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Determinants of self-rated health in socioeconomically disadvantaged women: a cross-sectional study in Iran

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Abstract

Background To reduce potential health disparities, it is critical to recognize health determinants among socioeconomically disadvantaged women. Therefore, we aimed to investigate the determinants of self-rated health in socioeconomically disadvantaged women supported by a Relief Foundation (RF).

Method This cross-sectional study was conducted on women in Iran who were supported by a RF as an aided institute. We collected demographic and socioeconomic data, as well as information on physical, mental, and social health and self-rated health status. Data analysis was performed by random forest, classification and regression tree (CART) techniques, and gamma regression.

Results The mean age of the 556 included disadvantaged women was 42.8 ± 12.4 years, and the mean self-rated health status was 66.5. Physical health was the most important factor affecting self-rated health. In disadvantaged women with physical problem, nonacademic and academic educated had significantly greater health perceptions than illiterate individuals (1.267, 95% CI: 1.106, 1.451) and (1.666, 95% CI: 1.251, 2.217) respectively. Also, anxiety and stress were both significant predictors of self-rated health status in disadvantaged women with physical health problem (0.765, 95% CI: 0.653, 0.896), and (0.872, 95% CI: 0.762, 0.999) respectively.

Conclusion The study of disadvantaged women revealed a significant influence of physical health on their overall sense of well-being. The findings suggest that education and anxiety have impacts on self-rated health of both diseased and healthy women. To improve the well-being of disadvantaged women, providing accessible physical and mental health support, along with expanding educational opportunities, would be beneficial.

Keywords Socioeconomic status, Disadvantaged, Health, Iran

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Introduction

Every individual's birth, growth, work, and age are different in discrete segments of the population or between societies, which disadvantages many people. Inadequate conditions lead to the segmentation of disadvantaged populations based on factors such as place of residence, race or ethnicity, occupation, gender, religion, education, socioeconomic status, social capital, age, sexual orientation, and disability [1, 2]. It is evident that socioeconomically disadvantaged populations have differential physical health [3] and mental health outcomes, such as depression, stress, and anxiety [4–7].

In studying the health of socioeconomically disadvantaged populations, it is crucial to build upon theoretical frameworks like Bronfenbrenner's ecological systems theory (1977), later adapted into the socio-ecological model [8]. This model emphasizes how individual health is influenced by various levels of society, ranging from personal biology to broader societal factors, such as socioeconomic status. Understanding health disparities through this multilevel lens provides insights into how non-medical determinants impact physical and mental health.

Women's health plays a pivotal role in family and society. In many cultures, including Iran, women are central to family well-being, responsible for caregiving and maintaining household health. Their well-being also affects broader society, as women constitute a significant portion of the workforce and are key participants in social life. However, an unequal distribution of socioeconomic opportunities and health disparities, particularly in Iran, has resulted in substandard health outcomes for disadvantaged groups, including women [9–13].

In Iran, public and nongovernmental organizations (NGOs) support socioeconomically disadvantaged groups. Such organization, offering aid to the most vulnerable populations, including women without supporters, poor families with disabled heads, and women whose husbands are imprisoned without income.

Socioeconomic factors, known as the social determinants of health (SDH), play a more significant role in health outcomes than medical care [14–16]. Addressing the health of socioeconomically disadvantaged women is vital as improvements in their health have ripple effects on families and communities. Therefore, it is crucial to identify the health determinants for these women and implement evidence-based interventions to improve their status. This study aims to explore the relationship between socioeconomically disadvantaged women's self-rated health and their physical, mental, and social well-being. Additionally, it seeks to analyze the impact of social determinants of health on self-rated health. It's practical aim is to provide evidence-based insights to policymakers, healthcare providers, NGOs, and the relief foundations to design effective health promotion programs specifically tailored to the needs of these women.

Material and method

The present study is a cross-sectional study of disadvantaged women in Shiraz, Iran, conducted in 2021, who received support from the RF Organization.

Among the various support systems available to assist socioeconomically vulnerable populations in Iran, the selected RF stands as the foremost organization that provides aid through both government and nongovernmental grants. The RF evaluates applicants for registration based on a set of criteria, and eligible individuals receive access to a range of social and economic services. Underprivileged women constitute the majority of those who benefit from RF services, and as such, they are a suitable sample for our study. At the time of our research, the RF registered 32,000 women as beneficiaries in Shiraz. The study included women aged 18 to 60 years who were members of RF and gave their consent. The study excluded women who did not meet the specified age range and those deemed incompetent to respond to the survey questions.

The initial sample size was determined to be 380 using a 0.05 error rate and a 95% confidence interval, as calculated using the sample size calculator available at (http://www.raosoft.com/samplesize.html). This initial sample size was then adjusted to account for a design effect of 1.2 and an estimated nonresponse rate of approximately 20%, resulting in a final required sample size of 550. We employed a stratified sampling method to obtain a representative sample of participants. It is important to note that all supported individuals were categorized according to the RF classification, which divided them into six categories based on geographical proximity and gender. The RF further established subcategories, including divorced women, women with disabled heads of household, women who had lost the head of household, and women with incarcerated husbands. Samples were then randomly selected from each category and subcategory, ensuring that the proportions were maintained throughout the process.

A team of qualified personnel from the RF conducted the data collection process for the study. The researchers trained these personnel on the study objectives and the appropriate interviewing techniques required to successfully complete the questionnaires. During the interview process, the researchers closely monitored the personnel to ensure adherence to the study procedures. The personnel, in turn, selected the participants from among the women referred to the RF centers based on specific inclusion criteria.

Participants were asked for demographic information, social determinants of health conditions, physical,

mental, and social health status, and self-rated health. The first part of the interview included a checklist of questions about education, occupation, residence and neighborhood, income, accessibility to health facilities, transport, utility, and experience of violence. The second part of the interview asked participants about their physical health and the number of chronic diseases they had, such as hypertension, diabetes, cerebrovascular disease, cancer, chronic respiratory disease, and any other chronic diseases.

Next, we assessed mental and social health using the Depression, Anxiety, and Stress Scale (DASS) and the Iranian Social Health Scale, respectively. The DASS was previously found to be valid and reliable by Asghari in Iran [17]. Furthermore, social health was measured with the "Iranian Social Health Scale." This questionnaire was designed and validated by Abachizadeh and colleagues in Iran. the "Iranian Social Health Scale," include 33 items, and assess the three dimensions: family, relatives, and community. The family factor pertains to interactions with parents and siblings, while relatives relate to other family members and friends [18].

Finally, we asked each participant to rate her health on a scale from zero to one hundred. Research has demonstrated the usefulness of this self-rated health measure in assessing the general health of various populations [19]. Indeed, to better understand the participants' lived experience of health and assess their perceptions of health, the self-rated health method was the appropriate method for achieving our goal.

Participants were informed that their involvement in the study would not affect support from agencies. Moreover, the interviewers explicitly identified themselves as researchers without administrative roles and conducted the data collection anonymously. We implemented these precautions to minimize the impact of social desirability bias on the study results.

The researchers decided to offer psychological counseling as an incentive to address some of the study participants' needs. The researchers extended this facility to the participants once they had completed the questionnaire.

We used several approaches to verify the quality of the data. Parts of the data were cross-checked with the participants' files; another part was double-checked, and we relied on responses based on their perceptions of the remaining information.

Data analysis

We applied a two-stage procedure to evaluate the effects of variables related to health perception. We used random forest in the first stage to identify important variables [20]. In the second stage, the top ten most important variables were entered into the classification and regression tree (CART) model as input [21]. In contrast to other machine learning methods with a black box nature, CART is capable of explaining complex relationships in a graphical output. Moreover, since the ranking of the variable importance in the random forest model was more accurate than that in the CART model, the random forest model was used for variable selection [22]. In addition, random forest is faster than bagging or boosting procedures, highly accurate, and robust to outliers [23]. The CART and random forest procedures were carried out using separate and random forest packages in R (ver. 3.6.3) [24, 25]. Gamma regression with log-links was applied to identify the major factors related to self-rated health. Gamma regression with a log link is suitable for analyzing positively skewed continuous outcomes. For gamma regression, the log link is the most common link. Contrary to the identity link, the log link does not require restrictions on coefficients [26]. **CsATR**.

CART

A machine learning procedure, utilize the dependent variable for both classification and regression. This tree-based procedure aimed to partition the dataset into homogeneous subsets (namely, terminal nodes) according to the dependent variable [27].

Random Forest

Random forest is a modification of CART [20]. To enhance the prediction performance, random forest can generate an ensemble of trees using bootstrap sampling and a randomized subset of predictors.

Ethical consideration

The ethics committee at Shiraz University of Medical Sciences approved the study (ethical code: IR.SUMS.REC.1399.1052). With the permission of the ethics committee, oral informed consent was duly obtained from all study participants before their participation. Following a detailed explanation of the study's objectives and procedures, the researchers emphasized that the completion of the questionnaire and the provision of responses constituted the participants' express consent to participate in the study. We omitted the participants' names from the data to protect their privacy. All the participants had the right to ask to delete their information at any time. No individual data were shared with any organization, including RF.

Result

In this study, 556 women who supported by the RF were included. An observation-to-covariate ratio of 20 [28] meets the minimal requirement of 10 occurrences per predictor variable. The analysis included no missing values for any of the variables. Women who had divorced/widowed made up the largest subgroup of all participants

Table 1 The frequency of qualitative variables ($N = 556$)

Qualitative variables			
Variable	**Subgroups**	**Frequency**	**Percent**
subcategory	Divorced	234	42.1
	Disabled	78	14.0
	Widowed	195	35.1
	Husband incarcerated	43	7.7
	other	6	1.1
Marital status	Single	143	25.7
	Married	102	18.3
	Divorced/Widow	311	55.9
Household size	1	67	12.1
	2	114	20.5
	3	184	33.1
	4	108	19.4
	more than 4	83	14.9
Education	Illiterate	119	21.4
	Nonacademic	379	68.2
	Academic	58	10.4
Physical Health*	without disease	303	54.5
	with 1 disease	137	24.6
	with 2 disease	68	12.2
	with 3 or more disease	48	8.6
Occupation	Jobless	455	81.8
	Transient occupied	68	12.2
	Permanent occupied	33	5.9
Insurance coverage	Yes	448	80.6
	No	108	19.4
House type	Ownership	146	26.3
	Rental	314	56.5
	Supportive**	96	17.3
Built up area	lower than 60 m	143	25.7
	60 to 100 m	313	56.3
	100 to 140 m	65	11.7
	higher than 140 m	35	6.3
Number of home room	Without room	27	4.9
	1 room	177	31.8
	2 rooms	317	57.0
	3 and more rooms	35	6.3
Residence injury	With injury	147	26.4
	Without injury	409	73.6
Difficulty in paying bill	Yes	386	69.4
	No	147	26.4
	Other***	23	4.1
Income-cost matching	Income > > Cost	11	2.0
	Income > Cost	8	1.4
	Income = Cost	11	2.0
	Income < Cost	85	15.3
	Income < < Cost	432	77.7
	Other	9	1.6
Primary health care access	Yes	287	51.6
	No	269	48.4
Transport	Private vehicle	25	4.5
	Public transportation without problem	388	69.8
	Public transportation with problem	143	25.7

Table 1 (continued)

Qualitative variables			
Variable	**Subgroups**	**Frequency**	**Percent**
High school in neighborhood	Yes	323	58.1
	No	233	41.9
Playground in neighborhood	Yes	298	53.6
	No	258	46.4
Public sport facilityin neighborhood	Yes	238	42.8
	No	318	57.2
Sanitary sewage	Yes	418	75.2
	No	138	24.8
Intimate violence experience	Yes	92	16.5
	No	464	83.5
Job violence experience	Yes	14	2.5
	No	542	97.5
Tobacco usage	Yes	70	12.6
	No	486	87.4
Stress	mild	79	14.2
	moderate	105	18.9
	severe	195	35.1
	normal	177	31.8
Anxiety	mild	28	5.0
	moderate	120	21.6
	severe	258	46.4
	normal	150	27.0
Depression	mild	71	12.8
	moderate	146	26.3
	severe	207	37.2
	normal	132	23.7

*Diseases including hypertension, diabetes, cerebrovascular disease, cancer, chronic respiratory disease, and any other chronic disease

**Supportive means the houses that were provided to subjects by government organizations or relatives

*** Other refers to subjects who had no information about the question

Table 2 The common descriptive statistics for quantitative variables ($N = 556$)

Variable	Minimum	Maximum	Mean	Std. Deviation
Self-Rated Health	0	100	66.510	25.359
Family Social Health	6	28	15.176	3.643
Friends and Relative's Social Health	8	36	19.390	5.421
Community Social Health	23	80	48.419	9.503

(55.9%). The mean age of the women was 42.8 ± 12.4 years, and the mean self-rated health status was 66.5. Most participants were unemployed and had no academic education, and poor housing conditions were prevalent among them. Approximately half of the participants had one or more chronic diseases, and many of them experienced stress, anxiety, or depression. Tables 1 and 2 report the subgroups of qualitative variables, their frequencies, and common descriptive statistics for quantitative variables, respectively.

Summary of analytical results

In this study, we used a two-stage approach to analyze factors associated with self-rated health among 556 socioeconomically disadvantaged women supported by the RF. First, random forest identified the most important variables, with physical health as the top predictor. Next, the top ten variables were further examined using a CART model, which confirmed physical health, social health, and built-up area as key factors. We then split the data by physical health status and applied gamma regression to account for the skewed data as well as CART model for better visualization of results. Gamma regression showed that, in women with physical health issues, education was associated with better self-rated health, while anxiety and stress were linked to poorer self-rated health. In women without physical health issues, education, and anxiety were also significantly associated with self-rated health. This combined approach highlighted the roles of physical, social, and mental health in relation to self-rated health.

Random forest

The variable importance measure, as one of the useful outputs of tree-based models, could reflect the effect of the predictor variables on the model. In this step, we used the random forest technique to rate the items based on their importance. In fact, the dependent variable (self-rated health) more effectively relates to the most important items. Figure 1 displays the variable importance based on the increase in the node purity measure. The importance of variables in the random forest model based on an increase in node purity are detailed in Additional file 1.

Classification and regression trees (CART)

The top ten most important variables, including physical health (PH), friends and relatives' social health (FRSH), community social health, number of household members, family social health, anxiety, education level, stress and built-up area (BUA), and depression, were entered into the CART model. The CART algorithm produces a tree with 8 nonterminal nodes and 9 terminal nodes.

According to the CART, physical health was the primary factor associated with self-rated health. Women without disease had a better perception of their health than women with disease. Among diseased women, the number of diseases affects self-rated health. Generally, increasing the number of diseases leads to a worse self-rated health status. Social health and BUA were items related to self-rated health in the healthy women group. The CART results are shown in Fig. 2.

Splitting dataset based on physical health

To further investigate the dataset, we divided individuals with and without physical health issues, with physical health being the most important variable. In addition to the CART model, we applied gamma regression with log-links to identify the factors related to health perception, given the highly skewed nature of the data. Figures 3 and 4 display the CART results for two sets of data.

Table 3 displays the results of gamma regression for individuals with physical issues. For individuals with physical health issues, nonacademic education was significantly more strongly associated with health perceptions than illiterate education was (1.267, 95% CI: 1.106, 1.451). In addition, compared with illiterate participants, participants who had an academic education had significantly greater health perceptions (1.665, 95% CI: 1.251, 2.217). Moderate and severe anxiety were significantly associated with lower health perceptions (0.765, 95% CI: 0.653, 0.896). For analysis, we classified normal and mild

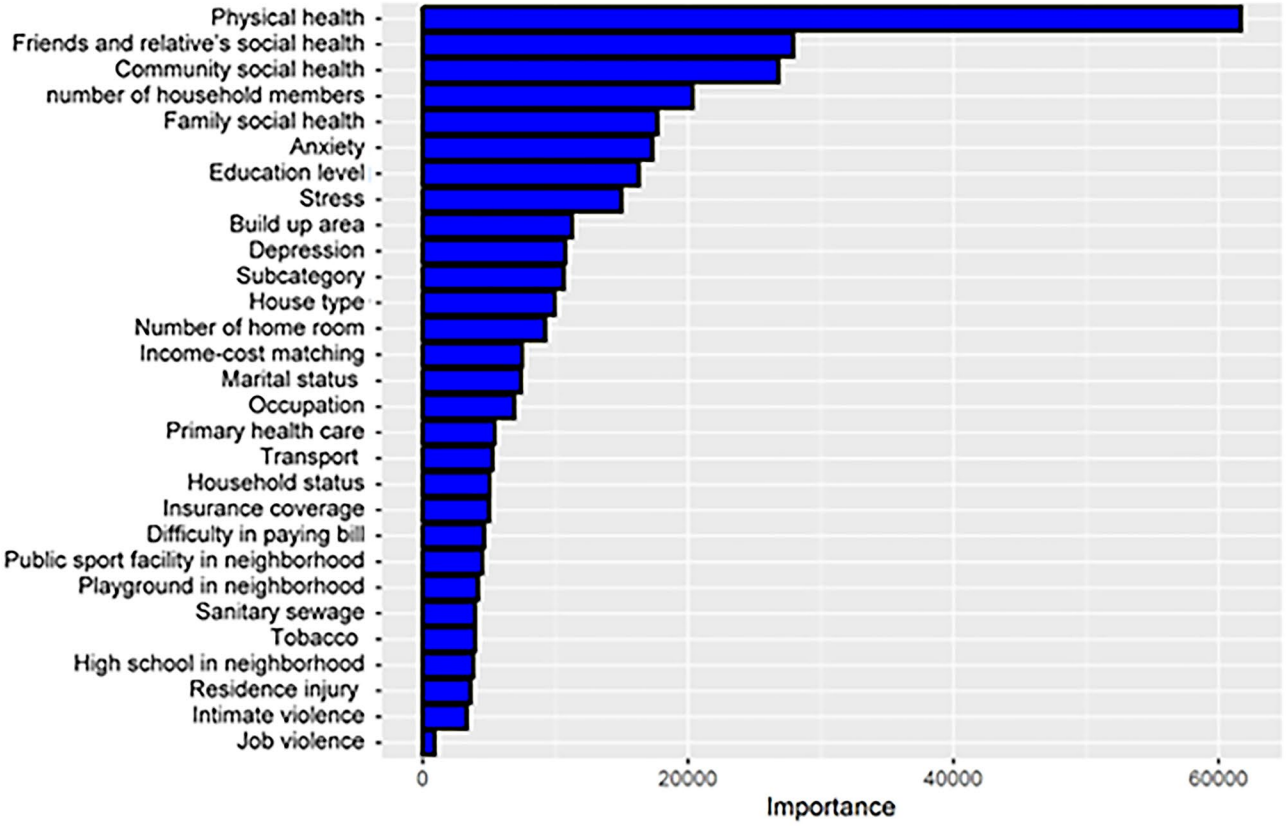

Fig. 1 The importance of variables in the random forest model was based on an increase in node purity

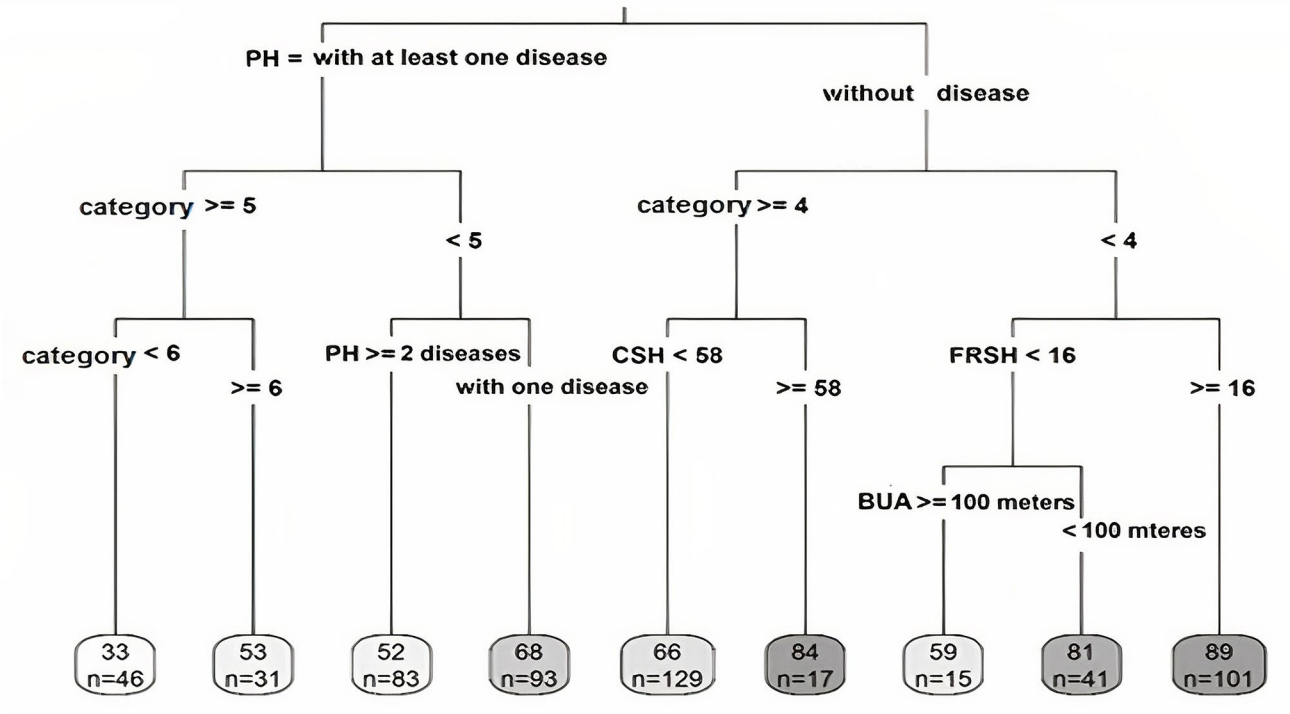

Fig. 2 Optimal tree created by CART. The number of participants and their associated means of self-rated health status are shown at each terminal node. PH physical health, category, FRSH friends and relative's social health, CHS community social health, BUA build-up area. The six categories in this model are based on the RF classification. Therefore, we did not use category in subsequent analyses

mental health problems as healthy and moderate and severe mental health problems as mental illness. Participants' perceptions of their physical health were considerably poorer for those who reported having moderate or severe stress than for normal participants and those with mild stress (0.872, 95% CI: 0.762, 0.999). Table 4 presents the results of gamma regression for individuals without physical issues. Participants with nonacademic education had significantly greater health perceptions than illiterate individuals without physical health issues (1.170, 95% CI: 1.067, 1.284). Moreover, participants with an academic education had significantly greater health perceptions than did those who were illiterate. (1.298, 95% CI: 1.150, 1.464). Compared with normal participants, individuals with moderate or severe anxiety and those with mild anxiety had significantly lower health perceptions (0.898, 95% CI: 0.836, 0.965). Additional File 2 provides the prediction performance indices for both the random forest and CART models. Table S1. The indices' values indicated a good fit to the data for each model. The results of two gamma regression models are also compared with those of log-normal regression, which is an alternative for analyzing positively skewed outcomes. The goodness of fit indices, Akaike's information criterion (AIC), and Bayesian information criterion (BIC) were used to compare these two models (Additional File 1: Table S2). The lower values of AIC and BIC for the gamma models indicate a better fit than for the log-normal models. Additional File 1: Table S3 provides the gamma regression model results for the entire population.

Discussion

This study aimed to uncover the relationships between self-rated health and physical, mental, and social health and to identify the social determinants of health that significantly influence health status in women's householder groups under socioeconomic support organization coverage. The results suggest that physical health, education, and anxiety are the most important factors in health perception.

The self-rated health question used in this study is a globally recognized measure in the field of health research. It has been shown in long-term cohort studies to be strongly associated with physical health outcomes, including mortality rates and the development of physical illnesses [29, 30]. However, in our study, we assessed this relationship cross-sectionally. This cross-sectional association between self-rated health and physical health indicators has been validated in other studies as well. For instance, better self-rated health has been linked to fewer chronic conditions, less severe disease, improved physical activity, better self-care practices, and reduced need for medications or physician visits [31–35]. Moreover, studies have investigated the relationship between better

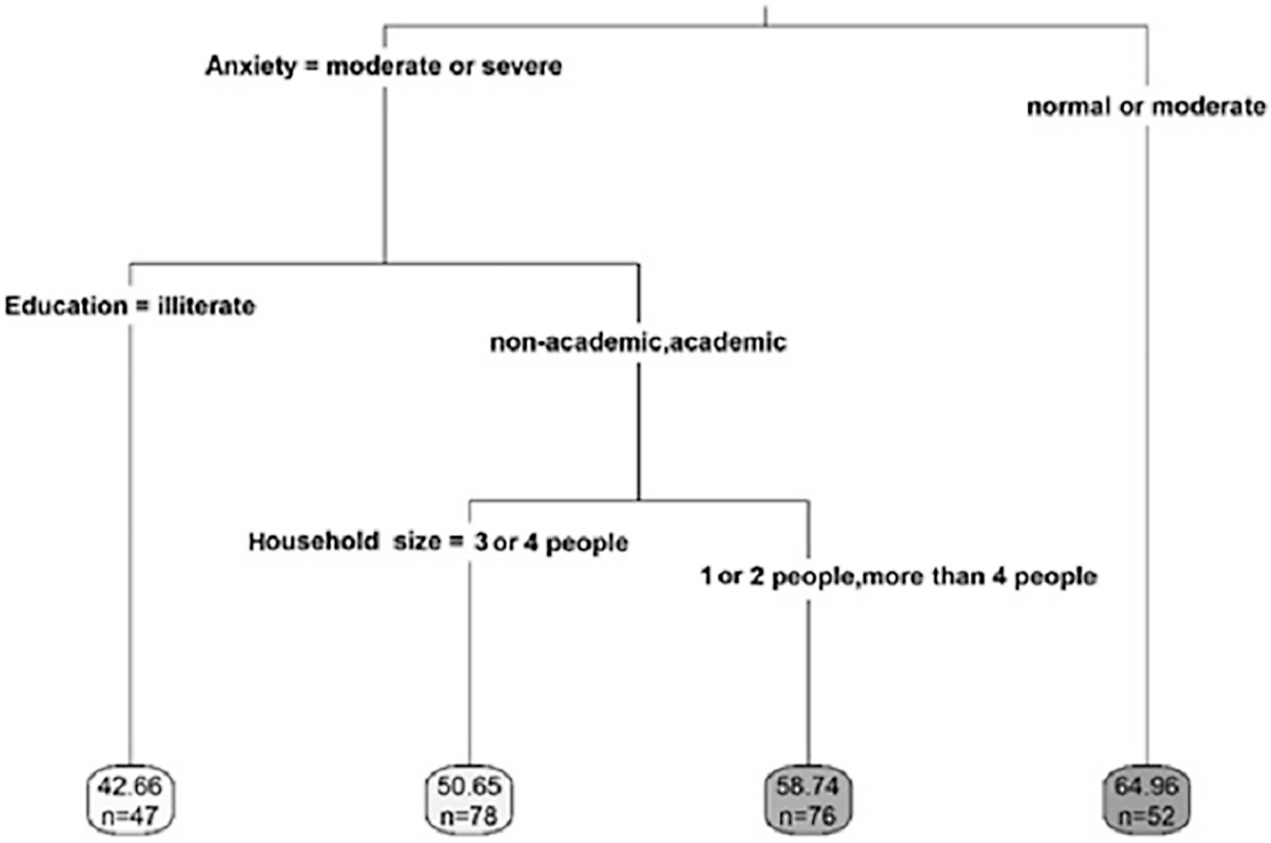

Fig. 3 CART model for individuals with physical health issues. The number of participants and their associated means of self- rated health status are shown at each terminal node

self-rated health and physiological parameters, such as lower hemoglobin A1C, less serum inflammatory markers, and increased HDL- cholesterol concentration, further reinforcing the connection between physical health and self-rated health [36–38]. These findings align with our results, suggesting that individuals with poorer physical health, especially those suffering from chronic conditions, tend to have a lower perception of their health status. Given the established link between self-reported health and physical health, we recommend active and continuous monitoring of the physical health of disadvantaged individuals, particularly those with chronic illnesses that require long-term follow- up. Since the presence of chronic diseases negatively impacts their perception of health, it is crucial to provide ongoing support, including addressing health-related concerns like financial assistance. This approach can help alleviate their health anxieties and improve overall well-being.

Additionally, our study shows that mental health, specifically anxiety, plays a significant role in self-rated health, particularly for women with chronic illnesses. Previous research has also emphasized the link between mental health and self-rated health, with studies indicating that anxiety is a strong predictor of poor self-rated health across different populations [19, 33, 39–44]. The high prevalence of anxiety in our sample suggests a need for continued mental health support for disadvantaged women, particularly in light of the COVID-19 pandemic, which has exacerbated anxiety levels worldwide. Studies have confirmed that the pandemic disproportionately affected vulnerable populations, potentially contributing to the increased anxiety observed in our participants.

Education was another significant factor influencing self-rated health in both healthy and diseased women. Our findings are consistent with research from multiple countries, such as Iran, Canada, Korea, and Germany, which have shown that higher education levels are associated with better self-rated health [19, 45–49]. This may be due to the fact that higher education often correlates with increased health literacy and better access to healthcare resources. Women with higher education levels may be better equipped to manage both physical and mental health challenges, leading to a more positive perception of their health.

Considering the simultaneous effect of education and anxiety on self-rated health in disadvantaged women, it is crucial to adopt a comprehensive approach that addresses multiple needs. The intersectionality framework can shed

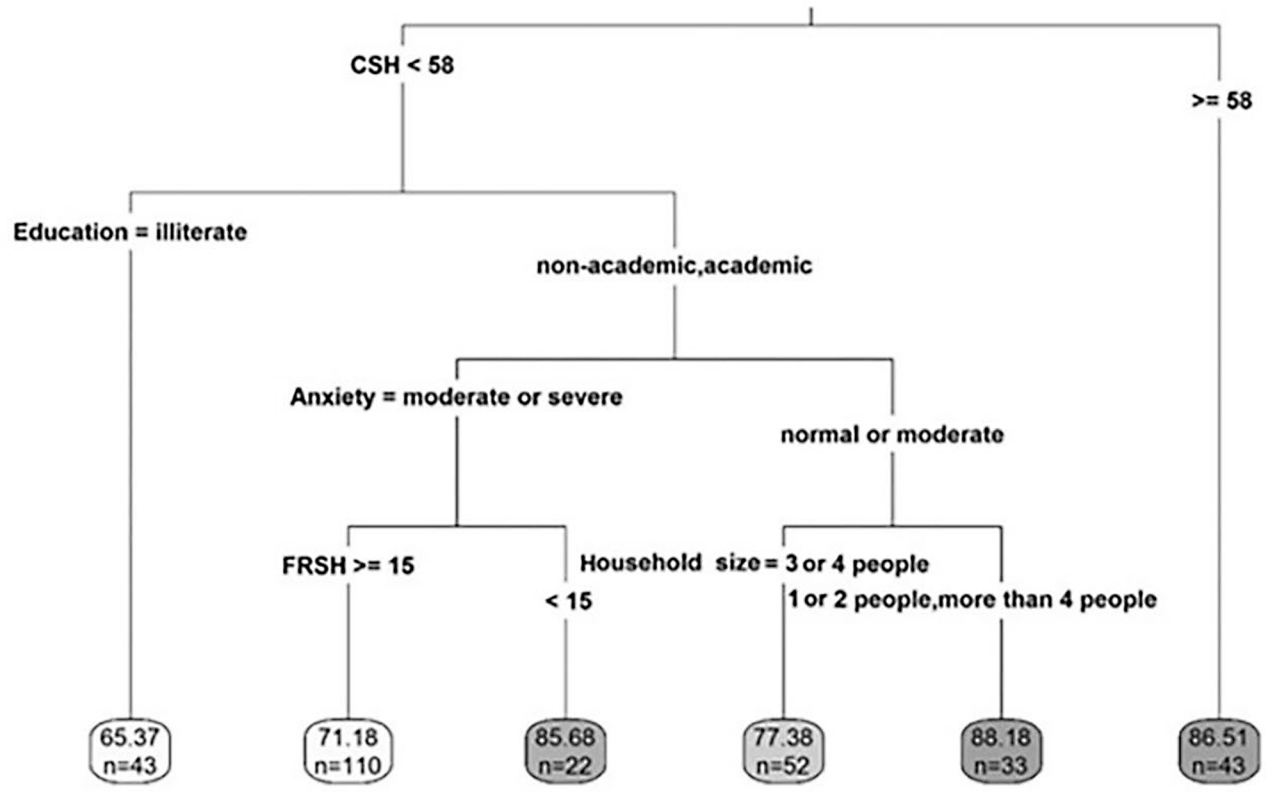

Fig. 4 CART model for individuals without physical health issues. The number of participants and their associated means of self- rated health status are shown at each terminal node. FRSH, friends and relatives' social health; CHS, community social health

Talbe 3 The results of gamma regression for individuals with physical health issues

	exp(b)	Std. Err.	*P*>z	(95% Confidence Interval)	
Friends and relative's social health	0.985	0.008	0.062	0.969	1.001
Community social health	1.000	0.005	0.988	0.990	1.010
Family social health	1.017	0.013	0.184	0.992	1.043
Built up area per person	0.927	0.070	0.310	0.800	1.074
Household size (1 people)					
2 people	0.881	0.112	0.318	0.686	1.130
3 people	0.794	0.108	0.089	0.609	1.036
4 people	0.810	0.122	0.161	0.602	1.088
more than 4 people	0.951	0.147	0.746	0.702	1.288
Anxiety (mild or normal)					
Moderate or severe	0.765	0.062	0.001	0.653	0.896
Education (illiterate)					
Nonacademic	1.267	0.088	0.001	1.106	1.451
Academic	1.665	0.243	0.000	1.251	2.217
Stress (mild or normal)					
Moderate or severe	0.872	0.060	0.048	0.762	0.999

Table 4 The results of gamma regression for individuals without physical health issues

	exp(b)	Std. Err.	*P*>z	(95% Confidence Interval)	
Friends and relative's social health	0.996	0.005	0.431	0.985	1.006
Community social health	1.005	0.003	0.098	0.999	1.011
Family social health	0.996	0.008	0.610	0.980	1.012
Built up area per person	0.971	0.045	0.531	0.887	1.064
Household size (1 people)					
2 people	0.957	0.069	0.539	0.832	1.101
3 people	0.926	0.072	0.328	0.795	1.079
4 people	0.933	0.078	0.406	0.791	1.099
more than 4 people	0.943	0.085	0.513	0.790	1.125
Anxiety (mild or normal)					
Moderate or severe	0.898	0.033	0.003	0.836	0.965
Education (illiterate)					
Nonacademic	1.170	0.055	0.001	1.067	1.284
Academic	1.298	0.080	0.000	1.150	1.464
Stress (mild or normal)					
Moderate or severe	1.035	0.038	0.355	0.962	1.113

light on the experiences of socioeconomically disadvantaged individuals who suffer from multiple social disadvantages. For example, a person who is low-income, unemployed, or disabled [50] might face more health challenges and be harder to reach with standard interventions. As a result, any intervention to improve the health and perceptions of these disadvantaged women should include a set of components—particularly mental health support and educational opportunities. Focusing solely on physical health while neglecting other health determinants like education and mental well-being leads to ineffective interventions and may not improve self-rated health appropriately.

SDH, such as employment, income, housing conditions, and violence, were also examined in our study, but no significant associations with self-rated health were found. This finding contrasts with numerous studies that have demonstrated the influence of SDH on health status [51–54], particularly showing that vulnerable populations experience even a greater impact from SDH [39, 55–58]. However, one exception in our findings was the built-up size of homes, which, according to the CART model, had a significant effect on self-rated health in women with chronic diseases. This aligns with studies showing that living in congested conditions can have a detrimental effect on mental health, particularly among vulnerable groups such as migrants [59]. A possible explanation for the broader lack of association between SDH and self-rated health, which requires further investigation, could be that the effects of SDH manifest differently through the specific categories present in our population. It is likely that the intersection of demographic traits, such as geographic location and socioeconomic status, plays a role in shaping the impact of SDH. Additionally, our participants were part of a vulnerable socioeconomic group that had already received assistance from the Foundation, which may have mitigated some of the typical effects of SDH. Further research is needed to explore these possibilities in more depth.

We found that healthy, disease-free women report greater self-rated health when they have positive relationships with relatives and friends or when they feel supported by their community. This finding is supported by studies showing that social connections and a sense of community belonging improve health perception [32, 39, 51, 56, 60, 61].

Limitations and strengths of the study

One limitation of our study is its cross-sectional design, which limits the ability to draw causal conclusions. Additionally, some participants may have underreported their income or economic standing. Due to the lack of a locally agreed-upon research tool, as well as participant hesitancy, spiritual health was not assessed and requires further research. Nonetheless, our use of two analytical methods (CART and gamma regression) allowed us to examine the relationships between various factors and self-rated health in an at-risk population, providing robust insights into the health perceptions of disadvantaged women.

Conclusion

The study of disadvantaged women revealed a significant influence of physical health on their overall sense of well-being. The findings suggest that education and anxiety have impacts on self-rated health of both diseased and healthy women. To improve the well-being of disadvantaged women, providing accessible physical and mental health support, along with expanding educational opportunities, would be beneficial.

Abbreviations

RF	The Relief Foundation
CART	Classification and regression trees
NGOs	Non-governmental organizations
SDH	Social determinants of health
DASS	Depression, Anxiety, and Stress Scale
PH	Physical health
FRSH	Friends and relatives's social health
BUA	Build-up area
AIC	Akaike's Information Criterion
BIC	Bayesian Information Criterion

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-025-21797-2.

Supplementary Material 1

Supplementary Material 2

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Author contributions

S.G. and S.A. both contributed equally: Supervision (lead), Investigation (lead), Methodology (equal), Formal Analysis (support), Writing – Original Draft Preparation, and Writing (equal) – Review & Editing (equal). H.J. Conceptualization (support), Methodology (equal), Investigation (support), Writing – Original Draft Preparation, and Writing (equal). M.S. Methodology (equal), Formal Analysis (lead), Writing – Original Draft Preparation, and Writing (equal). M.D. Formal Analysis (support), Writing (equal). KB.Lankarani. Conceptualization (lead), Supervision (support), Methodology (equal), Writing – Original Draft Preparation, and Writing – Review & Editing (equal). All authors have approved the submitted version AND have agreed both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, are appropriately investigated, resolved, and the resolution documented in the literature.

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Data availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

The ethics committee at Shiraz University of Medical Sciences approved the study (ethical code: IR.SUMS.REC.1399.1052). According to the permission of the ethics committee, oral informed consent was duly obtained from all study participants before their involvement. Following a detailed explanation of the study's objectives and procedures, the researchers emphasized that the completion of the questionnaire and the provision of responses constituted the participants' express consent to participate in the study. We omitted the participants' names from the data to protect their privacy. All the participants had the right to ask to delete their information at any time. No individual data was shared with any organization, including RF.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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