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Multidimensional Vulnerabilities and Child Health: Evidence from Displaced Households in Uganda

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Summary

Introduction

Uganda, often praised for its progressive refugee policy, currently hosts over 1.8 million refugees from neighboring conflict-affected countries such as South Sudan, the Democratic Republic of Congo, and Burundi. Among these populations, children represent a particularly vulnerable group, facing compounded risks related to poor access to healthcare, inadequate sanitation, food insecurity, unsafe shelter, and limited protection. These challenges are not isolated but deeply interconnected, threatening not only children's physical health but also their ability to attend school, develop emotionally, and integrate into society. In such a context, ensuring children's well-being is not only a moral imperative but also a cornerstone for achieving inclusive and sustainable development.

Our study aims to explore how multiple dimensions, including education, legal status, access to hygiene and sanitation infrastructures, and living conditions, intersect to shape children's health outcomes in refugee settlements in Uganda. Anchored in the framework of the Sustainable Development Goals (particularly SDG 3 on health and well-being, SDG 4 on education, and SDG 10 on reducing inequalities), we developed a composite health index to assess child vulnerability. Using this index, we applied clustering techniques to classify households into two groups: those with highly vulnerable children and those with relatively better health conditions.

To understand what drives these differences, we conducted regression analyses and trained machine learning models such as decision trees and random forests, to identify which variables most strongly predict child health vulnerability, and how interactions among them exacerbate risk. This approach provides a data-driven basis for identifying key leverage points for targeted humanitarian interventions. By analyzing not just individual risk factors but also their interactions, we offer insights that go beyond traditional sectoral assessments, helping stakeholders prioritize multisectoral strategies to protect the most at-risk children in refugee contexts.

1 Background and Literature review

1.1 Context and Motivation

Uganda has the largest refugee population in Africa. In 2025, the total number of refugees and asylum seekers was up over 1.8 million people. This is the 6th largest in the world. Refugees mainly come from South Sudan (54%) and from the Democratic Republic of the Congo (32%) (UNHCR Data,2025). Uganda is constantly receiving new arrivals, with over 98,232 new due to the Sudanese conflict.

Though Uganda is known for its welcoming refugee policy, the steady influx is straining its capacity. At the same time, the country faces natural disasters (like floods and droughts), disease outbreaks (such as cholera and Ebola), and worsening climate conditions.

Funding cuts for humanitarian aid are reducing access to food, hygiene, medicine, and support programs. This also puts pressure on already under-resourced public services in refugee settlements, such as water, health, and education, leading to harmful coping strategies and tensions with host communities.

The innovative aspect of our study lies in its holistic approach to examining **the impact of various factors on the health of displaced children who are the weakest and vulnerable population displaced and to explore the interactions between them with some innovative machine learning models, with the goal of identifying combinations that hold the greatest potential for high-impact and cost-effective interventions**. This integrative perspective is crucial for understanding the complex and multifaceted nature of child health outcomes in displaced populations.

Indeed, several studies have emphasized the effectiveness of bundled interventions. For example, Banerjee and Duflo's 2015 work highlights the importance of multi-component "package" approaches in alleviating poverty. Their findings suggest that integrated strategies, which combine health, education, nutrition, and financial support, can lead to significantly greater improvements than isolated actions. Inspired by this evidence, our study seeks to identify similar synergies among the determinants of child health in displacement contexts, with the ultimate aim of informing more efficient and impactful policy responses.

1.2 Literature review & Mechanisms

Children's health is shaped by a combination of multiples dimensions such as behavioral, physical and environmental factors and there is a growing evidences of the impact of those factors

WASH (Water, Sanitation, and Hygiene)

WASH interventions have been shown to significantly impact child growth, typically measured by weight and height. However, less is known about their effects on child development, encompassing motor skills, language, socio-emotional abilities, and cognitive skills like literacy. Given the interdependence of physical and cognitive development, it is likely that improved WASH services contribute positively to both. Poor sanitation, unsafe water, and inadequate hygiene can increase exposure to disease and environmental enteric dysfunction, limiting nutrient absorption and impeding development (Britto, 2016).

Food Assistance and Nutrition

Researchers agree that proper nutrition is critical for optimal growth and development of children and adolescents, even starting in utero. In fact, extensive research demonstrates that "sound and appropriate nutrition" in early childhood is one of the basic foundations of lifelong health established during early childhood. Furthermore, chronically hungry and malnourished children are more likely to experience adverse health outcomes (Hannah Wagner, 2024).

Education and Early Childhood Programs

Education is one of the most important social determinants shaping the development and well-being of children (WHO,2008). Education has a direct impact on health indicators such as life expectancy, as well as certain health-related behaviors (e.g., smoking, diet, sexual health) and medical problems (e.g.,depression, obesity, chronic illnesses) (Fillol et .al, 2024). In our current context of displaced households, education can shape the health status of children through the mechanism whereby they are more likely to be advised on good habits, have access to health care programs, school feeding and moral support that can impact their health.

2 Data presentation

The data used in this study stem from the 2018 Uganda Joint Multi-Sector Needs Assessment (JMSNA), which combined both quantitative and qualitative approaches. For our analysis, we relied exclusively on the quantitative household-level survey, covering both refugee settlements and host communities. In urban areas such as Kampala, systematic random sampling was applied to households across selected vulnerable neighborhoods, achieving representativeness at a 95% confidence level with a 3% margin of error. Due to the initially low number of refugee respondents, a complementary snowball sampling phase was implemented to reach more refugee households. Sampling in refugee settlements and host districts across Uganda was based on GPS-generated points and probability proportional to size. The final dataset covers all 30 refugee settlements and 11 host community districts across Uganda's Midwest, Northwest, and Southwest regions, allowing for robust comparisons across population groups and geographies.

3 Methodology

3.1 The Health Index Construction

To assess child health vulnerability among refugee households in Uganda, based on the avalaible data, we constructed a **composite Health Index** using six health-related indicators drawn from the 2018 Uganda Joint Multi-Sector Needs Assessment (JMSNA) survey. The variables include: Recent diarrhoea in young children, Recent diarrhoea in other children, Polio vaccination, Measles vaccination, Vitamin A supplementation, Use of insecticide-treated mosquito nets.

Each variable was recoded to reflect a **positive or negative contribution** to child health. Favorable health outcomes (e.g., vaccination received, no diarrhea): +1. Unfavorable outcomes: -1. Missing or uncertain responses: 0.

We applied **Principal Component Analysis (PCA)** to the six standardized health indicators to reduce dimensionality and compute a weighted composite index. Let X_{ij} represent the standardized value of variable j for individual i.

PCA decomposes the data into uncorrelated components:

$$Z_{ik} = \sum_{j=1}^{p} \phi_{jk} X_{ij}$$

Where: Z_{ik} is the score of individual i on component k, ϕ_{jk}: loading (weight) of variable j on component k. We used the first two components (PC1 and PC2) that captured most of the variance.

For the variables Weighting, we extracted the absolute value of the variable loadings $|\phi_{jk}|$ and normalized them column-wise:

$$w_{jk} = \frac{|\phi_{jk}|}{\sum_{j=1}^{p} |\phi_{jk}|}$$

Each variable's contribution to the index was then computed as:

$$I_{ik} = \sum_{j=1}^{p} w_{jk} \cdot X_{ij}$$

Where I_{ik} is the intermediate score of individual i on component k.

Finally, we compute the composite Health Index. First A weighted average of the first two components was computed, with weights based on their explained variances λ_1 and λ_2:

$$\text{Index}_i = \frac{\lambda_1 I_{i1} + \lambda_2 I_{i2}}{\lambda_1 + \lambda_2}$$

Finally, the index was scaled to lie in the interval $[0, 1]$:

$$\text{HealthIndex}_i = \frac{\text{Index}_i - \min(\text{Index})}{\max(\text{Index}) - \min(\text{Index})}$$

3.2 Other dimensions variables

The explanatory dimensions of the health outcome included in our analysis are: WASH (Water, Sanitation, and Hygiene), food assistance, school attendance, environment, and legal status. For each of these dimensions, we constructed indices calculated as the simple arithmetic mean of binary (dummy) variables. As a result, each index ranges from 0 to 1, with higher values indicating greater access or better conditions in the respective domain.

Examples of the questions used to construct each index are as follows:

- WASH: access to latrines by children, access to clean drinking water, and use of soap for handwashing;
- Food Assistance: sources of food assistance and diversity of food consumed, including the presence of proteins, vegetables, fruits, and cereals;
- Environment: type and condition of the household's shelter, availability of a kitchen, and exposure to environmental hazards such as recent flooding or roof leakage;
- School Attendance: a dummy variable indicating whether children in the household are currently attending school, based on a set of questions related to common barriers to education;
- Legal Status: a binary indicator reflecting whether the household is formally registered as a refugee in Uganda.

We have as well a bunch others variables as control which included the general characteristics of the children and household (size, number of children, age, respondent status, household gender, household ressources...)

The data is structured at the household level, meaning the health index represents the average health status of children within household h. We assume that the explanatory variables are uniform for all children within the same household, and therefore apply equally across members of that household.

3.3 Empirics specification

To analyze the effect of the different dimensions on the children's health index, we perform a linear regression analysis. We opt for this specification given the nature of our data, which consists of cross-sectional observations from refugee households in Uganda, collected in 2018 across various refugee settlements.

In order to causally identify the effect of the different explanatory variables on the health index, a quasi-experimental strategy would be ideal. The most plausible approach in this context would be an instrumental variable (IV) strategy, which could help address the multiple endogeneity issues that a simple regression may fail to account for. However, identifying valid instruments that satisfy both the exogeneity and relevance conditions for each dimension proves to be highly challenging.

Although we also have access to data from 2019, the survey questions differ significantly, making it impossible to construct a panel dataset or a repeated cross-sectional structures which could help build a fixed effect model to control for unobserved heterogeneity and omitted variable bias.

Consequently, we rely on a linear regression approach, including a comprehensive set of control variables in an attempt to minimize omitted variable bias as much as possible.

We include district fixed effects δ_d in our regression specification to control for unobserved heterogeneity across broader geographic areas that may influence child health outcomes. Districts may differ substantially in terms of public infrastructure, climate exposure, access to services, and implementation of national policies. By including district fixed effects, we account for any time-invariant district-level characteristics, such as local governance quality, funding allocations, or regional climate, that may simultaneously affect both the explanatory variables (e.g., WASH, food assistance, education) and child health. While fixed effects at the settlement level would allow us to control for more granular variation, the large number of settlements in the dataset poses risks of overfitting and a substantial reduction in degrees of freedom, especially in smaller samples. Moreover, many settlements are nested within the same district and may share administrative, environmental, or socioeconomic traits. District-level fixed effects therefore offer a reasonable compromise: they allow us to control for unobserved local heterogeneity while preserving sufficient within-district variation for identification.

Moreover, we cluster standard errors at the settlement level to correct for intra-group correlation. Observations within the same the same settlement are unlikely to be statistically independent. For example, household children in the same settlement may be affected by the same public infrastructure or local policies. If we fail to account for this dependence, standard errors may be underestimated, leading to overstated statistical significance. Clustering addresses this by adjusting the variance-covariance matrix to reflect the structure of the data, ensuring more robust and reliable inference.

However, We are therefore cautious in interpreting the results: in this analysis, we do not claim causal inference but aim to assess more associational and correlation patterns.

The mathematical specification used is as follows:

$$HealthIndex_h = \beta_1 \text{WASH}_h + \beta_2 \text{Food}_h + \beta_3 \text{School}_h + \beta_4 \text{Environment}_{ih} + \beta_5 \text{LegalStatus}_h + \mathbf{X}_h \gamma + \delta_d + \epsilon_h \tag{1}$$

where:

- $HealthIndex_{ih}$ is the health index of the children in household h;
- WASH_h, Food_h, School_h, Environment_h, and LegalStatus_h are the indices (ranging from 0 to 1) representing access or exposure to each respective domain;
- $\mathbf{X}_h$ is a vector of child and household-level control variables (e.g. household size, number of children, household head characteristics, and household resources...);
- δ_d are district fixed effects to control for location-specific unobservables;
- ϵ_h is the error term.

3.4 Machine Learning model for interactions analysis

Our overall goal is to understand what drives differences in child health among refugee households. A predictive model like Random Forest helps us, identify the most influential variables, test whether combinations (interactions) of factors matter more than individual ones and explore whether we can anticipate vulnerability using available household data.

In our analysis, we employed the Random Forest algorithm to predict the health status of children in refugee households. Random Forest is an ensemble learning method that combines the predictions of multiple decision trees to improve accuracy and reduce overfitting.

The Random Forest algorithm works by building multiple decision trees on bootstrap samples of the data and averaging their predictions. At each node of the trees, a random subset of predictors is considered to split the data. Formally, the final prediction $\hat{y}$ is the majority vote among all B trees:

$$\hat{y} = mode(T_1(x), T_2(x), ..., T_B(x))$$

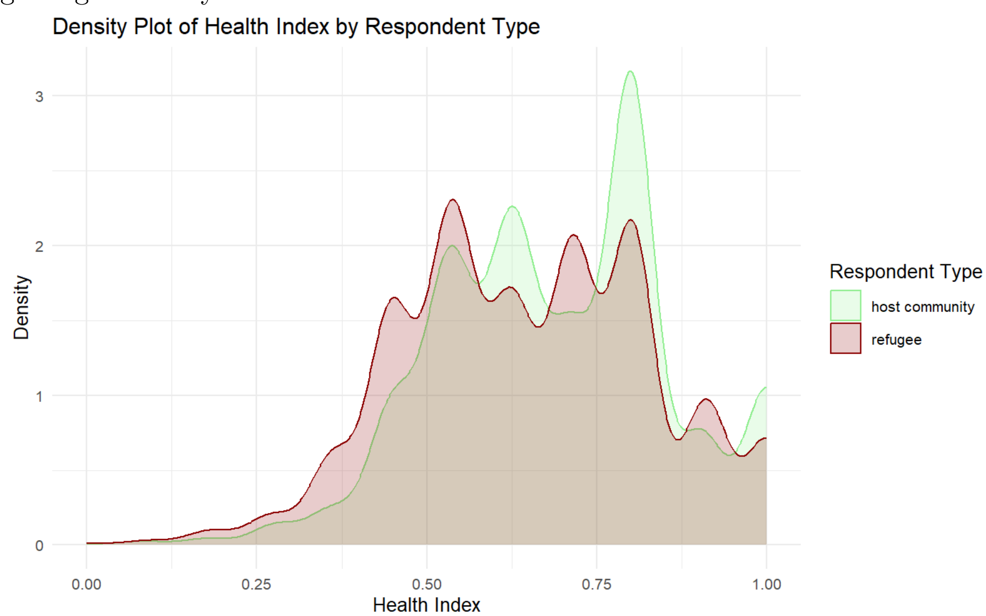
This method is robust to noise, captures nonlinear relationships and complex interactions, and provides estimates of variable importance.

4 Results

4.1 Summary statistics

4.1.1 Health status by household type

The density plot of the health reveals some differences in the distribution of the Health Index between refugees and host community members. While both groups share a central concentration around mid-range values, the refugee curve shows a slightly broader spread and higher density in the lower half of the index, indicating a greater share of children with poorer health outcomes. In contrast, the host community distribution is more concentrated toward higher index values, suggesting relatively better overall health conditions.



The following graph illustrates the average Health Index by respondent type (host community vs. refugee) and vulnerability status. Across both respondent types, being in a vulnerable group (vulnerability = 1) is not associated with a lower or a higth average Health Index. This suggests that vulnerability, regardless of being a host or refugee, does not tend to negatively affect children's health outcomes. Overall, the graph reveals slight health gap between host communities and refugees: in both vulnerable and non-vulnerable groups, children in host households tend to have slightly higher average Health Index scores compared to those in refugee households.

The error bars, which reflect standard deviations or confidence intervals, overlap across all subgroups. This implies that the trend is not really clear, differences might not be statistically significant, more analysis is needed.

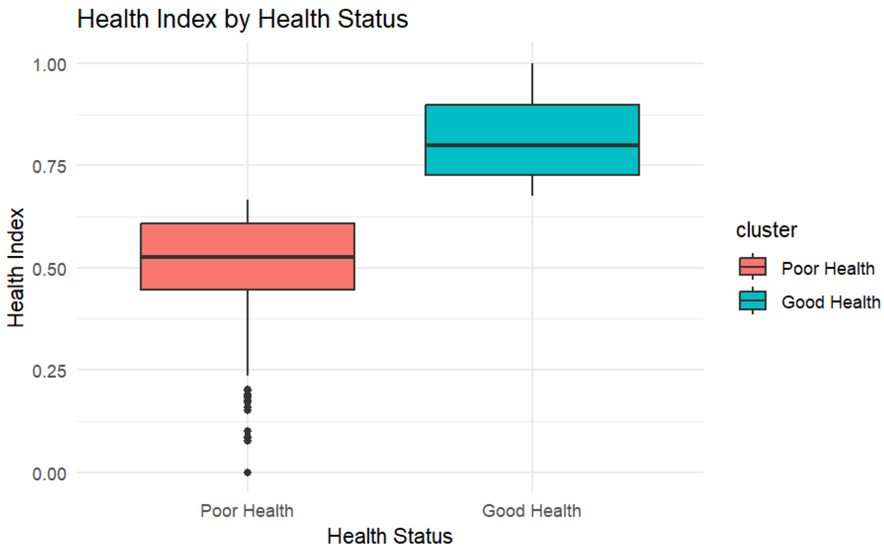
4.2 Clustering

To identify distinct profiles of child health vulnerability among households, we performed an unsupervised classification using the **K-means clustering algorithm**. We applied K-means with $K = 2$ clusters on the health index, aiming to distinguish between two interpretable health profiles: **"Poor Health"** and **"Good Health"** households.

The results show that approximately 51.3% of households fall into the "Poor Health" cluster and 48.7% into the "Good Health" group:

Cluster	**Proportion**
Poor Health	51.3%
Good Health	48.7%

We observe that the “Poor Health” cluster corresponds to households with a lower health index, with a mean of 0.52 and a maximum of 0.66, whereas the “Good Health” group has consistently higher index values (mean = 0.82, min = 0.67). This clear separation supports the relevance of the two-cluster solution.



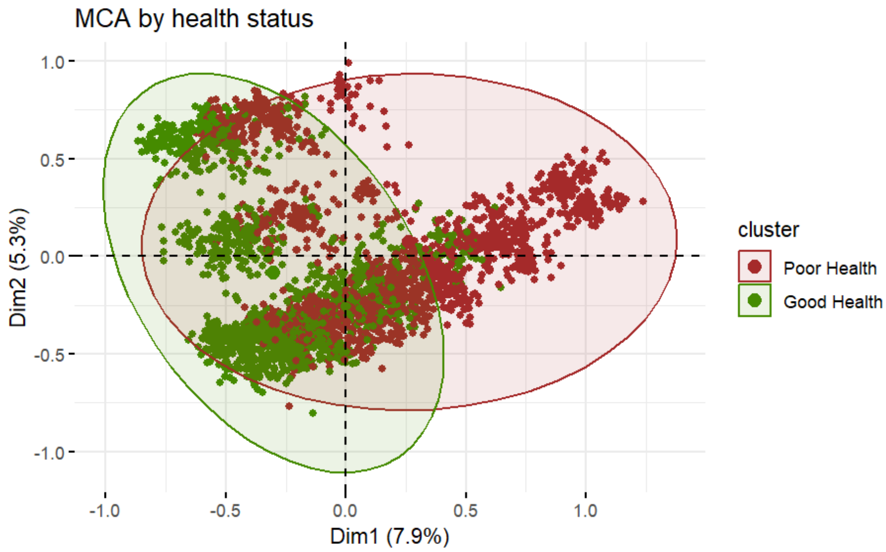
Profiling Health Clusters Through Multiple Correspondence Analysis (MCA)

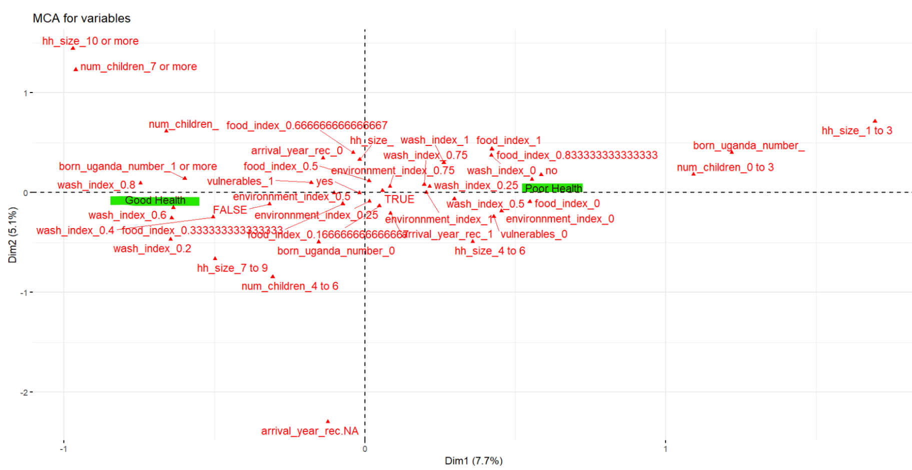
To better understand the multidimensional characteristics associated with the two health clusters, we conducted a **Multiple Correspondence Analysis (MCA)** on a set of categorical and recoded variables related to education, legal status, household composition, and living conditions. This technique allowed us to explore how these factors intersect and contribute to the observed health disparities among children.

The projection of households on the MCA individual plot reveals a relatively clear spatial separation between the two health groups. Households classified as **“Poor Health”** tend to cluster on the right-hand side of the graph, while those in the **“Good Health”** group appear more concentrated on the left. This visual distinction supports the validity of the clustering and indicates underlying structural differences between the two groups.

When analyzing the variable plot, we observe that the **“Poor Health”** group is predominantly associated with poor hygiene conditions (low `wash_index`), poor dietary habits (low `food_index`), inadequate environmental conditions (low `environment_index`), and an absence of legal documentation. These patterns highlight a convergence of vulnerabilities that likely exacerbate health risks for children in these households.

In contrast, the **"Good Health"** cluster is more closely linked with better hygiene and nutritional practices, suggesting that improvements in these dimensions may be strongly associated with improved child health outcomes. The MCA thus reinforces the multidimensional and intersectional nature of child health and provides valuable insights for targeted interventions.





4.3 Models results

Across all specification, the analysis highlights the importance of environmental conditions and WASH services in improving children's health, there is an evidence but weak for the Food assistance. While school attendance and legal registration are essential in broader child development, their direct relationship with health may not be statistically significant . The inclusion of district fixed effects improves model reliability by accounting for regional heterogeneity, and clustering standard errors at the settlement level accounts for intra-settlement correlation.

Precisely for the environment index of the household, the coefficients range from 0.059 to 0.068, all significant at the 1% level, indicating a consistent and robust relationship. This suggests that better environmental conditions (e.g., cleaner surroundings, safer shelters, proper kitchen,...) are strongly correlated with improved child health. This result is consistent with the Unchr report on Joind Multi-sector needs assessment, in Uganda 2018 which found that the shelter leaking was found to be positively correlated with household members having malaria in refugee households.

The results suggests as well that WASH conditions remain important for child health. In the main specification in column (3), we find a statistically significant result of 0.0458 at 1% level of confidence suggesting that within a district, the household with good wash conditions are more likely to have better children health.

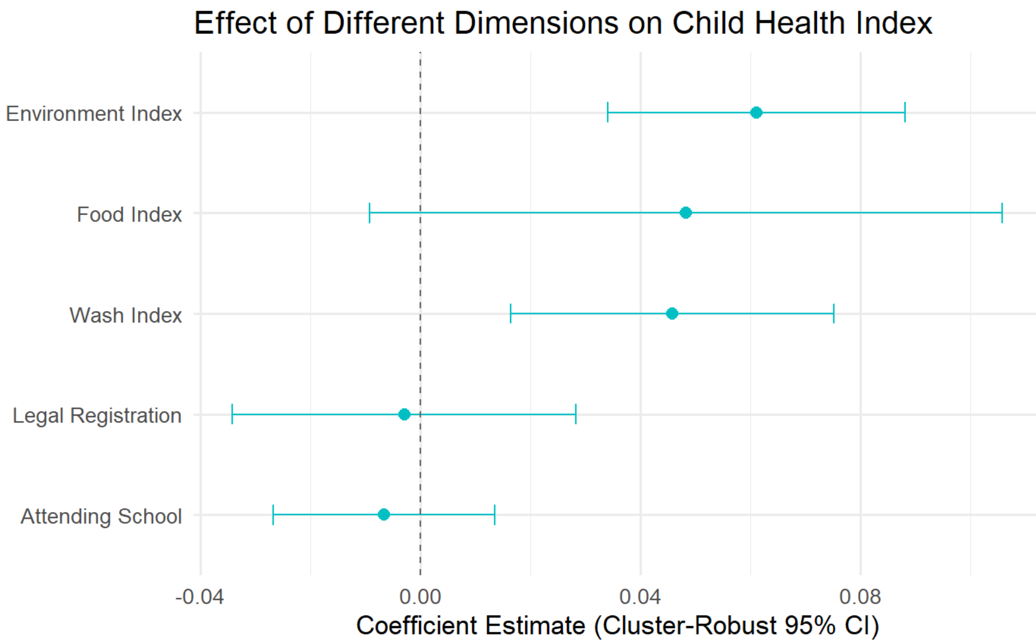
Interestingly, school attendance is negatively associated with health in model (2), but no more significant in the main specification in model (3). And finally across all models, legal registration which represents the legal status of refugee recognize by Uganda state shows no significant association with children's health status. This may imply that, while registration is important for legal identity and access to services, its direct effect on health is limited.

Table 1: Effects on Children Health Index

Dependent Variable:		I_norm Health Index	
Model:	(1)	(2)	(3)
Variables			
Wash index	0.039**	0.0178	0.0458***
	(0.012)	(0.0147)	(0.0150)
Food index	0.066***	0.0762**	0.0483
	(0.016)	(0.0310)	(0.0294)
Attending school	-0.010	-0.0355***	-0.0066
	(0.007)	(0.0122)	(0.0103)
Environment index	0.059***	0.0684***	0.0611***
	(0.013)	(0.0162)	(0.0138)
Legal registration	0.003	0.0229	-0.0029
	(0.015)	(0.0198)	(0.0159)
Fixed-effects			
district	No	Yes	Yes
Controls added	Yes	No	Yes
Fit statistics			
Observations	4289	4,292	4,289
R^2	0.111	0.08015	0.26911
Within R^2	-	0.01749	0.21932

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The dependent variable is a standardized health index for children.
Column (1) uses the specification of a simple linear regression with additional controls.
Column (2) includes the district fixed effects and no controls.
Column (3) includes the district fixed effects and additional controls.
For the 2 last columns, the standard errors are clustered at the settlement level in parentheses.
And for the first column, robust standard errors are presented.



4.4 Interations analysis

Predicting Child Health Status with Random Forest and Interaction Effects

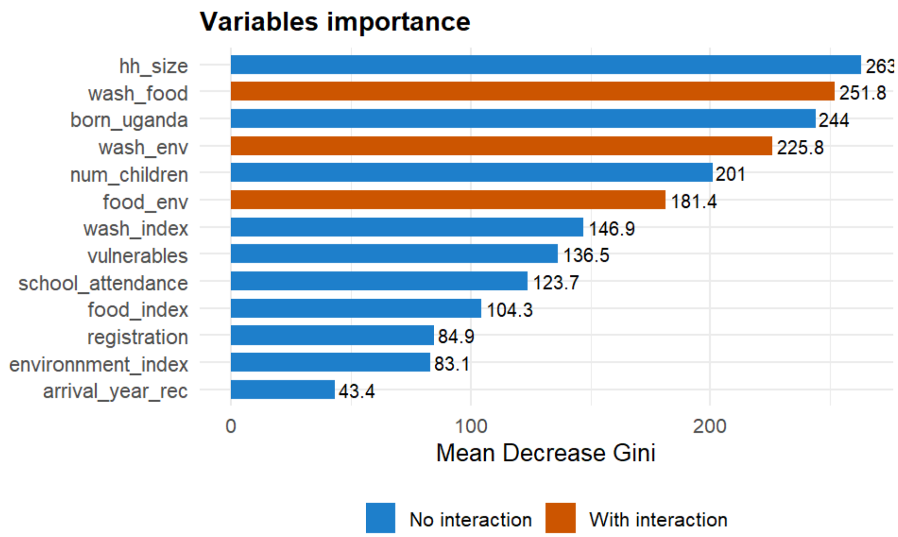
To further analyze the drivers of child health disparities, we implemented a predictive model using a **Random Forest classifier**. This machine learning approach is well-suited for capturing non-linear relationships and interactions between variables without requiring explicit model specification.

Before training the model, we enriched the feature set by constructing several **interaction variables**, including: `wash_food`: interaction between hygiene and dietary conditions, `wash_env`: hygiene and environmental conditions, `food_env`: dietary and environmental conditions, `school_legal`: interaction between school attendance and legal registration.

These variables were included alongside core household characteristics (e.g., number of children, household size) and health-related indices. We then trained the model using hyperparameter optimization to improve performance.

The final model achieved an error rate of approximately **13%** and an **accuracy of 65%** on the test set. While not perfect, these results suggest that the selected features carry meaningful predictive information about child health status.

Importantly, the variable importance plot revealed that interaction terms—especially wash_food, food_env, and wash_env were among the most influential predictors of child health outcomes. Poor hygiene practices may not be as harmful in isolation, but when coupled with inadequate nutrition (wash_food) or unsafe environments (wash_env), the risks of disease transmission, malnutrition, and weakened immunity are amplified. Similarly, a household facing both food insecurity and poor environmental conditions (food_env) may struggle to provide children with both the physiological and psychological stability essential for healthy development. These interactions reflect real-world vulnerabilities where multiple forms of deprivation coexist and reinforce each other.



5 Holistic approaches to addressing vulnerabilities and policy recommendations

This project aligns strongly, but not exclusively with Sustainable Development Goal (SDG) 3 on Good Health and Well-being, as well as SDG Target 10.7, which calls for the implementation of well-managed migration policies. By focusing on displaced households in Uganda, the study sheds light on how multidimensional vulnerabilities affect children's health outcomes in fragile and often under-resourced contexts.

The findings from this analysis provide actionable insights for policymakers and humanitarian actors. Specifically, we identify that WASH conditions, living environment quality, and food assistance are the three dimensions that significantly influence child health. Moreover, through our Multiple Correspondence Analysis (MCA) and Random Forest modeling, we uncover strong interactions between these dimensions, indicating that their combined effects are greater than their individual contributions.

A particularly important insight is the amplifying effect of food assistance when implemented alongside improved WASH and environmental conditions. In other words, the deterioration of hygiene and living conditions can disproportionately harm displaced children's health. This highlights the need for integrated, cross-sectoral interventions in refugee settings.

The emphasis on multidimensional synergies is especially valuable for developing child-centered programs that move beyond simple approaches and reflect the complex realities of displacement. So we recommend for stakeholders and policy makers to:

- Adopt Integrated Programming: Humanitarian and development actors should jointly implement programs that combine food security, WASH, and shelter/environmental improvements rather than tackling these issues separately.

- Prioritize Vulnerable Subgroups: Given the disproportionate effects on displaced and female-headed households, targeting those with compounded vulnerabilities will enhance the equity and effectiveness of interventions.

Conclusion

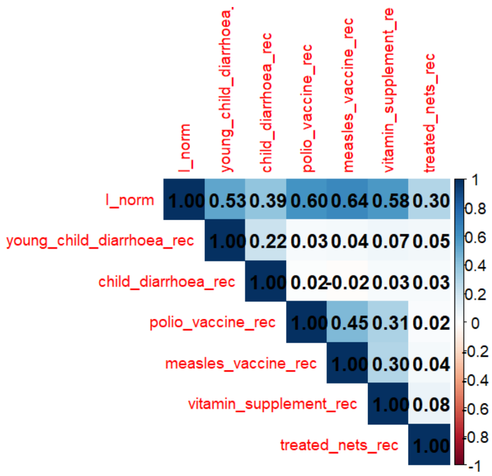
This project investigated the determinants of children's health among displaced and host communities in Uganda, using data from the 2018 Uganda Household Survey, by constructing a health index and examining how multidimensional factors, such as hygiene, food security, and living environment individually and interactively influence child health outcomes. Through clustering and descriptive methods, we identified distinct household profiles associated with poor and good child health. We then used fixed effects and simple regression models to explore the impact of each dimension, and applied Random Forest modeling to highlight key predictors and their interactions.

Our findings reveal that poor WASH conditions, inadequate food diversity, and unsafe environments jointly contribute to deteriorated health outcomes, more so than when considered separately. Interaction terms, particularly between hygiene, food, and environment, emerged as crucial predictors, emphasizing the importance of integrated, multisectoral interventions.

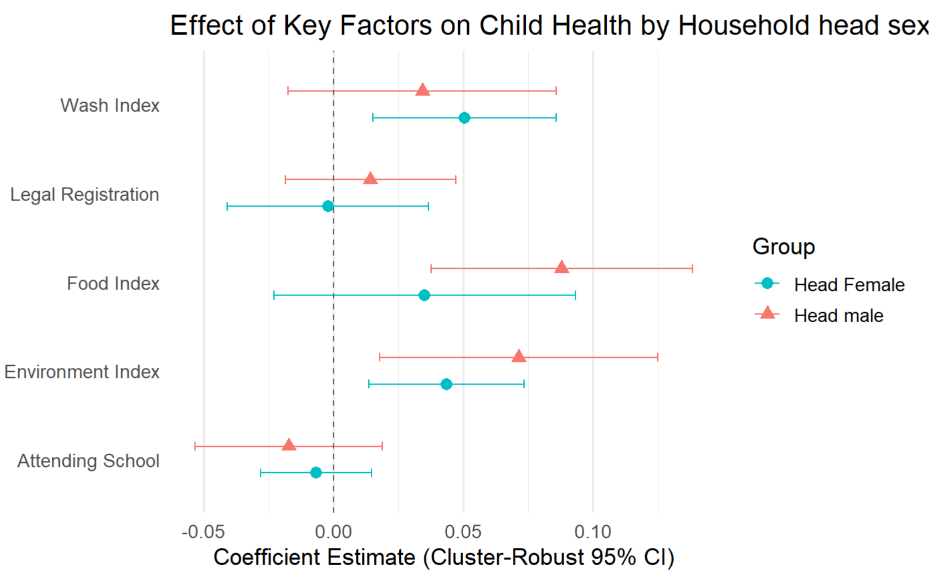
However, the study has limitations. The survey was household-focused rather than child-specific, which led us to use proxy variables to approximate child-level health. Some indicators used in the health index, such as mosquito net use or vaccination, reflect access to services rather than direct health outcomes, but were included due to data constraints as they are strongly correlated with child health. Finally, although cross-country comparisons were encouraged, we focused solely on Uganda mainly due to time constraints.

Despite these limitations, our work provides valuable insights for developing holistic, child-centered interventions in humanitarian contexts.

Appendice



l_norm
young_child_diarrhoea_rec
child_diarrhoea_rec
polio_vaccine_rec
measles_vaccine_rec
vitamin_supplement_rec
treated_nets_rec
1.00 0.53 0.39 0.60 0.64 0.58 0.30
1.00 0.22 0.03 0.04 0.07 0.05
1.00 0.02 -0.02 0.03 0.03
1.00 0.45 0.31 0.02
1.00 0.30 0.04
1.00 0.08
1.00



Effect of Key Factors on Child Health by Household head sex
Wash Index
Legal Registration
Food Index
Environment Index
Attending School
-0.05
0.00
0.05
0.10
Coefficient Estimate (Cluster-Robust 95% CI)
Group
Head Female
Head male

Table 2: Descriptive Statistics of Uganda 2018 Survey Data

Variable	Proportion (%)
Respondent Type	
Host Community	36.73
Refugee	63.27
Household Size	
1 to 3	12.23
4 to 6	34.18
7 to 9	31.94
10 or more	21.26
No answer	0.38
District	
Adjumani	22.58
Arua	19.09
Hoima	4.75
Isingiro	8.67
Kamwenge	4.72
Kiryandongo	5.25
Koboko	5.59
Kyegegwa	4.98
Lamwo	4.95
Moyo	8.18
Yumbe	11.25
Number of Children	
0 to 3	34.68
4 to 6	41.73
7 or more	22.63
No answer	0.96
Arrival Year	
Before 2016	63.22
After 2016	36.78
Households with Vulnerable members	
Without Vulnerable members	33.52
With Vulnerable members	66.48

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