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HOUSEHOLD FOOD SECURITY AND ACCESS TO MEDICAL CARE IN MAPUTO, MOZAMBIQUE

CAMERON MCCORDIC[1]

SERIES EDITOR: JONATHAN CRUSH[2]

[1] Balsillie School of International Affairs, 67 Erb St West, Waterloo, Ontario, Canada N2L 6C2; cmccordic@balsillieschool.ca
[2] Balsillie School of International Affairs, 67 Erb St West, Waterloo N2L 6C2, Canada, jcrush@balsillieschool.ca.

Abstract

The relationship between household access to medical care and food security is a potentially circuitous and challenging relationship to model. This discussion paper uses multiple modelling techniques to determine the quality of the relationships between these variables using household survey data collected by the Hungry Cities Partnership in 2014 in Maputo, Mozambique. The results of the investigation are framed according to the Sustainable Livelihood Framework and indicate a predictive relationship between household food security status and consistent household medical care access among the sampled households. The results also identify potential conditional independence in the relationship between other demographic variables and these two dependent variables among the surveyed households.

Keywords

food security, medical care, households, health, urban poor

This is the seventh discussion paper in a series published by the Hungry Cities Partnership (HCP), an international research project examining food security and inclusive growth in cities in the Global South. The five-year collaborative project aims to understand how cities in the Global South will manage the food security challenges arising from rapid urbanization and the transformation of urban food systems. The Partnership is funded by the Social Sciences and Humanities Research Council of Canada (SSHRC) and the International Development Research Centre (IDRC) through the International Partnerships for Sustainable Societies (IPaSS) Program.

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Introduction

While food security has been defined in various ways, the most common operationalization of the term is taken from the 1996 World Food Summit and asserts that "food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO 2008). Much of the research building on this definition focuses on the availability, accessibility and effective utilization of food by humans. Less attention has been focused on another dimension of the definition; that is, the food security outcome of "an active and healthy life." This dimension of food insecurity has often been a neglected (or assumed) dimension in many food security studies.

The relationship between urban household food security and chronic illness in Africa has been the subject of some previous research (Crush et al 2011, Goudge et al 2009, Ivers et al 2009, De Waal and Whiteside 2003, Rosegrant and Cline 2003). However, researchers have tended to focus on the influence of illness on food utilization or food security through its secondary impacts on employment. Little research has focused on food security per se as a predictor of household medical care access. Understanding this relationship is particularly important in African cities where rapid, and predominantly unplanned, development has resulted in large informal settlements associated with widespread chronic poverty and ill-health in most cities (van Gelder 2013, Sverdlik 2011). As a result, food security and its relationship with medical care access among the urban poor represents a recurring challenge in the African city.

De Waal and Whiteside (2003) suggest that malnutrition increases the susceptibility of humans to chronic conditions such as HIV/AIDS and also highlight a secondary impact of these diseases on household livelihoods. They argue that the disease limits the ability of a household to earn income, may force members into precarious work, and can force households to sell off important assets. Crush et al (2011) further explain that there may be a cyclical relationship between food security and HIV in which the increasingly severe social and physical impacts of the disease limit food access and utilization and therefore quicken the progression of the disease. This is consistent with Ivers et al (2009) who identify how malnutrition can compound the impact of HIV/AIDS and result in increased vulnerability to other diseases.

The relationship between food insecurity and limited medical care access may also be broadly defined by poverty. Sen's (1981) analysis of famines suggested that food insecurity during times of famine commonly resulted from limited household entitlements. This assertion is validated by Frayne et al's (2010) survey findings among poor urban households in Southern Africa. Similarly, poverty can also impact access to medical care. Goudge et al (2009) identified several potential reasons for limited medical care access among low-income households suffering from chronic illness in South Africa. These included exhausted assets from previous illness, limited income, the high cost of medical care and the inefficient provision of medical care services. In a household survey of Bangalore, Bhojani et al (2012) found that healthcare costs associated with chronic illnesses have the potential, when paid out-of-pocket, to drive households deeper into poverty.

These studies have particular relevance to Maputo, Mozambique, where a two-tiered and inequitable medical care system (private and public) governs household medical care access in the city (McPake et al 2011). The Mozambique INE (2012) estimate that over 80% of deaths in Mozambique are the result of infectious, maternal, perinatal, and nutritional conditions in 2006 and 2007 despite the fact that just over 60% of patients who died from illness during this period sought clinical treatment (INE 2012: 25-7). This suggests that disease and food insecurity have taken a striking toll on the population and many who die from disease do not access clinical treatment.

The challenge of medical care access is particularly acute for households in Maputo, a city with large areas of informality and poor household access to infrastructure resources (Barros et al 2014). While it is estimated that over 90% of households in Maputo's wealthier downtown district (district 1) have electricity, only between 54% and 67% of households in districts 2-5 have electricity (and rates of access to water and sanitation are even lower) (Barros et al 2014). In addition to limited infrastructure access, households in the poor areas of Maputo face unpredictable or seasonal access to employment and high rates of food insecurity (Raimundo et al 2014).

This paper aims to make a contribution to untangling the relationship between medical care access and household food security (as well as the demographic variables which may mediate this relationship). The potentially cyclical nature of this relationship, however, can complicate regression modelling approaches. This investigation therefore applies two modelling techniques (logistic regression and Bayesian networks) to understand the relationship. The results are then framed using two social vulnerability models (the Pressure and Release Model and the Sustainable Livelihood Framework) to interpret the empirical findings.

Methodology

To assess the relationship between household food security and access to medical care, the analysis of household survey data from of Maputo focuses on three research questions: (a) what variables predict food security among the sampled households in Maputo? (b) are there any conditionally dependent or independent relationships among these predictors of food security? and (c) what variables predict medical care access among the sampled households?

The data used in this analysis is from a baseline household food security survey administered by the Hungry Cities Partnership in Maputo in October 2014. The total survey sample size of 2,071 was spread over 19 randomly selected wards in Maputo. The sample size assigned to each ward was approximately proportionate to the contribution of each ward's population to the total population of the city (using the 2007 Mozambican census data to estimate those population sizes). Within each ward, households were systematically selected by enumerators with instructions to cover the entire ward they were surveying.

The survey was administered using digital surveys on android tablets and validity checks were performed in the field. All enumerators were undergraduate students attending Eduardo Mondlane University, who received a two-day training workshop on the administration of the household survey. The survey instrument was pilot tested prior to its implementation in the field. The instrument was a revised version of an earlier survey conducted in Maputo by AFSUN in 2008 (Raimundo et al 2014) and was designed to collect data on household food sources, food security, food purchasing behaviour, poverty, and household demographic data.

This paper uses the following variables from the household survey data:

- The Household Food Insecurity Access Prevalence scale (HFIAP);
- The presence of chronically ill household members in the household (Chronic Illness);
- The size of the household (Household Size);
- Whether the household is female-centred (Female-Centred) or not. Female-centred households are defined as households with a single woman as the head of the household;
- The consistency of household clean water access in the last year (Water Access);
- The consistency of household electricity access in the last year (Electricity Access);
- The consistency of household cash access in the last year (Cash Access); and
- The consistency of household medical care access in the last year (Medical Care Access) (Table 1).

TABLE 1: Variable Descriptions

Variable	Level	Values	
HFIAP	Binary	Food secure	Food insecure
Chronic Illness	Binary	No ill members	Chronically ill members
Household Size	Binary	<=5 members	>5 members
Female-Centred	Binary	Not female-centred	Female-centred
Water Access	Binary	Consistent water access	Inconsistent water access
Electricity Access	Binary	Consistent electricity access	Inconsistent electricity access
Cash Access	Binary	Consistent cash access	Inconsistent cash access
Medical Care Access	Binary	Consistent medical care access	Inconsistent medical care access

In the analysis, chronically ill household members are defined as household members with a medically confirmed diagnosis of diabetes, heart problems, obesity, malnutrition, hypertension, asthma, arthritis, tuberculosis, chronic diarrhoea or cancer.

The analysis used the HFIAP and the Medical Care Access variables as the dependent variables in the Bayesian network and logistic regression models. The HFIAP is an ordinal level variable derived using a weighted scoring algorithm calculated across 9 ordinal-level questions regarding the frequency with which households experience food access challenges. The food access challenges covered in these questions include the financial, social, and physical aspects of limited food access (Coates et al. 2007). This variable therefore provides a good indication of household food security. The variable was collapsed to a binary-level variable indicating household food security (a score of 1 on the HFIAP) or food insecurity (a score of 2-4 on the HFIAP). This was done to keep the same level of measurement with the independent variables in this investigation, to allow for comparability across the analyses (especially between the odds ratios and logistic regression analysis), to facilitate the interpretation of the investigation's results, and to maintain comparability with previous urban food security models using the HFIAP.

To assess the probability relationships between the independent and dependent variables in this investigation (and to conceptually measure household vulnerabilities), the paper makes use of three analytical approaches. First, in order to describe the uncontrolled association between the independent variables and household food insecurity or inconsistent household medical care access, it uses odds ratio calculations. Odds ratios present the change in odds that a given household will be categorized in one of the two groups in the dependent variable given the household's categorization in one of the two groups in the independent variables (where a value greater than 1 indicates an increase in odds and a value lower than 1 indicates a decrease in odds). These odds ratio calculations are paired with Pearson Chi-Square calculations in order to assess the statistical chance that the observed distribution between any two binary variables was due to chance. The challenge with this form of analysis is that it is difficult to control for the influence of any other variable in the odds ratio calculations between any independent variable and the dependent variable.

Second, in order to calculate whether any given independent variable is still associated with increased odds of either household food insecurity or inconsistent household access to medical care, the paper uses logistic regression analysis. Logistic regression allows for a binary dependent variable and can accept independent variables at the binary, ordinal, or continuous level of measurement. The coefficients in logistic regression analysis represent the log-odds for the association between each independent variable and the dependent variable in the model (which are determined using Maximum Likelihood Estimation). The log-odds can be transformed to represent the odds ratio calculations for the relationship between the independent variables and the dependent variables in this model. However, the model assumes a linear additive relationship between the log-odds associated with each independent variable and the dependent variable. In other words, the model assumes that one can calculate the probability of a household being categorized as food insecure on the HFIAP by adding together the log-odds associated with each independent variable. The challenge is that this assumption does not allow for any conditionally dependent relationships among the independent variables in the model. This assumption is difficult to satisfy given the complex nature of relationships between assets, access, and food security among households in Maputo.

Third, in order to assess any conditionally dependent (or independent) relationships, the paper uses Bayesian network analysis. This form of analysis uses a combination of Pearson's Chi-Square analysis and Bayes' Theorem to determine the conditionally dependent and independent relationships between the variables included in the model. The structure of the network is learned as a Markov blanket (a graphical representation of the conditionally independent and dependent relationships between the target variable and closely related with conditionally dependent relationships to the variable). The learning algorithm used to construct these networks begins by assuming all variables in the model are dependent on one another. This assumption is tested using Pearson Chi-Square analysis. Any two variables which are not independent (with a p-value less than 0.05 on the test) are linked by an edge (a line). Any variable which is independent of any other variable or which lies outside the Markov blanket of the target variable (the HFIAP) is removed from the network.

Conditionally dependent relationships are constructed in this model by determining whether the statistical significance of the Chi-Square independence tests hold between any two variables, given subsets of adjacent variables that are not independent. If the independence tests do not hold between any two variables, the edge is removed between the two variables while the edges between these two variables and the adjacent variable are kept (indicating that the relationship between these two variables is conditionally dependent on the adjacent variable). The direction of the edges in the network is then determined using arc orientation rules in the algorithm. It should be noted that the direction of these edges does not indicate causality. The network is then used to calculate a conditional probability table for every variable pairing in the network. These conditional probability tables are constructed using Bayes Theorem and Maximum Likelihood Estimation, and assuming a Dirichlet prior distribution, to estimate the model parameters. To test the predictive accuracy of the network, the paper assesses the Receiver Operating Characteristic (ROC) curve for the model and the model's misclassification table. In addition, 10% of the sample is held out during the model building phase in order to test the predictive accuracy of this model. All of the calculations are carried out using IBM SPSS Statistics 23 and IBM SPSS Modeler 18.

The paper uses two theoretical frameworks to interpret the findings of the analysis: the Pressure and Release Model and the Sustainable Livelihood Framework. The Pressure and Release Model explains how a disaster (like food insecurity) can impact human populations. The model hypothesizes that disasters are the impacts of hazards on vulnerable populations (Birkmann 2006). In order to conceptualize vulnerabilities, this investigation treats any variable which increases the odds of a hazard impact occurring (which is conceptualized here as food insecurity) as a vulnerability indicator. The hazards which give rise to food insecurity are not investigated in this paper, however. The Sustainable Livelihood Framework explains how dynamic processes can transform the household vulnerability context (in the form of shocks) and impact the livelihood outcomes of livelihood assets (which can be human, social, natural, physical, or financial capital) (Birkmann 2006). This framework is used in this investigation to explain how vulnerabilities to hazards can be conditional upon the occurrence of dynamic shocks to household assets or household access to resources and services.

Clustering effects in the sample design are not accounted for in the logistic regression models, given the small sample size in the highest hierarchy of the nested model (ward level) which would have yielded unreliable standard errors in a multilevel logistic regression model (Maas and Hox 2005). The findings should not be interpreted as causal given the use of survey data and the lack of a control group. Due to constraints in the sampling and analysis, the results may not necessarily be generalizable and need to be verified by further research to determine the replicability of the findings in this paper.

These models are not able to account for all significant predictors of either food security or medical care access. While the logistic regression models have high predictive accuracy and relatively high pseudo R^2 values, other variables may be more important predictors of the dependent variables in the models. The conditionally dependent relationships observed in the Bayesian network may change as additional variables are taken into account. The observed conditionally independent relationships in the Bayesian networks in this investigation were established at an alpha of 0.05. Changing this alpha would likely also change the conditionally independent status of these variable relationships. Both dependent variables in these models indicate varying degrees of imbalance. The HFIAP demonstrated a 70%/30% imbalance while the Medical Care Access variable indicated a 75%/25% imbalance. These imbalances, however, are too small to benefit from the use of misclassification costs and re-sampling methods have the potential of biasing the representation of the household sample.

Predicting Household Food Security

In relation to the first question - which variables predict food security among households in Maputo - the distributed frequencies in the relationships between the independent variables and the dependent variable (HFIAP) provide some interesting insights. For example, while 46% of the sampled households in Maputo contain chronically-ill household members, almost 80% of those households were categorized as food insecure on the HFIAP. The highest proportion of food insecure households in the sample occurred among those households with inconsistent access to medical care (almost 94% food insecure) (Table 2).

All of these independent variables share a statistically significant relationship with the HFIAP dependent variable according to a Pearson Chi-Square analysis at an alpha of .001, indicating a low probability that these relationships are due to chance. In addition, all of these independent variables are associated with increased odds that a sampled household was categorized as food insecure on the HFIAP (Table 3). Inconsistent household medical care access is associated with the highest odds of a sampled household being categorized as food insecure on the HFIAP (more than eight times the odds for households with consistent medical care access). Household size is associated with the lowest odds ratio value, where sampled households with greater than five members have 50% higher odds of being categorized as food insecure on the HFIAP when compared to smaller households.

The logistic regression model of the HFIAP dependent variable demonstrates robust model test statistics. This model demonstrates tolerance values between .357 and .956 and VIF values between 1.046 and 2.801 for all independent variables included in the regression model. In addition, the highest correlation observed between the independent variables is 0.39 between the Water Access variable and the Electricity Access variables. Together, these statistics indicate that multicollinearity is not a confound in this model.

The model also demonstrates a statistically significant Chi-Square value of 491.243 at an alpha of .001 in the Omnibus tests of model coefficients. In addition, the model demonstrates a Cox and Snell R^2 value of 0.217 and a Nagelkerke R^2 value of 0.311, indicating a relatively significant increase in the log-likelihood of this regression model when compared to the null model. This regression model also demonstrates an accuracy of 75.9 in categorizing the sampled households according to the HFIAP dependent variable (in comparison to the 71.2% accuracy observed in the null model).

That said, this model does demonstrate a statistically significant Hosmer and Lemeshow Test result ($x2(8)=19.853$, $p=0.011$), indicating that there may be an issue with model fit (although this result should be interpreted along with the statistically significant Omnibus tests of model coefficients).

TABLE 2: Sample Frequency Distributions Across Study Variables and HFIAP

Variables	Values		Food Secure	Food Insecure	Total
Chronic Illness	No ill members	n	387	724	1,111
		%	34.80	65.20	100
	Chronically ill members	n	202	743	945
		%	21.40	78.60	100
Household Size	<=5 members	n	439	952	1,391
		%	31.60	68.40	100
	>5 members	n	150	514	664
		%	22.60	77.40	100
Female-Centred	Not female-centred	n	446	963	1,409
		%	31.70	68.30	100
	Female-centred	n	136	495	631
		%	21.60	78.40	100
Water Access	Consistent water access	n	507	836	1,343
		%	37.80	62.20	100
	Inconsistent water access	n	74	615	689
		%	10.70	89.30	100
Electricity Access	Consistent electricity access	n	440	529	969
		%	45.40	54.60	100
	Inconsistent electricity access	n	140	918	1,058
		%	13.20	86.80	100
Cash Access	Consistent cash access	n	532	826	1,358
		%	39.20	60.80	100
	Inconsistent cash access	n	51	626	677
		%	7.50	92.50	100
Medical Care Access	Consistent medical care access	n	552	988	1,540
		%	35.80	64.20	100
	Inconsistent medical care access	n	31	468	499
		%	6.20	93.80	100

TABLE 3: Odds Ratio and Chi-Square Analyses

Independent Variables	Odds ratio	95% Confidence interval		Pearson chi-square	Df	P-Value (2-sided)	N
		Lower	Upper				
Chronic Illness**	1.966	1.612	2.398	45.245	1	<.001	2,056
Household Size**	1.58	1.276	1.958	17.685	1	<.001	2,055
Female-Centred**	1.686	1.352	2.101	21.806	1	<.001	2,040
Water Access**	5.04	3.866	6.571	162.727	1	<.001	2,032
Electricity Access**	5.454	4.385	6.784	256.335	1	<.001	2,027
Cash Access**	7.906	5.824	10.73	221.282	1	<.001	2,035
Medical Care Access**	8.435	5.779	12.311	162.077	1	<.001	2,039

* p<.05
** p<.01

The logistic regression model of the HFIAP demonstrates that when all other independent variables in the model are held constant, all of the included independent variables are associated with increased odds of household food insecurity on the HFIAP (Table 4). Holding all other independent variables in the model constant, households in the sample with inconsistent access to cash in the last year had almost four times the odds of being categorized as food insecure on the HFIAP when compared to households in the sample with consistent access to cash. Similar to the odds ratio calculations performed in Table 3, households in the sample with more than five members had the smallest increase in the odds of food insecurity when compared to households with fewer household members.

Relationships among Predictors of Food Security

Bayesian network analysis was used to test the conditionally dependent or independent relationships among the predictors identified in the logistic regression model predicting the HFIAP dependent variable among the sampled households. The network relies on Maximum Likelihood Estimation with Bayes adjustment for small cell counts as a parameter learning method. Pearson Chi-Square analysis was used for all independence tests with an alpha of 0.01. The Maximal Conditioning Set size was set to 5 for this model.

The Bayesian Network demonstrates that the female-centred variable is conditionally independent of the HFIAP variable given the other variables in the model (Figure 1). In addition, the Electricity Access, Cash Access, Chronic Illness, Household Size and Water Access variables were found to be independent given the HFIAP variable and the Medical Care Access variable. Surprisingly, the relationship between the Chronic Illness variable and the Medical Care Access variable is conditionally independent given the HFIAP variable in this model (although this relationship is not validated in the logistic regression analysis in Table 9).

The Bayesian network in Figure 1 is 74.8% accurate in classifying households in the training data set and 74.75% accurate in classifying households in the testing data set according to food security status in the HFIAP. However, the outcome statistics of this model demonstrate a greater sensitivity in the model to food insecurity than food security (the model was more accurate in predicting household food insecurity than food security) in both the training and testing data sets. The Receiver Operating Characteristic (ROC) curve demonstrated an Area Under Curve (AUC) value of 0.792 and Gini coefficient of 0.584 for the training data set and an AUC value of 0.789 and Gini Coefficient of 0.578 for the testing data set (Figure 2).

The Bayesian network predicting consistency of medical care access is 79.07% accurate in classifying households in the training data set and 79.8% accurate in classifying households in the testing

TABLE 4: HFIAP Logistic Regression Model

Variables	B	S.E.	Wald	Df	P-Value	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Chronic Illness**	0.432	0.116	13.812	1	<.001	1.54	1.226	1.933
Household Size*	0.296	0.126	5.499	1	0.019	1.344	1.050	1.722
Female-Centred**	0.348	0.127	7.482	1	0.006	1.416	1.104	1.818
Water Access**	0.662	0.16	17.02	1	<.001	1.939	1.415	2.655
Electricity Access**	0.922	0.132	49.185	1	<.001	2.515	1.944	3.254
Cash Access**	1.326	0.168	62.088	1	<.001	3.766	2.708	5.238
Medical Care Access**	1.093	0.21	27.134	1	<.001	2.984	1.978	4.502
Constant**	-0.487	0.094	26.891	1	<.001	0.614		

* p<.05
** p<.01

data set according to the consistency of household medical care access (Figure 1). That said, the outcome statistics of this model demonstrate a greater sensitivity to consistent household medical care access than inconsistent household medical care access (the model is more accurate in predicting consistent household medical care access) in both the training and testing data sets. The ROC curve demonstrates an Area Under Curve (AUC) value of 0.819 and Gini coefficient of 0.637 for the training data set and an AUC value of 0.833 and Gini Coefficient of 0.666 for the testing data set (Figure 3).

FIGURE 1: Bayesian Network Model of Household Food Security and Medical Care Access

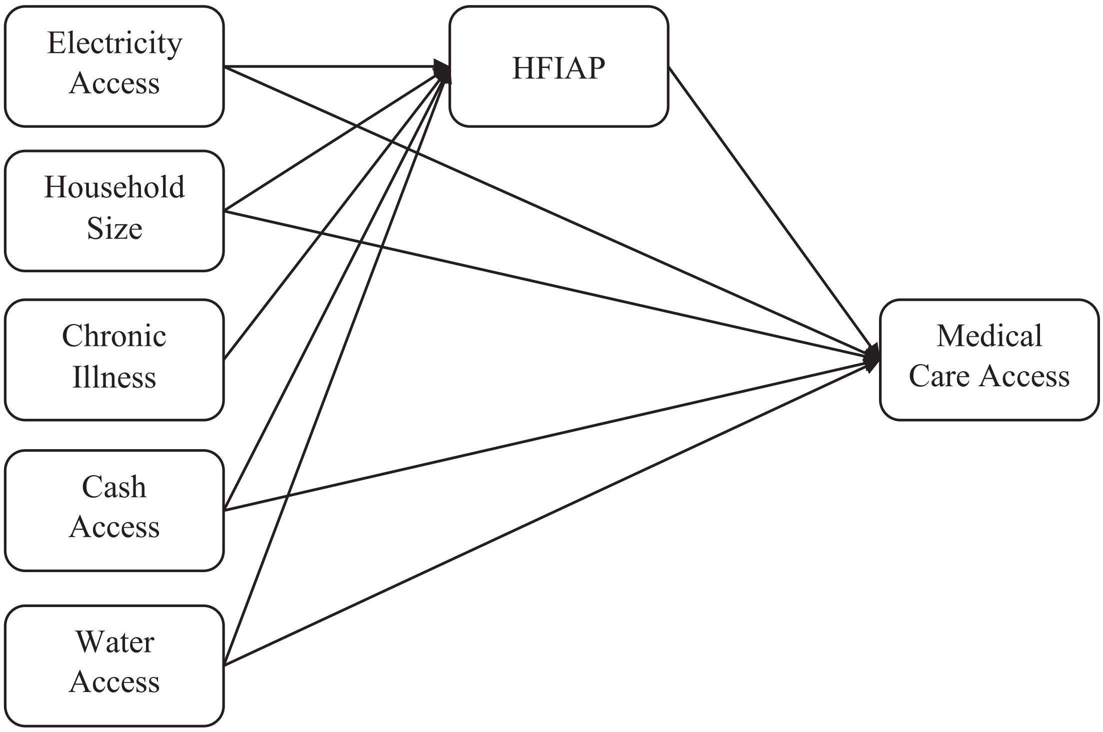


FIGURE 2: ROC Curve for the HFIAP Bayesian Network Node

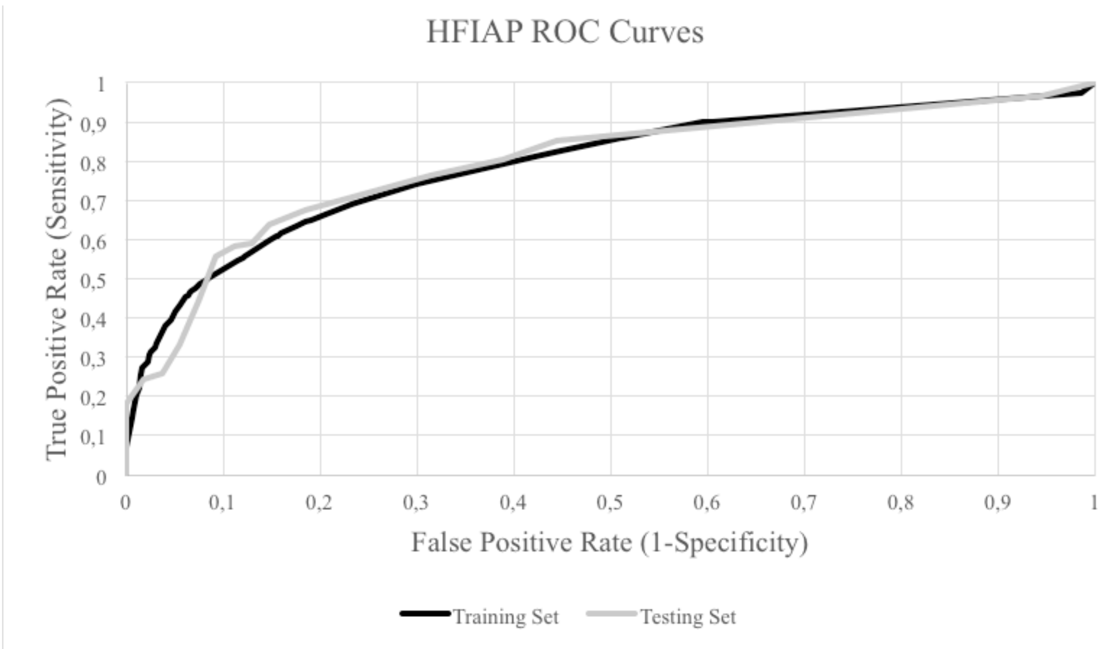
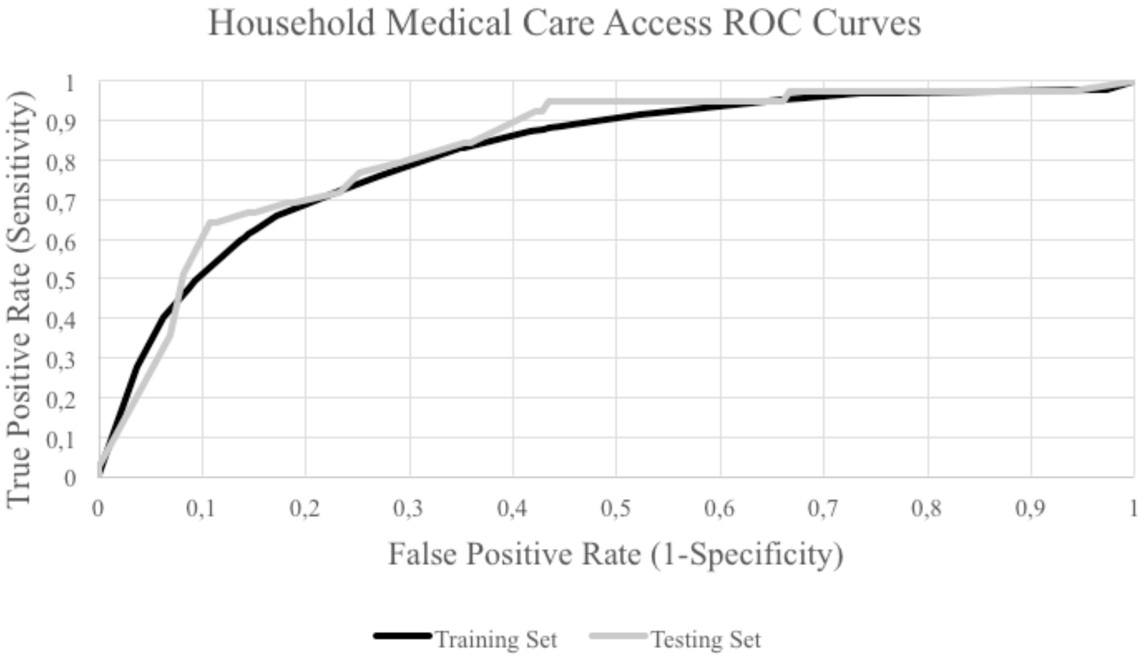


FIGURE 3: ROC Curve for the Household Medical Care Access Bayesian Network Node



The conditional probability tables for the HFIAP Bayesian Network are represented in Tables 5 and 6. Table 5 represents the conditional probabilities for the HFIAP variable in the Bayesian Network. Table 6 represents the conditional probabilities for the Medical Care Access variable in the Bayesian network. As expected in the HFIAP model, the sampled households with the highest probability of being categorized as food insecure were those with chronically ill household members, more than 5 members, and with inconsistent access to cash, water, and electricity in the previous year (98% chance among these households). Sampled households with the opposite conditions (no chronically ill members and consistent access to all of these resources) only have a 34% chance of being food insecure in this model. Similarly, in the Medical Care Access model, sampled households that are food insecure, have more than 5 members, and have inconsistent access to water, electricity and cash in the previous year have the highest probability in the model of also having inconsistent medical care access (62% chance among these households).

Together, these conditional probability tables indicate that food insecurity may play a role in predicting the consistency of household medical care access. In order to better understand this role, the same logistic regression analysis used to build the HFIAP model was used to build a household medical care access model.

TABLE 5: Bayesian Network HFIAP Conditional Dependence Probability Table

Chronic Illness	Household Size	Water Access	Electricity Access	Cash Access	Food Insecure	Food Secure
Chronically ill members	>=6 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.98	0.02
Chronically ill members	>=6 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.85	0.15
Chronically ill members	>=6 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.75	0.25
Chronically ill members	>=6 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.82	0.18
Chronically ill members	>=6 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.88	0.12
Chronically ill members	>=6 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.76	0.24
Chronically ill members	>=6 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.83	0.17
Chronically ill members	>=6 members	Consistent water access	Consistent electricity access	Consistent cash access	0.54	0.46
Chronically ill members	<=5 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.96	0.04
Chronically ill members	<=5 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.83	0.17
Chronically ill members	<=5 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.85	0.15
Chronically ill members	<=5 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.5	0.5
Chronically ill members	<=5 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.98	0.02
Chronically ill members	<=5 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.73	0.27
Chronically ill members	<=5 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.97	0.03
Chronically ill members	<=5 members	Consistent water access	Consistent electricity access	Consistent cash access	0.61	0.39
No ill members	>=6 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.95	0.05
No ill members	>=6 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.93	0.07
No ill members	>=6 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.66	0.34
No ill members	>=6 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.87	0.13
No ill members	>=6 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.94	0.06
No ill members	>=6 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.73	0.27
No ill members	>=6 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.87	0.13
No ill members	>=6 members	Consistent water access	Consistent electricity access	Consistent cash access	0.58	0.42

No ill members	<=5 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.95	0.05
No ill members	<=5 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.81	0.19
No ill members	<=5 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	1.00	0.00
No ill members	<=5 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.76	0.24
No ill members	<=5 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.95	0.05
No ill members	<=5 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.66	0.34
No ill members	<=5 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.62	0.38
No ill members	<=5 members	Consistent water access	Consistent electricity access	Consistent cash access	0.34	0.66

TABLE 6: Bayesian Network Medical Care Access Conditional Dependence Probability Table

HFIAP	Household Size	Water Access	Electricity Access	Cash Access	Inconsistent Access	Consistent Access
Food insecure	>=6 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.62	0.38
Food insecure	>=6 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.25	0.75
Food insecure	>=6 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.75	0.25
Food insecure	>=6 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.38	0.62
Food insecure	>=6 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.49	0.51
Food insecure	>=6 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.25	0.75
Food insecure	>=6 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.34	0.66
Food insecure	>=6 members	Consistent water access	Consistent electricity access	Consistent cash access	0.12	0.88
Food insecure	<=5 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.71	0.29
Food insecure	<=5 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.23	0.77
Food insecure	<=5 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.47	0.53
Food insecure	<=5 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.14	0.86
Food insecure	<=5 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.44	0.56
Food insecure	<=5 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.16	0.84
Food insecure	<=5 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.27	0.73

Food insecure	<=5 members	Consistent water access	Consistent electricity access	Consistent cash access	0.08	0.92
Food secure	>=6 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.34	0.66
Food secure	>=6 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.4	0.6
Food secure	>=6 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.34	0.66
Food secure	>=6 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.34	0.66
Food secure	>=6 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.15	0.85
Food secure	>=6 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.15	0.85
Food secure	>=6 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.17	0.83
Food secure	>=6 members	Consistent water access	Consistent electricity access	Consistent cash access	0.06	0.94
Food secure	<=5 members	Inconsistent water access	Inconsistent electricity access	Inconsistent cash access	0.38	0.62
Food secure	<=5 members	Inconsistent water access	Inconsistent electricity access	Consistent cash access	0.07	0.93
Food secure	<=5 members	Inconsistent water access	Consistent electricity access	Inconsistent cash access	0.97	0.03
Food secure	<=5 members	Inconsistent water access	Consistent electricity access	Consistent cash access	0.00	1.00
Food secure	<=5 members	Consistent water access	Inconsistent electricity access	Inconsistent cash access	0.01	0.99
Food secure	<=5 members	Consistent water access	Inconsistent electricity access	Consistent cash access	0.02	0.98
Food secure	<=5 members	Consistent water access	Consistent electricity access	Inconsistent cash access	0.12	0.88
Food secure	<=5 members	Consistent water access	Consistent electricity access	Consistent cash access	0.01	0.99

Predicting Medical Care Access

When the frequency distribution of the independent variables are cross-tabulated with the medical care access dependent variable, only about 70% of sampled households with chronically ill members had consistent medical care access in the previous year (Table 7). The sampled households with inconsistent cash access in the previous year had the highest rate of inconsistent medical care access (about 50% of the households). These cross-tabulations also indicate that the rate of inconsistent household medical care access is approximately the same regardless of whether or not a household is female-centred.

The observed frequency distribution trends among these independent variables are validated by the odds ratio calculations for these variables. All of the independent variables share a statistically significant relationship (at an alpha of 0.01) with the exception of the female-centred household variable (according to the Pearson Chi-Square test). The HFIAP variable is associated with the highest odds ratio value for these calculations. Sampled households categorized as food insecure on the HFIAP have over eight times the odds of having inconsistent household medical care access when compared to sampled households that are categorized as food secure. In addition, the Cash Access variable is associated with a very high odds ratio value for this calculations (Table 8).

TABLE 7: Sample Frequency Distributions Across Study Variables and Medical Care Access

Variables	Values		Consistent Access	Inconsistent Access	Total
Chronic Illness	No ill members	n	895	213	1,108
		%	80.80	19.20	100
	Chronically ill members	n	657	288	945
		%	69.50	30.50	100
Household Size	<=5 members	n	1087	306	1,393
		%	78.00	22.00	100
	>5 members	n	465	194	659
		%	70.60	29.40	100
Female Centred	Not female centred	n	1070	342	1,412
		%	75.80	24.20	100
	Female centred	n	479	156	635
		%	75.40	24.60	100
Water Access	Consistent water access	n	1150	200	1,350
		%	85.20	14.80	100
	Inconsistent water access	n	394	298	692
		%	56.90	43.10	100
Electricity Access	Consistent electricity access	n	874	102	976
		%	89.50	10.50	100
	Inconsistent electricity access	n	665	396	1,061
		%	62.70	37.30	100
Cash Access	Consistent cash access	n	1212	157	1,369
		%	88.50	11.50	100
	Inconsistent cash access	n	335	342	677
		%	49.50	50.50	100
HFIAP	Food secure	n	552	31	583
		%	94.70	5.30	100
	Food insecure	n	988	468	1,456
		%	67.90	32.10	100

TABLE 8: Odds Ratio and Chi-Square Analyses

Independent Variables	Odds ratio	95% Confidence interval		Pearson chi-square	Df	P-Value (2-sided)	n
		Lower	Upper				
Chronic Illness**	1.842	1.502	2.258	35.004	1	<.001	2,053
Household Size**	1.482	1.201	1.829	13.551	1	<.001	2,052
Female Centred	1.019	0.819	1.267	.028	1	0.866	2,047
Water Access**	4.349	3.516	5.379	197.978	1	<.001	2,042
Electricity Access**	5.103	4.014	6.486	198.748	1	<.001	2,037
Cash Access**	7.881	6.297	9.863	374.560	1	<.001	2,046
HFIAP**	8.435	5.779	12.311	162.077	1	<.001	2,039

* $p<.05$
** $p<.01$

The logistic regression model of the medical care dependent variable demonstrates more robust model test statistics than the HFIAP logistic regression model. This model demonstrates tolerance values between .369 and .969 and VIF values between 1.046 and 2.780 for all independent variables included in the regression model. In addition, the highest correlation observed between the independent variables is 0.357 between the Water Access and Electricity Access variables. Together, these statistics indicate that multicollinearity is not a confound in the model.

The model also demonstrates a statistically significant Chi-Square value of 544.468 at an alpha of .001 in the Omnibus tests of model coefficients. In addition, the model demonstrates a Cox and Snell R^2 value of 0.238 and a Nagelkerke R^2 value of 0.355, indicating a relatively strong increase in the log-likelihood of this regression model when compared to the null model. This regression model also demonstrates an accuracy of 80.9% in categorizing the sampled households according to the HFIAP dependent variable (in comparison to the 75.6% accuracy observed in the null model). This model also does not indicate a statistically significant Hosmer and Lemeshow Test result ($x2(8)=4.907$, $p=0.767$), indicating little evidence of any model fit issues.

All of the independent variables included in this model are statistically significant at an alpha of 0.05, with the exception of the female-centred variable ($p=0.052$). In addition, a one-step increase in the values of the independent variables with statistically significant log-odds values (at an alpha of 0.05) is associated with increased odds of inconsistent medical care access among the sampled households. Holding all other variables in the model constant, households with inconsistent cash access in the previous year have the highest odds of having inconsistent medical care access when compared to households with consistent cash access (almost five times the odds of having inconsistent medical care access). This compares with the HFIAP variable, which indicated that, holding all other variables in the model constant, food insecure households in the sample have just over triple the odds of having inconsistent medical care access when compared to food secure households.

TABLE 9: Medical Care Access Logistic Regression Model

Variables	B	S.E.	Wald	Df	P-value	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Chronic Illness**	0.446	0.123	13.179	1	<.001	1.563	1.228	1.989
Household Size*	0.276	0.127	4.733	1	0.03	1.317	1.028	1.688
Female-Centred	-0.254	0.131	3.772	1	0.052	0.776	0.601	1.002
Water Access**	0.786	0.132	35.547	1	<.001	2.195	1.695	2.843
Electricity Access**	0.646	0.149	18.708	1	<.001	1.909	1.424	2.558
Cash Access**	1.581	0.126	158.131	1	<.001	4.86	3.798	6.217
HFIAP**	1.138	0.21	29.482	1	<.001	3.12	2.069	4.704
Constant**	-3.762	0.22	291.657	1	<.001	0.023		

* p<.05
** p<.01

Conclusion

The logistic regression models presented in this paper demonstrate that most of the independent variables do predict household food insecurity and inconsistent household medical care access and the Bayesian Network validates a potentially significant relationship between household food security status and medical care access. It therefore appears that: (1) household food insecurity predicts household medical care access, (2) there is a conditionally dependent relationship between household medical care access and household food security status (given the variables included in this investigation and the sampled households), and (3) the relationship between female-centred households and household food insecurity appears to be conditionally dependent on other variables included in this investigation.

In addition, it appears that the predictive relationship between the other independent variables in the models are conditionally independent given the food security status of the household and the consistency of household medical care access. These results suggest food insecurity and medical care access may be closely tied to the loss of access to other resources. Further research will be needed to determine the directionality, representativeness, and generalizability of this relationship. For example, it may be that the extent to which households in Maputo can maintain consistent medical care access is dependent upon a household's food security status. However, this analysis cannot determine any causal relationships (due to the analytical methods used and, more importantly, the fact that this investigation is based on survey data).

The results of this investigation also provide further validation of the findings of previous research into the relationship between household access to infrastructure resources and household food security in Maputo (Frayne and McCordic 2015, McCordic 2016). Infrastructure development in Maputo has been a key political issue, given the large informal areas in the city. However, further research is needed to determine whether other variables better explain this relationship or if this is a causal relationship (this paper merely asserts a predictive relationship between these variables in the context of the independent variables included in the models).

The results are consistent with the Sustainable Livelihood Framework. According to the Framework, access to key social and physical capital will influence the kind of livelihood outcomes that a household experiences. The results indicate that access to electricity and water appeared to predict household food security and medical care access. These findings may be explained by trade-offs between access to different resources (where households give up access to some resources in order to maintain access to other resources). Further work may be needed to elaborate how the shocks theorized in this framework can impact household livelihood assets (for example, whether households respond to these shocks by trading off assets or simply lose access to those assets). The Pressure and Release model can explain how the demographic variables included in this investigation can predict food insecurity. According to this model, the included variables may be indicators of vulnerability. When a food security hazard occurs, households carrying these traits may be more likely to experience food insecurity. This does not imply that these traits caused the food insecurity, merely that these traits are associated with an increased sensitivity of households to food insecurity.

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