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THE ROLE OF INFRASTRUCTURE ACCESS IN URBAN HOUSEHOLD VULNERABILITY TO FOOD INSECURITY IN SOUTHERN CITIES

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Abstract

The geographical concentration of poverty in informal neighbourhoods across cities is a common socio-economic feature of the urban form. Many of these impoverished areas also suffer from limited access to urban infrastructure. Given the expense and planning necessary to develop urban infrastructure, these areas are socially vulnerable in part because of their exclusion from urban master plans. This vulnerability is made more severe by the knock-on impacts of limited infrastructure access on other aspects of human insecurity. This paper uses HCP data to assess the predictive relationship between household infrastructure access and food insecurity across five case-study cities (Mexico City, Kingston, Maputo, Nairobi, and Nanjing). It determines the food security status of households with limited infrastructure access and finds that access to infrastructure is not conditionally independent of any measured characteristics of household heads. The observed relationship between urban infrastructure and food insecurity across cities in the Global South highlights the importance of urban planning as a means of influencing future urban vulnerability.

Keywords

food security, urban infrastructure, Global South

Suggested Citation

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This is the 42nd 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

Food security is commonly understood as the stable availability, accessibility and consumption of sufficient nutritious food for a healthy life (FAO 2008). While most of the research into this phenomenon has focused on rural environments, centring on the challenges of food production, urban food security has emerged over the past decade as an important area of development research (Crush and Frayne 2010, Frayne et al 2018). This shift in focus from the rural to the urban has an important impact on the conceptualization of household food insecurity. In particular, the discussion has shifted from the production of food to the accessibility of food. As Sen (1981) once noted, food access can play a significant role in household food security, perhaps even more significant than food supply. In balancing these two factors, it is likely that while food supply is a necessary condition for household food security, it is not a sufficient condition. Households need to negotiate food access to become food secure.

In urban environments, where food is primarily accessed via transactions at food markets, food access becomes a strong indicator of a household's ability to maintain food security (Cohen and Garrett 2010). In this environment, vulnerability to food insecurity can be measured by the factors that influence a household's ability to command sufficient assets to negotiate food access. These factors can either directly limit household assets (by increasing expenditures or limiting a household's ability to acquire sufficient assets) or mediate the value of those assets (by changing the price of food or the purchasing parity of household income).

Previous studies have identified several variables that may influence household vulnerability to food insecurity, and the lack of available healthy food is a common factor cited by many food security researchers. For example, some studies have tied limited food availability to low dietary diversity, food insecurity, and increased incidence of chronic illness (Eisenhauer 2001, Lamichhane et al 2012, Sadler et al 2013). Volatile food prices have also been a focus of recent urban food security research. Headey (2011), for example, suggests that the 2008 food price crisis drove millions of individuals into greater food insecurity. Minot (2010) argues further that over-reliance on food imports may be a factor in household vulnerability to food prices. Tawodzera's (2012) study of Harare, Zimbabwe, highlights the impacts of hyperinflation on household food security in the city.

Quite apart from these broader mediators of vulnerability to food insecurity, urban households have their own characteristics that can increase the odds of food insecurity. In addition to low household income, which is often cited as a determinant of vulnerability of food insecurity (Barrett 2002, Carter and Barrett 2006), other demographic characteristics have been identified as potential drivers of household vulnerability to food insecurity. The presence of a chronic illness, for example, may predispose households to insecure food access. Crush et al (2011) suggest that HIV/AIDS impacts the productivity of household members and limits their ability to access food. Brown and Funk (2008) argue that disease may actually explain half the cases of malnutrition globally. Gender has also been identified as a factor to be taken into account in food access research. Riley and Caesar (2017) remind us that the relationship between gender and food insecurity should also take the broader cultural context into account. Education and the migration status of household members have also been identified as important factors mediating household food insecurity (Crush 2013, Rosegrant and Cline 2003, Vatsa 2004).

In addition to the social characteristics of a household, there is an emerging area of research around the importance of infrastructure access to a household's overall vulnerability. The Disaster Risk Reduction literature has a long history of evaluating infrastructure from the standpoint of social vulnerability. As an example, Doberstein and Stager (2013) highlighted the role that physical infrastructure (e.g. building structural integrity) and social infrastructure (e.g. land tenure) can have in mitigating hazard exposure. Birkmann (2006) highlighted how infrastructure is often characterized in this dualistic manner in disaster risk reduction literature and this characterization helps to understand the broad components of urban infrastructure. As a result, infrastructure can be understood as both physical networks (like electrical and water grids) as well as social systems (like medical care systems and institutions).

The potential impact of household infrastructure access on food security is conceptually circuitous. It is possible, as Bosher and Dainty (2011) posit, that infrastructure can mitigate the environmental hazards that could, in theory, result in food insecurity. While this is a valid point, the chronic and widespread nature of food insecurity in many developing cities makes this explanation unlikely as the sole justification for the relationship. McCordic (2017) suggests that the relationship may emerge from a series of household trade-offs, where, households forced into poverty may need to trade infrastructure access for food or other resources. Given that infrastructure networks often provide basic needs (like water and medical care), the inconsistent accessibility of infrastructure could indicate severe food insecurity since a household would not likely go without those resources without limiting food consumption first.

When modelling and collecting data on the topic, it is important to ensure that the responses cover a wide variety of household characteristics beyond income or household size. Instead, what is required is a more nuanced analysis of economic, environmental, social, and geographical factors which attempt to better encompass the true lived experience of food and nutrition insecurity. Given the conceptual challenges around understanding the impact of infrastructure on urban household food insecurity, further investigation is needed to evaluate the generalizability of the relationship and the extent to which it can be explained by other demographic variables. This paper seeks to contribute to this question by evaluating this relationship across five cities in the Hungry Cities Partnership.

Methodology

This paper addresses four basic research questions: (a) does household access to infrastructure resources and services predict household food insecurity? (b) What is the predictive strength of infrastructure access when compared to household head demographic characteristics as predictors of household food insecurity? (c) Does infrastructure access predict household food insecurity when household head demographic characteristics are controlled? and (d) Is the relationship between household infrastructure access and household food insecurity conditionally dependent on the demographics of the heads of household?

The data comes from a uniformly distributed sample of randomly selected household heads across 5 cities surveyed by the Hungry Cities Partnership between 2014 and 2016: Kingston, Jamaica; Maputo, Mozambique; Mexico City, Mexico; Nairobi, Kenya; and Nanjing, China. In each of these cities, the household sample size was stratified across randomly selected wards using proportionate allocation and the most recently available census data. Households were then selected for the survey using a combination of random and systematic sampling. To account for the variability in sample sizes across these cities, and the impact this variability would have on the analysis, we randomly selected 500 households from each city data set. The same survey instrument was administered to every household sampled in this investigation. The instrument includes measures of household food security, food consumption, poverty, income and expenditures, and the demographic characteristics of household members including the household head.

The dependent variable (food security status of the sampled households) in the analysis is the Household Food Insecure Access Prevalence Scale (HFIAP). This scale measures the frequency with which households experienced various dimensions of limited food access in the previous month. The scale consists of 9 Likert questions about the frequency of these household experiences. The HFIAP score is calculated by applying a scoring algorithm to these nine questions that takes into account the severity and frequency with which each of the food access challenges are experienced. The scoring algorithm ranks households according to the following categories: food secure, mildly food insecure, moderately food insecure, and severely food insecure. For the purposes of this investigation, this variable was binned into two categories: food secure and food insecure (representing mild, moderate and severe food insecurity) (Table 1).

The independent variables include household access to medicine or medical care, clean water for home use, and electricity. Access to these resources and services is measured by the frequency with which households have gone without access to these resources and services in the previous year. These variables were binned to indicate whether households had consistent or inconsistent access to any of these variables. In addition to these variables, we included measures of the following household head demographics: migrant status, employment status, sex, food responsibility, education level, and health status. The migrant status of the household head was defined by whether the household head was born within the city or outside it. The employment status of the household head was measured by whether the individual was employed (either self-employed or employed in full-time/part-time wage work) or unemployed (including for medical reasons). The food responsibilities of the household head were measured by whether or not they had any role in the production, purchase, preparation or allocation of food in the household. The education level of the household head was defined by whether or not they had formal education. Finally, the health status of the household head was defined by whether they had a confirmed diagnosis of any of the following chronic illnesses: diabetes, heart problems, obesity, hypertension, asthma, tuberculosis, chronic diarrhoea, or cancer.

The first research question uses a combination of odds ratio, Pearson's chi-square analysis, and Fisher's exact tests to determine whether changes in the independent variables are associated with increased odds of household food insecurity and whether the distribution of food security scores across these independent variables is statistically significant (in other words, whether the distribution of these scores is significantly non-random).

The comparative predictive strength of each independent variable as a predictor of household food security is established using a linear support vector machine algorithm. This algorithm transforms the n-dimensional space between independent variables in order to fit a straight line between the values of each variable to best categorize data points according to household food security status. As a result, the algorithm efficiently creates a fitted predictive model of household food security and provides a ranking of each independent variable according to its importance to the model's predictions.

TABLE 1: Investigation Variables

Variables	L.O.M.	Values	
HFIAP	Binary	Food secure	Food insecure
Household water access	Binary	Consistent access	Inconsistent/No access
Household electricity access	Binary	Consistent access	Inconsistent/No access
Household medical care access	Binary	Consistent access	Inconsistent/No access
Head migrant status	Binary	Born in city	Born outside city
Head employment status	Binary	Employed	Unemployed
Head sex	Binary	Male	Female
Head food responsibility	Binary	No food roles	≥ One food role
Head education level	Binary	Formal education	No formal education
Head health status	Binary	Not chronically ill	Chronically ill

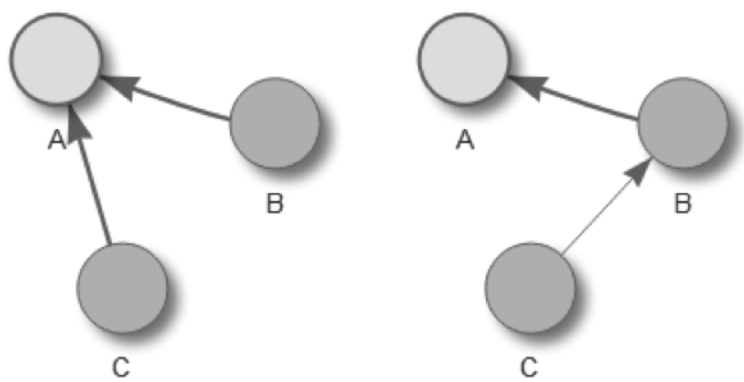
To determine whether the observed predictive relationships between these independent variables and household food insecurity is explained by other variables, the analysis relies on the calculation of unadjusted and adjusted odds ratios. Odds ratios calculate the change in odds of an event (like food security) occurring, given the presence of another event (like infrastructure access). Using binary logistic regression, it is possible to identify the change in these odds ratios when controlling for the influence of other variables.

Our concern is to better understand the vulnerabilities of those identified as being food insecure. While a logistic regression and odds ratio analysis may suggest that consistent access to medical care, electricity, and water play a large role in categorizing whether a household is food insecure, we also need to 'map' a network for food security using all of the previously identified variables. Rather than focus on how each variable relates to food security alone, there is value in investigating how predictive variables interrelate among each other. In many cases, the relationship from one node to another is indirect, with many intermediate nodes being connected along the path. A Bayesian network is a modelling tool that uses a directed acyclic graph to measure varying conditional probabilities between variables.

The role of Bayesian networks here is two-fold. First, Bayesian networks offer greater insight into exactly how all variables interrelate with one another. Since Bayesian networks create a graph-like structure with variables interacting through connected edges, or arcs. We are thus able to discern whether the variables directly impact the response variable, or whether this relationship is mediated through other variables. An example is provided below (Figure 1) where the response variable (node A) in the graph to the left is affected by both node B and C, while the graph to the right would suggest node A and C are conditionally independent given B (Chen et al 2015). An implication from such a finding would be that node B might act as a proxy for node C when trying to better understand node A. Second, each arc between nodes has a unique score that indicates the strength of the proposed relationship. Not only does the arc score allow us to measure the strength relationship between two variables, it also opens the opportunity to evaluate the overall structure of the graph. This in turn leaves the potential to apply machine learning algorithms that optimize any given Bayesian network.

For the creation of the Bayesian network, the Hill Climbing algorithm was applied. This algorithm seeks to find an optimal network score by systematically proposing potential arcs. Arcs that contribute to a better overall network score are retained, and those deemed detrimental are forgone. The network model is created by machine learning algorithms that establish any statistically significant relationships (determined by Pearson's chi-square tests). The algorithm then tests whether the significance of these tests changes conditional upon subsets of other variables in the analysis. In other words, the algorithm establishes whether the relationship between two given variables is still significant when assessed given the values of other variables.

FIGURE 1: Demonstration of Conditional Independence in the Bayesian Network



In the realm of food security, Bayesian network modelling techniques have been applied to better understand local food chains and food systems (Barker et al 2009, Stein 2004). Belief networks – an alternative form of Bayesian networks – have also been used to map the different actors in complex systems that revolve around rural agriculture in the Global South (Banson et al 2015). A study conducted by Muetzelfeldt (2010) applied Bayesian networks to dynamically represent the different drivers of food security for the purpose of better understanding how policy interventions might disrupt the network as a whole. In each of these examples, Bayesian networks have been useful in elucidating how a greater network of independent and interrelated actors (or drivers) influence key aspects of food security.

Predictors of Food Insecurity

The majority of the households in the sample were able to maintain consistent access to medical care (85%), electricity (82%) and water (75%) in the previous year (Table 2). Most household heads were also male (71%), had at least one food role (80%) and did not have chronic illnesses (72%). Most of the sampled household heads also had at least some formal education.

The majority of the independent variables were associated with a statistically significant increase in the odds of household food insecurity (Table 3). Inconsistent household access to water, electricity and medical care were all associated with significantly increased odds of household food insecurity (the greatest change in odds was observed among those households with inconsistent access to medical care). The sex, migrant status, education level, and food responsibilities of the household head were also all associated with a significant change in odds of household food insecurity. All of these variables remained statistically significant predictors of household food insecurity when the sum influence of the other independent variables was controlled, with the exception of household head education level. Thee employment status and health status of the household head did not show a significant change in the odds of household food insecurity.

TABLE 2: Cross-Tabulation of Independent Variables Against Household Food Security Status

		Household Food Security Status					
		Secure		Insecure		Total	
		No.	%	No.	%	No.	%
Household water access	Consistent access	857	46.8	973	53.2	1,830	74.6
	Inconsistent/No access	146	23.4	478	76.6	624	26.4
Household electricity access	Consistent access	811	50.1	809	49.9	1,620	81.5
	Inconsistent/No access	194	23.1	646	76.9	840	19.5
Household medical care access	Consistent access	964	46.2	1,123	53.8	2,087	85.1
	Inconsistent/No access	39	10.7	327	89.3	366	14.9
Head migrant status	Born in this city	654	46.9	739	53.1	1,393	56.7
	Born outside the city	348	32.7	715	67.3	1,063	43.3
Head employment status	Employed	730	40.5	1,073	59.5	1,803	73.0
	Unemployed	271	41.6	380	58.4	651	27.0
Head sex	Male	771	43.7	995	56.3	1,766	71.2
	Female	241	33.8	472	66.2	713	28.8
Head food responsibility	No food roles	270	55.0	221	45.0	491	19.8
	≥ One food role	740	37.3	1,245	62.7	1,985	80.2
Head education level	Formally educated	936	41.7	1,308	58.3	2,244	94.7
	Not formally educated	41	32.8	84	67.2	125	5.3
Head health status	Not chronically ill	733	41.4	1,039	58.6	1,772	71.6
	Chronically ill	277	39.3	427	60.7	704	28.4

TABLE 3: Unadjusted and Adjusted Odds Ratios

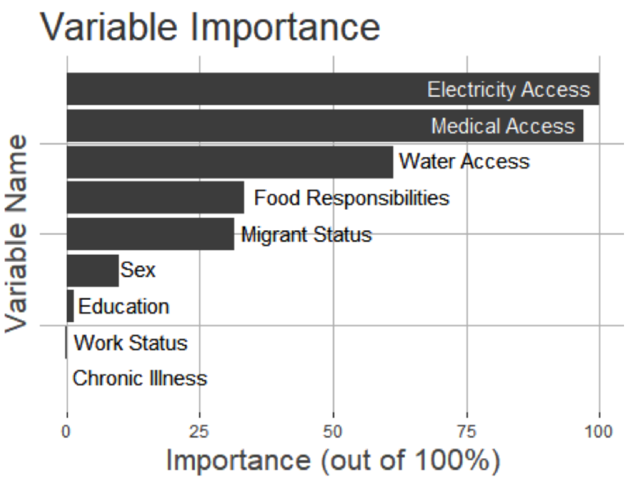
Independent variables	Original	95% C.I.		Adjusted	95% C.I.	
	O.R.	Lower	Upper	O.R.	Lower	Upper
Household water access	2.884**	2.345	3.546	1.648**	1.292	2.103
Household electricity access	3.338**	2.767	4.027	2.179**	1.752	2.71
Household medical care access	7.197**	5.108	10.143	4.879**	3.353	7.102
Head migrant status	1.818**	1.541	2.146	1.514**	1.258	1.822
Head employment status	0.954	0.795	1.144	0.873	0.701	1.088
Head sex	1.518**	1.266	1.820	1.301*	1.049	1.613
Head food responsibility	2.055**	1.683	2.510	1.851**	1.471	2.329
Head education level	1.466*	1.000	2.150	1.170	0.754	1.816
Head health status	1.088	0.910	1.300	1.004	0.810	1.244

* p<.05 on Pearson's Chi-Square or Wald Test
** p<.01 on Pearson's Chi-Square or Wald Test

After tuning the model for an optimal root-mean square error (with a cost function of five and a gamma value of 512) the accuracy rate is 70%. We can be 95% confident that the true value of the accuracy rate lies between 68% and 72%. With a p-value of less than 0.001, we can confirm that this test is statistically significant. The creation of this model relied on 1,618 support vectors. After a complete case analysis, this figure comprises 70.4% of the observations. Such a high level of support vectors suggests that the model is navigating a rather complex feature space (Hare et al 2011). This comes as no surprise since it attempts to categorize real life households in all of their complexity into only two categories – food secure and not food secure. A large number of support vectors is not unexpected, although it does build the case that there are several complex factors that go into whether a household is food secure. As a natural component of the machine learning process, specific variables that were more and less valuable in the categorization process are recorded. Figure 2 shows the importance of each variable in the process for the HFIAP.

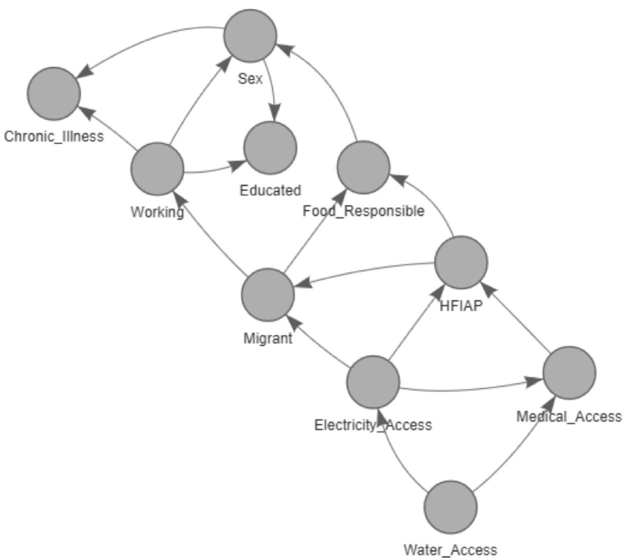
Each variable is expressed in relation to the top variable, so electricity access is pinned to 100%. Each variable's explanatory value is shown as a percentage relating to electricity access. For example, water access in this model appears to hold roughly two thirds of the explanatory value of electricity access. A logical extension of this procedure is that each variable can be ranked in order of importance: with 100%, 97%, and 61% respectively, the three infrastructure variables are at the top of the chart. To answer the first research question, then, based upon the findings of the support vector machine, infrastructure resources and services play an important role in predicting household food insecurity. In contrast to the odds ratio analysis below, electricity access holds a slightly higher predictive value. What is of greater importance is that specific groups of variables are close together. Food responsibilities and migrant status group together at 33% and 32% respectively, followed by sex at the 10% level. Education, work status, and chronic illness have little or no predictive importance in this model.

FIGURE 2: Support Vector Machine Variable Importance Calculations



To offer greater insight into the relationship between infrastructure access and food security, a Bayesian network was modelled through machine learning. The binary logistic regression model used to calculate the adjusted odds ratios was 66% accurate in categorizing sampled households (an increase from the null model's accuracy at 59%). The model also demonstrated a statistically insignificant Hosmer and Lemeshow test (x2=5.362, p=0.718), a Cox and Snell R2 score of 0.147 and a Nagelkerke R2 score of 0.198. The highest Pearson R correlation observed among the independent variables was 0.337, indicating that multicollinearity was not a significant confound in the resulting model. After applying the Hill Climbing algorithm to create an optimized network, Figure 3 results.

FIGURE 3: Bayesian Network Model



Within this directed acyclic graph, the nodes follow a distinct hierarchy, with the 'parent' nodes closer to the bottom right, and the 'child' nodes closer to the top left. Food security, as measured through the HFIAP (binned into two categories) appears to have only three ancestors. That is, the only parent nodes connected to HFIAP are electricity access and medical access. This in turn suggests that in an optimized Bayesian network, the two binary variables that most closely impact food security are whether or not the household has access to medical care and electricity. A conditional probability table of HFIAP predicts a 53.4% likelihood that a household is food secure given that they have access to electricity and medical care. However, this figure drops to a 6.5% likelihood when the household does not have access to either. In other words, households in this sample are 46.9% more likely to be food secure given that they have access to electricity and medical care, holding all else constant. This finding is in line with the overall findings from the logistic regression where households with access to both medical care and electricity are 83% more likely to be food secure holding all else equal.

Within the odds ratio analysis household water access was listed as the third most important variable in predicting food security. Based on the model network, water access appears to impact the likelihood that the house has consistent electricity and medical access. This in turn helps mediate the relationship between electricity and medical access as it relates to food security. As the model suggests, households that have consistent water access are 54% more likely to have electricity. The same applies for medical access, though both water and electricity access appear to mediate this relationship. Without either water or electricity access, there is a 667% likelihood that the house has access to consistent medical care. This figure rises to 95% when households have access to both. Geographically, those who live in close proximity to a medical centre are more likely to be a part of the same power grid, although this assumption may not hold in informal settlements. The Bayesian network suggests that when electricity is provided at a household level, water is also more likely to be provided. The same logic applies to medical access, creating a clustering effect whereby these services tend to form within closer proximity to one another.

The direct descendants of the HFIAP node relate to migrant status and whether or not the household head is responsible for providing food to their family. While the direction of the arcs in the graph are often at the mercy of the scoring algorithm used in model creation, it is important to note that reversing arc direction does not yield the same network, even though the skeleton of the graph may remain the same. From a machine learning perspective, the score of the arcs will differ. Table 4 identifies each arc by its parent and child node and its corresponding arc strength. These scores can be understood as the difference that would result from that specific arc being omitted from the overall model. Hence, larger negative numbers contribute more to the overall model's score.

The null model of this network with no connected arcs has an overall network score of -12558.41. A learned network where all arcs are optimized through the Hill Climbing algorithm has an overall network score of -11833.22 – an increase of over 700 points. The strongest relationship between nodes is between water access and electricity access. The likelihood of having consistent electricity rises from 33% to 77% when water access is guaranteed. The second strongest relationship is between working status and whether the household head is chronically ill. The likelihood that the household head is working is 36% less likely in male- headed households, and 69% less likely in female-headed households. Going down the list, male- headed households are more likely to have the household head partaking in an income generating activity, and are less likely to buy, prepare, allocate, or grow food. The next four highest arc strengths relate to infrastructure access. In terms of arc strength, electricity access appears to hold a slightly stronger relationship to medical care than water access, though both are strongly related in the final model. Regarding the model as a whole, household head characteristics appear to relate together just as infrastructure access variables relate together. This is displayed visually in the network, as the two distinct groupings tend not to interrelate amongst each other (with the exception of electricity access and migrant status).

Because the three infrastructure access variables are the only ancestors to HFIAP, it can be concluded that: not only are infrastructure access measurements effective at predicting household food security levels, the relationship exists regardless of the household head characteristics found later in the network. That is, infrastructure access is not conditionally independent to food security given the characteristics of the household head. Despite the fact that infrastructure is related to food security, this effect is not felt equally among the three measurements. Instead, medical access consistently displays a stronger arc score contrasted than electricity access. Since the term 'food secure' relates to ensuring safe, adequate, and nutritious food on a consistent basis, it is important to continue to ensure food security is paired with nutrition

TABLE 4: Bayesian Network Arc Interaction Strength

Arc	From	To	Strength
1	Water_Access	Electricity_Access	-174.5803885
2	Working	Chronic_Illness	-76.7231619
3	Food_Responsible	Sex	-68.3281377
4	Working	Sex	-51.2497529
5	Medical_Access	HFIAP	-50.1750146
6	Electricity_Access	HFIAP	-43.4145757
7	Electricity_Access	Medical_Access	-36.6273718
8	Water_Access	Medical_Access	-31.3151644
9	Sex	Chronic_Illness	-18.8941864
10	Working	Educated	-17.8555145
11	HFIAP	Food_Responsible	-13.1848892
12	HFIAP	Migrant	-8.3399004
13	Electricity_Access	Migrant	-4.8964753
14	Migrant	Food_Responsible	-4.6144216
15	Sex	Educated	-2.4274005
16	Migrant	Working	-0.6421644

security. In the pursuit of ensuring that food is safe, access to clean water and sanitation is vital (Pinstrup-Andersen 2009).

So long as a nodal structure exists where both medical and electric access are parents of HFIAP, an additional arc connecting water access directly to HFIAP results in a positive arc score. In other words, water access as a parent of HFIAP worsens the model, justifying the notion that it should remain as a common parent to medical and electricity access. This finding helps contextualize the role of water access in the logistic regression. In the odds ratio measurement, water access remained the third most important predictor of food security, but a Bayesian network helps elucidate that perhaps the role water access plays in the model more strongly relates to impacting medical and electrical access. Bayesian inference in this context helps to further explain how each variable identified in the logistic regression contributes to food security.

Conclusion

To summarize, this analysis found that inconsistent household access to water, electricity and medical care predicts household food security status across the five cities for which data was available. It also found that these infrastructure variables were stronger predictors of household food insecurity than the demographic characteristics of the household head. The predictive relationship between access to water, electricity, and medical care, and household food insecurity also exists even when household head demographic characteristics are controlled. Finally, this relationship is not made conditionally independent given any of the household head demographic characteristics that were included in the analysis. These findings confirm our previous investigation of the role of infrastructure access in predicting household food insecurity in cities of the Global South (Frayne and McCordic 2015, McCordic 2017). By using a different data set, it also geographically extends the validity and implications of these findings. Further research is required to untangle the reasons driving this relationship (whether resulting from household trade-offs in assets, qualitative changes in vulnerability or other explanations). Future research would benefit from the incorporation of GIS analytical approaches in order to determine whether this relationship is also explainable by spatial patterns of infrastructure.

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