosyncratic situations that lead households to experience VLFS.

Objective: We used classification and regression tree (CART) analysis, which can handle complex combinations of predictors, to identify patterns of characteristics that distinguish VLFS households in the United States from other households.

Methods: Data came from 3 surveys, the 2011–2014 National Health Interview Survey (NHIS), the 2005–2012 NHANES, and the 2002–2012 Current Population Survey (CPS), with sample participants aged ≥18 y and households with income <300% of the federal poverty line. Survey participants were stratified into households with children, adult-only households, and older-adult households (NHIS, CPS) or individuals aged 18–64 y and individuals aged ≥65 y (NHANES). Household food security was measured with the use of the 10-item US Adult Food Security Scale. Variables from multiple domains, including sociodemographic characteristics, health, health care, and participation in social welfare and food assistance programs, were considered as predictors. The 3 data sources were analyzed separately with the use of CART analysis.

Results: Household experiences of VLFS were associated with different predictors for different types of households and often occurred at the intersection of multiple characteristics spanning unmet medical needs, poor health, disability, limitation, depressive symptoms, low income, and food assistance program participation. These predictors built complex trees with various combinations in different types of households.

Conclusions: This study showed that multiple characteristics across multiple domains distinguished VLFS households. Flexible and nonlinear methods focusing on a wide range of risk characteristics should be used to identify VLFS households and to inform policies and programs that can address VLFS households' various needs. *J Nutr* 2017;147:1992–2000.

Keywords: very low food security, household composition, classification and regression tree, decision tree, medical needs, food assistance program

Introduction

In 2015, ~6.3 million households (5.0%) in the United States experienced very low food security (VLFS) in which ≥1 household member had reduced food intake or disrupted eating patterns because there was not enough money for food (1). VLFS is associated with serious negative health, developmental, and psychosocial consequences (2–11). Although the overall prevalence of VLFS is low, reaching these households with effective intervention is important. Identifying households with VLFS for intervention is difficult. Descriptively, the risk of experiencing VLFS varies with sociodemographic, household, contextual, and geographic characteristics. For instance, households are more likely to have VLFS if they are single female–headed and low income, or if they are located outside of metropolitan areas, or if they are located in the South (1). VLFS is more prevalent in households without children (5.1%) than in those with children (4.9%) and is least

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Abbreviations used: AUC, area under the receiver operating characteristic curve; CART, classification and regression tree; CPS, Current Population Survey; FPL, federal poverty line; NHIS, National Health Interview Survey; SNAP, Supplemental Nutrition Assistance Program; VLFS, very low food security.

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prevalent in households with elders (3.2%) (1). Within any of these higher-risk categories, the prevalence of VLFS is still low, making each characteristic inefficient as a basis for targeting outreach or intervention.

Previous studies have focused on identifying the strongest individual predictors of VLFS, generally with the use of traditional variable-centered regression modeling. These efforts have found limited success, however, in part because this modeling is poorly suited for identifying the idiosyncratic situations that lead households to experience VLFS or to generalizing those situations from the small numbers of VLFS households captured in available data sets (12). Qualitative findings indicate that VLFS happens at the intersection of nuanced and complex patterns of risk characteristics rather than when 1 or 2 risk characteristics become particularly extreme (13). Additionally, paths to VLFS differ across households, situations, and contexts, reflecting the multiple ways that life circumstances, needs, and resources can combine synergistically to result in households with VLFS. In an effort to account for the range of interdependent risks related to household food security, one recent study created risk factor indexes with the use of multiple risk factors in each of several domains (e.g., financial strain, maternal poor health and risky health behaviors, family disruption and conflict, and parenting disruption). The findings suggested that different risk indexes distinguished households between different levels of food security (14). This study showed different impacts of cumulative risk factors on each food security level, but it did not consider the potential synergistic impacts of risk factors across multiple domains and could not clarify the specific constellations of experiences within and across risk domains that might best predict which specific households are likely to experience VLFS.

Because VLFS is conditioned on patterns of characteristics rather than the presence of 1 or 2 characteristics, classification and regression tree (CART) analysis, a powerful analytic method for finding prediction models from data, is well-suited to identify VLFS households. CART partitions data recursively by using a series of decision rules, identifying a best single predictor at each step to split the sample between those with the outcome of interest (VLFS in this case) versus others (15). CART analysis requires no assumptions regarding data distribution, thus this nonparametric method can be used to analyze data of any distribution. This flexible method allows complicated interactions among variables and nonlinearities. Therefore, CART analysis is particularly appropriate for distinguishing VLFS households, supporting explicit modeling of these households' complex situations. CART analysis has been used in subgroup identification and risk profiles for health conditions; for example, CART analysis was used to identify risk characteristics of preterm birth (16) and groups of people who are at a high risk of overweight (17–19) and excessive gestational weight gain (20). CART analysis has also been used to identify factors associated with diet quality (21), malnutrition (22), and fruit and vegetable consumption (23). Despite the potential power of CART analysis to identify population subgroups at risk of food insecurity, to our knowledge, only 2 studies have used CART analysis to identify factors associated with household food insecurity (24, 25).

The current study applied CART analysis to identify patterns of characteristics that distinguish VLFS households in the United States from those with greater food security. We hypothesized equifinality (i.e., the same end state can be reached by many different means) (26) in the processes that lead household systems to experience VLFS and therefore expected to observe multiple patterns of characteristics, reflecting different pathways through which households with different characteristics become VLFS.

Methods

Data and participants

We used data from 3 national surveys, the National Health Interview Survey (NHIS), the NHANES, and the Current Population Survey (CPS), to consider a wide range of variables that may help predict VLFS. NHIS is a cross-sectional household interview survey conducted by the National Center for Health Statistics, CDC. The multistage area probability design of the NHIS allows a nationally representative sample of households in the United States. One adult household member is asked questions about the household and its members, including questions related to sociodemographic characteristics, health status, health care access and use, food assistance program participation, and adult food security during the past 30 d. We used data from 4 cycles of the NHIS (2011–2014).

NHANES is a series of cross-sectional surveys to assess the health and nutritional status of adults and children in the United States conducted by the National Center for Health Statistics. By using complex multistage probability samples, the participants of the NHANES represent the noninstitutionalized US civilian population (27). Data from 4 waves of NHANES (2005–2006, 2007–2008, 2009–2010, and 2011–2012) were used.

The CPS is a monthly labor force survey that uses a complex probability sample to select a nationally representative sample of the civilian population in the United States. Selected households participated in a face-to-face or telephone survey once a month for 4 consecutive months. Then, after a window of 8 mo, the sampled households returned to the survey for another 4 mo. People who are ≥15 y of age, noninstitutionalized, and not in the armed forces are eligible to participate in the survey. Among the CPS survey participants between 2002 and 2012, those who entered the survey in December and stayed until March of the following year were included in our sample, because the food security supplement was measured only in December, and social and economic supplements were conducted in March. We only used data collected during the first 4 mo for the analysis.

Households with incomes <300% of the federal poverty line (FPL) were included in the analysis, because food insecurity is more prevalent at lower income levels and instances of food insecurity among higher-income households likely involve quite different situations than those at the focus of this analysis. Survey respondents who were <18 y old or who did not complete the household food security scale were excluded from the analysis.

Food security

The NHIS, NHANES, and CPS used the 10-item US Adult Food Security Scale to measure household food security. The NHIS measured household food security during the last 30 d. The NHANES measured household food security during the last 12 mo. The CPS measured household food security both during the last 30 d and 12 mo. Households were classified based on the number of items affirmed as follows: no affirmation represents food security, 1–2 affirmations represents marginal food security, 3–5 affirmations represent low food security, and ≥6 affirmations represents very low food security (VLFS).

Predictor variables

Because the goal was to identify patterns of characteristics that reflect pathways to VLFS, predictor variables were selected from the data sets based on empirical evidence and dominant conceptualizations of the pathways to food insecurity (1, 6, 8, 11, 24, 28–32). Variables proximal to food insecurity and those more distal on the paths were included (**Table 1**), but we excluded variables that represented expressions of VLFS rather than its causes (e.g., having to eat at a soup kitchen). A large body of evidence demonstrates that sociodemographic characteristics of individuals and households are associated with food security (1, 28, 29). All 3 surveys had information on sex, race and ethnicity, household income and its sources, marital status, labor force participation, education level, household size and composition, home ownership,

TABLE 1 Variables included in the analysis[1]

Domain	Variable
Sociodemographic characteristics	Sex, race and ethnicity, income, marital status, occupation, education level, household size and composition, home ownership, country of birth, citizenship (all)[2]
Health status and behaviors	General health status, disability, work and physical limitation, morbidity (NHIS, NHANES), obesity, depression and related limitation, dietary behaviors, physical activity, alcohol consumption, smoking, prescribed medication (NHANES)
Health care access and use	Health insurance (all), clinic visits, hospitalization (NHIS, NHANES), delayed or unmet medical care, difficulties with medical bill (NHIS)
Governmental assistance program	Social security disability insurance, supplemental security income, housing assistance (NHIS, CPS), energy assistance (CPS)
Governmental food assistance program	Supplemental Nutrition Assistance Program or food stamps, Special Supplemental Nutrition Program for Women, Infants, and Children (all), free- or reduced-cost school meal (NHIS, CPS)

[1] CPS, Current Population Survey; NHIS, National Health Interview Survey.
[2] Parentheses indicate data sources of variables.

country of birth, and citizenship. Although the direction is not clear, physical and mental health and health behaviors affect or are affected by food security (6, 11, 24, 28, 29, 31), and food insecurity is associated with different patterns of health care access and use (30). Variables related to health status were obtained from the NHIS and NHANES. Given that participation in public assistance programs is an important source of income and economic stability for many families that also struggle with food-related needs (1, 28), we included participation in major public social welfare and food assistance programs in the analysis.

Because this study focused on household rather than personal food security, all variables from CPS and NHIS were aggregated to the household level. For example, the employment status of each individual in a household was collapsed to reflect whether "anyone in the household is employed" or "everyone in the household is unemployed."

Sample stratification. Because different types of households may have different paths to VLFS, we stratified the samples for analysis. The CPS and NHIS data were analyzed separately for households with children (≥1 member aged <18 y), adult-only households (only adults aged between 18 and 64 y), and older-adult households (those without any child, and with ≥1 adult aged ≥65 y). The NHANES data did not provide household-level characteristics, so these data were stratified and analyzed separately for adults (aged 18–64 y) and older adults (aged ≥65 y).

Analysis

CART analysis was used to build classification trees, identifying the sequence of binary splits that best sorts the sample on food security status. Beginning with the whole sample as one group, the procedure selects from all variables the one variable and the one cutoff for that variable that best splits the group into 2 subgroups, maximizing differences on the outcome, in this case, food security status. Within each subgroup there is then again the selection of the variable that best further differentiates that subgroup by food security status. This process continues, with binary splits flowing from binary splits, resulting in a tree with a "root node" (full sample) from which "branches" emerge and "derivative nodes" at each point where a subgroup is further split until there are "terminal nodes" from which no more splits can be made (e.g., no significant additional differentiation on the outcome is possible) (**Figure 1**).

Each sample stratum from each of the 3 data sources was analyzed separately. Each was randomly partitioned into 2 data sets, keeping similar proportions of food security, low food security, and VLFS; one data set was used for model fitting, and another was used for assessing the robustness of the models. The number of surrogate rules for missing values was set to 4, which means 4 different variables were used to identify missing values. Receiver operating characteristic curves for each classification tree were plotted, and areas under the receiver operating characteristic curve (AUCs) were examined to assess the accuracy of each tree in predicting VLFS status. An AUC of 1.0 represents perfect accuracy; 0.8–0.9 represents good accuracy, 0.7–0.8 represents fair accuracy, 0.6–0.7 represents poor accuracy, and 0.5 represents chance. For each node, we also calculated the proportion of VLFS in that node out of all VLFS households in the entire sample and the proportion of VLFS in that node out of all households or individuals in that sample stratum. SAS Enterprise Miner version 13.2 (SAS Institute) was used for analysis.

We did not use sampling weights or account for cluster sampling because our analyses did not require population weighting or adjustment of SEs to address our research questions. Our analysis focused on identifying characteristics of subgroups that are at a high risk rather than understanding food security prevalence at the population level. Nevertheless, as a sensitivity analysis, we estimated the weighted food security prevalence using SAS survey procedures (SAS Institute) to account for the complex sampling in each data set. The weighted food security prevalence was used as a prior probability in classification tree analysis. Weighted and unweighted food security prevalence in the analytic sample were similar, as were classification trees for which weighted and unweighted food security prevalence were used.

Results

NHIS. Having unmet medical care needs (did not get medical care when it was needed) was the first characteristic to distinguish VLFS households in all 3 sample strata (**Table 2**). Among households with children, having unmet medical care needs was the only distinguishing predictor, and the prevalence of VLFS was 23.3% among households with unmet medical care needs compared with 6.5% among households that were able to meet medical care needs (AUC = 0.647). Identification based on this predictor would include 46.2% of all VLFS households with children.

In older-adult households, unmet medical care needs and duration of Supplemental Nutrition Assistance Program (SNAP) participation were distinguishing predictors. Among households that had unmet medical care needs and that received SNAP benefits for ≥2 out of the last 12 mo, the prevalence of VLFS was 27.4% compared with 3.2% among households that did not have unmet medical care needs (AUC = 0.684; **Figure 2**). Identification based on both predictors would include 42.2% of VLFS older-adult households.

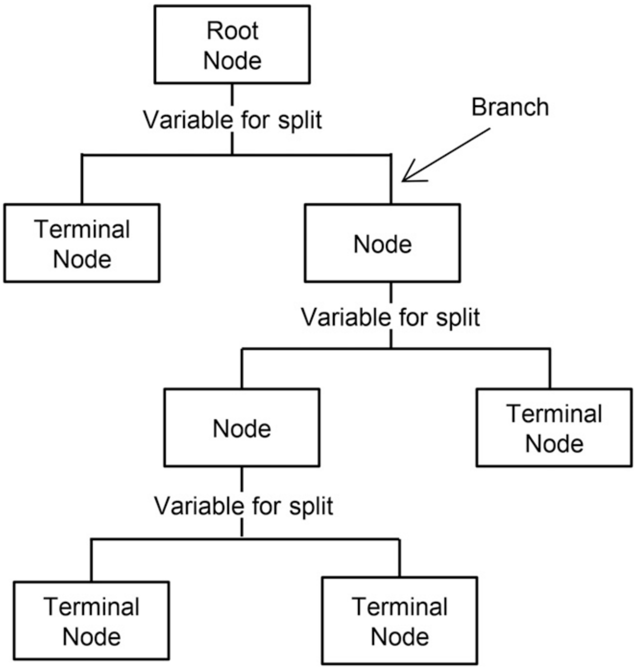

FIGURE 1 Structure of classification tree.

Adult-only households had complex patterns of characteristics to distinguish the VLFS households from those with greater food security. In addition to unmet medical care needs, 6 other predictors helped to identify which households were VLFS, including health characteristics, SNAP participation, family size, and home ownership (AUC = 0.740). The highest prevalence of VLFS was among households with unmet medical care needs and in which ≥1 person had memory problems and the household received SNAP benefits for ≥2 mo (60.0%). The prevalence of VLFS among households with unmet medical needs in various strata ranged from 25.9% to 60.0%, and identification based on this one predictor would include 55.3% of all VLFS households. Among households that were able to meet all medical care needs, the higher prevalence of VLFS occurred in those that received SNAP benefits at some point in the last year and those in which members had fair or poor health. Single-adult households in which the individual had poor health, memory problems, and received SNAP benefits were at particular risk (39.3% VLFS compared with 5% for those with none of these characteristics).

NHANES. For individuals aged 18–64 y in NHANES, receiving SNAP benefits in the last 12 mo was the first distinguishing predictor, followed by having depressive symptoms in the last 2 wk; these predictors together reflected a VLFS prevalence of 31% and included 15.5% of all VLFS households in the sample strata (**Table 3**). Subsequent splits distinguished VLFS households based on SNAP benefit receipt in combination with the number of household members, use of dietary supplements, and education level, and had VLFS prevalence ranging from 12.9% to 16.8% compared with 8.3% among those who did not receive SNAP benefits (AUC = 0.623). For individuals aged ≥65 y, household income was the single predictor to distinguish VLFS households. The prevalence of VLFS was 9.0% among individuals with household incomes <125% FPL compared with 1.9% among individuals with household incomes between 125% and 299% of the FPL (AUC = 0.689).

CPS. For households with children in the CPS, VLFS households were distinguished by children's participation in free or reduced-cost

TABLE 2 Summary of classification trees for VLFS in the last 30 d, National Health Interview Survey[1]

	Unmet medical care needs	Received SNAP in the last 12 mo	Anyone has fair or poor health	Anyone is limited by memory problem	Number of family members	Duration of SNAP receipt in the last 12 mo	Home owned	VLFS prevalence (%)	% of total VLFS[2]	% of total sample[3]
Households with children (*n* = 15,816)[4]	Yes	—	—	—	—	—	—	23.3	46.2	19.4
	No	—	—	—	—	—	—	6.5	53.8	80.6
Older-adult households (*n* = 8453)[4]	Yes	—	—	—	—	≥2	—	27.4	15.0	2.7
	Yes	—	—	—	—	0 or 1	—	21.4	27.2	6.3
	No	—	—	—	—	—	—	3.2	57.8	91.0
Adult-only households (*n* = 15,754)[4]	Yes	—	—	Yes	—	≥2	—	60.0	8.6	1.9
	Yes	—	—	Yes	—	0 or 1	No	47.7	3.9	1.1
	No	Yes	Yes	Yes	1	—	—	39.3	4.8	1.6
	Yes	—	—	Yes	—	0 or 1	Yes	33.3	2.0	0.8
	Yes	—	—	No	—	—	—	25.9	40.8	20.8
	No	Yes	Yes	No	—	—	—	23.4	8.1	4.6
	No	Yes	Yes	Yes	≥2	—	—	23.3	1.3	0.7
	No	Yes	No	—	—	—	—	13.1	7.5	7.6
	No	No	—	—	—	—	—	5.0	23.1	60.9

[1] AUC = 0.647 for households with children, 0.684 for older-adult households, and 0.740 for adult-only households. AUC, area under the receiver operating characteristic curve; SNAP, Supplemental Nutrition Assistance Program; VLFS, very low food security.
[2] Proportion of VLFS households in the node among the total VLFS households in the training set.
[3] Proportion of VLFS households in the node among the total households in the training set.
[4] Sample size includes only those in the training set, ~50% of the total sample size.

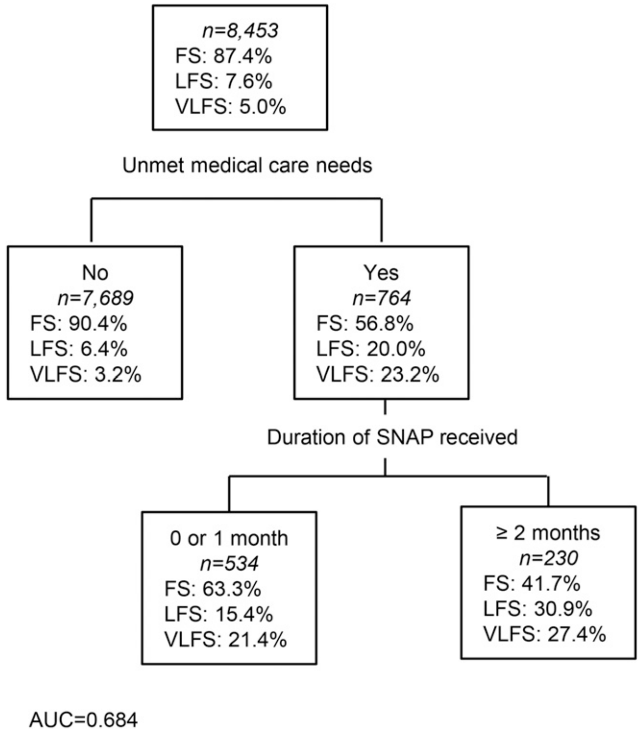

FIGURE 2 Classification tree for very low food secure older adult households in the National Health Interview Survey. The sample size in each node includes only those in the training set, ~50% of the total sample size in the node. FS, food security; LFS, low food security; SNAP, Supplemental Nutrition Assistance Program; VLFS, very low food security.

school lunch program and by employment status (AUC = 0.691, **Table 4**). Among households in which children did not receive free or reduced-cost school lunches, 3.1% were VLFS, whereas VLFS prevalence was 9.2% among those in which children received free or reduced-cost school lunch. Within this free or reduced-cost lunch group, VLFS prevalence climbed to 15.2% among households in which all adult members were unemployed.

For older-adult households, the first predictor distinguishing households experiencing VLFS during the last 30 d was receipt of SNAP benefits during the last 12 mo. Households that received SNAP benefits during the last 12 mo and had a person with a disability had the highest prevalence of VLFS (9.1%). Households that did not receive SNAP benefits during the last 12 mo had a VLFS prevalence ranging from 0.6% among those who had some interest income to 3.0% among those without interest income and in which someone had poor health. These low-prevalence groups included 66.2% of all VLFS older-adult households (AUC = 0.822, **Figure 3**).

For adult-only households, the only predictor distinguishing households experiencing VLFS was receipt of SNAP benefits during the last 12 mo (23.7% VLFS compared with 5.6% for households that did not receive SNAP benefits; AUC = 0.614). Classification trees for food security during the last 12 mo were similar to trees for food security during the last 30 d (data not shown).

Discussion

Household experiences of VLFS were associated with different characteristics for different types of households and often occurred at the intersection of multiple characteristics spanning

TABLE 3 Summary of classification trees for VLFS in the last 12 mo, NHANES[1]

	Received food stamps in the last 12 mo	Depressive symptoms in the last 2 wk	Household members, *n*	Use of dietary supplements	Education level	Household income	VLFS prevalence, %	% of total VLFS[2]	% of total sample[3]
Individuals aged	Yes	Moderate to severe	—	—	—	—	31.0	15.5	5.8
18–64 y (*n* = 5389)[4]	Yes	None to mild	1–5	—	—	—	16.8	27.9	19.1
	Yes	None to mild	≥6	Yes	—	—	14.1	1.8	1.4
	Yes	None to mild	≥6	No	Less than ninth grade	—	13.0	1.1	1.0
	Yes	None to mild	≥6	No	Ninth grade or higher	—	12.9	4.7	4.2
	No	—	—	—	—	—	8.3	49.1	68.5
Individuals aged ≥65 y	—	—	—	—	—	<125% FPL	9.0	76.0	39.9
(*n* = 1590)[4]	—	—	—	—	—	125–299% FPL	1.9	24.0	60.1

[1] AUC = 0.623 for individuals aged 18–64 y and 0.689 for individuals aged ≥65 y. AUC, area under the receiver operating characteristic curve; FPL, federal poverty line; VLFS, very low food security.
[2] Proportion of VLFS individuals in the node among the total VLFS households in the training set.
[3] Proportion of VLFS individuals in the node among the total households in the training set.
[4] Sample size includes only those in the training set, ~50% of the total sample size.

TABLE 4 Summary variables of classification trees for VLFS in the last 30 d, Current Population Survey[1]

	Received free or reduced-cost school lunch	Anyone employed	Received SNAP benefits during the last 12 mo	Anyone has disability	Interest income	Anyone has fair or poor health	VLFS prevalence, %	% of total VLFS[2]	% of total sample[3]
Households with children (n = 4592)[4]	Yes	No	—	—	—	—	15.2	22.6	7.9
	Yes	Yes	—	—	—	—	7.6	40.3	28.2
	No	—	—	—	—	—	3.1	37.0	63.9
Older-adult households (n = 3923)[4]	—	—	Yes	Yes	—	—	9.1	19.1	3.6
	—	—	Yes	No	—	—	6.9	14.7	3.7
	—	—	No	—	No	Yes	3.0	38.2	22.0
	—	—	No	—	No	No	0.8	11.8	26.3
Adult-only households (n = 4531)[4]	—	—	No	—	Yes	—	0.6	16.2	44.4
	—	—	Yes	—	—	—	23.7	40.7	13.9
	—	—	No	—	—	—	5.6	53.9	86.1

[1] AUC = 0.691 for households with children, 0.822 for older-adult households, and 0.614 for adult-only households. AUC, area under the receiver operating characteristic curve; SNAP, Supplemental Nutrition Assistance Program; VLFS, very low food security.
[2] Proportion of VLFS households in the node among the total VLFS households in the training set.
[3] Proportion of VLFS households in the node among the total households in the training set.
[4] Sample size includes only those in the training set, ~50% of the total sample size.

health, economic, food assistance program participation, and family structural domains. Key characteristics distinguishing VLFS households were as follows: *1*) food assistance programs and benefits, and *2*) health and health care access.

Food assistance programs and benefits. Participation in government food assistance programs was one of the key characteristics distinguishing VLFS households from those that were more food secure. On the one hand, this is not surprising, because those with greater food needs are more likely to accept the burdens (i.e., time, hassle, and embarrassment) of participating in food assistance programs (33). On the other hand, this is powerful evidence that food assistance programs are inadequate to meet the most severe food-related needs; even families that receive benefits regularly are at significant risk for the most severe food insecurity. In the CPS sample, SNAP participation was the first distinguishing characteristic for older-adult and adult-only households, but free or reduced-cost lunch participation rather than SNAP mattered among households with children (who are often eligible for both). It may be that SNAP benefits are more adequate for households with children, that participation is more accessible, or that it is less stigmatizing and therefore more universally used by those who are eligible. School meals, in contrast, may be reserved for times of greater food hardship, particularly if that program is associated with greater stigma, children do not prefer the foods that are served, or parents perceive greater barriers to establishing eligibility.

Households that did not receive food assistance benefits also experienced VLFS. In the CPS data, ~65% of older-adult VLFS households and 54% of adult-only VLFS households did not receive SNAP, and 37% of VLFS households with children did not receive free or reduced-cost school lunch. This may involve barriers to participation, such as a lack of awareness of programs and eligibility, fear of stigma, and lack of time and transportation to go to the program offices (34–36).

Health and health care access. Unmet medical care needs, poor health, disability, limitation due to memory problems, and depressive symptoms were important in identifying VLFS households across the sample strata and across data sets. Households with VLFS struggle to meet competing demands (e.g., food, housing, electricity, and health care) with scarce financial resources (30, 37, 38). Postponing medical care may be chosen as a coping strategy when food shortages become most dire, and it may be part of a cycle that ultimately exacerbates overall economic vulnerability and food insecurity. Forgoing medical care can lead to emergency department visits, to more serious and less tractable health problems, and to a range of economic consequences as medical bills pile up and illness gets in the way of sustained employment (30). The ensuing economic strains can lead to more severe food insecurity, and the associations between food insecurity and poor physical and mental health conditions are well documented (8, 31, 32). In this way, health care compromises may be both an effect and a cause of food insecurity.

Household-type differences. There are a number of differences in the trees between household types and between data sets, but it stands out that adult-only households consistently had more complex trees (e.g., more characteristics across more domains) in the NHIS and NHANES. This population stratum had the highest overall prevalence of VLFS, so it may be that there are simply more households with VLFS, with more unique life situations, and thus more distinct paths to VLFS. This may

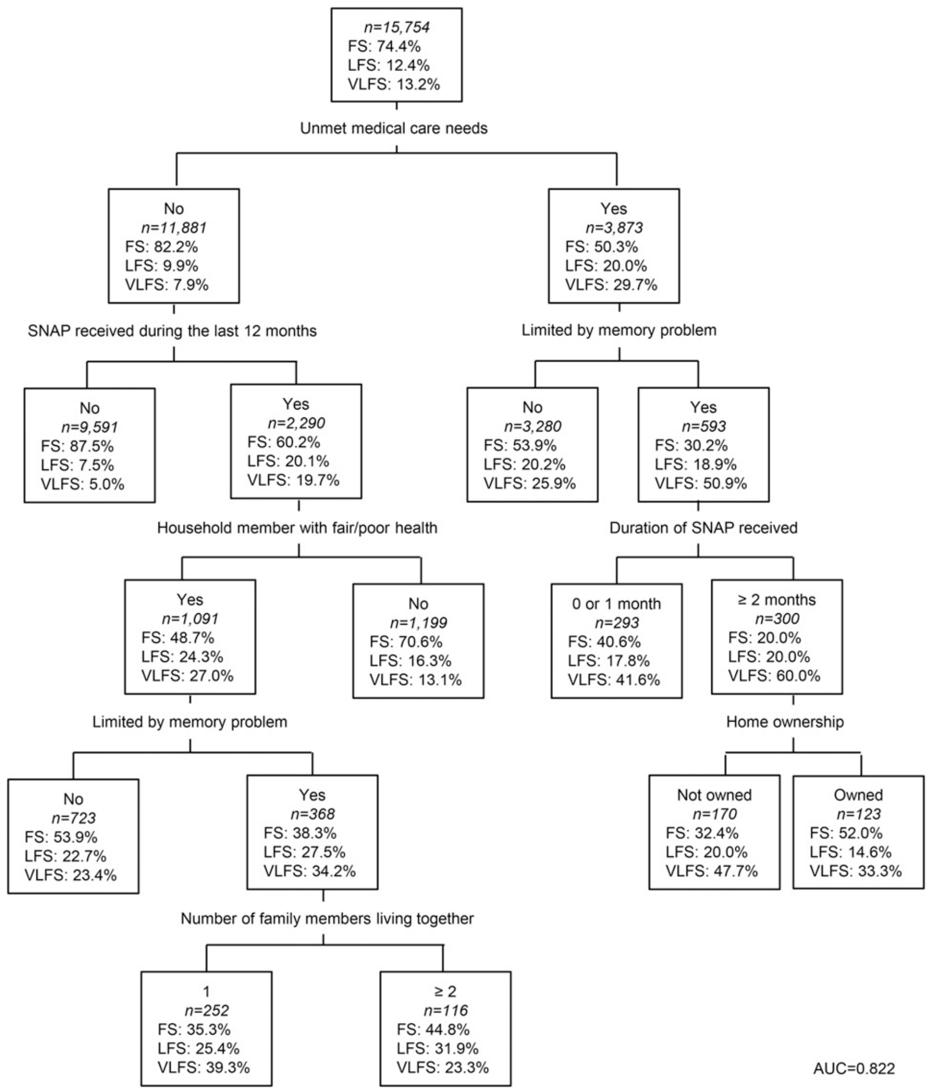

FIGURE 3 Classification tree for very-low-food-secure adult-only households in Current Population Survey. The sample size in each node includes only those in the training set, ~50% of the total sample size in the node. FS, food security; LFS, low food security; SNAP, Supplemental Nutrition Assistance Program; VLFS, very low food security.

be a product in part of the failure of our helping systems to address the needs and circumstances of working-age adults. When wage earning is inadequate, this population has fewer buffers against VLFS because they are less often eligible for social welfare programs, which tend to prioritize children and older adults. In addition, there is no single program that specifically addresses the food-related needs of working-age adults. Thus, the higher program participation among families with children and for older adults may mask differences in the underlying circumstances that lead to eligibility for these groups. This would suggest that the adult-only models may most clearly identify the situations, contexts, and challenges that lead to VLFS.

Limitations. The focus of this study was on the identification of households with VLFS. Although we identified important characteristics that distinguished groups with higher and lower prevalences of VLFS, the AUC values of classification trees in this study ranged from 0.614 to 0.822, which correspond to fair to good accuracy. The mean AUC value was 0.684, indicating that most of the resulting classification trees would not be ideal to identify VLFS households in practice. In part, this is because even though groups with very low prevalence were identified by the trees, those groups tended to have large shares of the total population and thus large numbers of VLFS households. In short, additional information would be needed to "find" VLFS households that are not identified by the characteristics used to build these trees. None of our data included information on sociocultural or relational factors (e.g., food preferences and parent–child relationships) or contextual factors (e.g., proximity to grocery stores and local policy or service environment). Consequently, we could not include such possibly important information in the analyses. Future research should consider broader constellations of factors that may, in combination, better predict VLFS.

Implications and conclusion. This study has important implications for understanding VLFS and for identifying and responding to the needs of those who experience VLFS. First, findings point to the importance of understanding VLFS as being about more than just food. Health, depression, disability, employment, income from interest, and other characteristics predicted the experience of VLFS, suggesting that VLFS (and perhaps food security broadly) may be a proxy for bio–psycho–social distress generally. A holistic perspective is needed to further clarify the causal paths, complex patterns, and contexts that undergird affirmations of food security scale items.

Second, this study suggests several promising directions for identifying VLFS households. The first splits in classification trees identified characteristics that can be used to target screening efforts. So, because VLFS households are concentrated among those that already use food assistance programs (SNAP and free or reduced-cost school meals), improving the adequacy of these program benefits or linking participants to additional resources would likely reduce VLFS prevalence. Similarly, because having unmet medical care needs was a first-split factor for all household types, outreach might effectively focus on medically underserved populations. For instance, the use of a food-security screener at emergency departments and free health care clinics could help identify those experiencing VLFS so that they can be connected to appropriate services.

Third, the analysis points to combinations of characteristics (splits below that first level) that yield higher prevalence of VLFS households. The combination of SNAP participation and depression, for instance, identified a population group that was 31% of VLFS households. So, if a depression screener were administered at SNAP offices, people with recent depressive symptoms could be identified as being at high risk for VLFS, and more intensive case-management services could be used to link them to additional supportive services. Screening for health and mental health problems at community-based settings (schools, churches, and activity centers) could become an entry point to both health- and food-related supportive services. Similarly, among adult-only households (in the NHIS), although having unmet medical care needs was the first predictor of being VLFS, other groups at high risk could be identified through a combination of several characteristics: 39.3% of people who did have medical care still experienced VLFS if they *1*) received SNAP benefits, *2*) had fair or poor health, *3*) were limited by memory problems, and *4*) lived alone. This population may come to the attention of home health care providers or family caregivers who could screen for and respond to food security problems.

In conclusion, multiple characteristics across multiple domains distinguished VLFS households, and identifying and responding to the needs of this population will require nuanced attention to a wide range of social, economic, health, and contextual challenges. Households with VLFS may need other supports (e.g., better access to physical and mental health services) along with better access to food. Therefore, multiple domains and flexible, nonlinear methods should be used to identify VLFS households and to inform policies and programs that can address the needs of households with VLFS.

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