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ARTIFICIAL INTELLIGENCE IN DETERMINING OPTIMAL QUESTIONS IN ASSESSING SOCIAL ECONOMIC STATUS OF INDIVIDUALS FOR ROUTINE IMMUNIZATION SERVICES IN TANZANIA

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ABSTRACT

This study aimed to determine the lowest optimal questions that could accurately determine the socio-economic status (SES) score of the participants and determine their validity when compared to the standard wealth index. Principal Component Analysis (PCA), Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) techniques were applied using DHS wealth index as the gold standard. Eight DHS questions were found to be optimal for assessing household's SES with high sensitivity (76.9%) and specificity (94.2%). The correlation with DHS standard wealth index was R^2 = 0.76. The study has also shown the potential for using CNN as a method to identify valid questions that can be applied in other domains. Our findings open the possibility of using SES as one of the factors to determine access and completion of routine immunization services. This is important in identifying and targeting populations at risk to enable focussed interventions to increase vaccine coverage.

KEYWORDS

Artificial Intelligence, Social economic status, PCA, ANN, CNN.

1. INTRODUCTION

The introduction of vaccines is one of the most cost-effective interventions in the history of preventing childhood illnesses. It has led to a 28% decline in the global mortality of children under 5 years of age, from 90 per 1000 live births in 1990 to 65 per 1000 live births in 2008 [1]. However, to be effective, all eligible infants must be immunized, and a 90-95% immunization coverage as dictated by the World Health Organization (WHO), has been shown to be adequate in eliciting herd immunity [2]. The trend in global vaccine coverage has been variable across the regions but is nevertheless still lagging the WHO targets of 90% coverage and there are significant disparities in completion of the vaccination package. Globally, in 2018, the trends in vaccination showed a relatively high coverage for Bacille Calmette-Guérin vaccine (BCG) and Oral Polio Vaccine (OPV0) given at birth; a high coverage of Diphtheria, Tetanus toxoid and Pertussis-containing vaccine (DPT1) of 90%; and a rise in completion of DPT3 from 84% (2010) to 86% (2018). There was also a relatively high coverage of first dose of Measles-Containing Vaccine (MCV1) of 86%, but MCV2 was still very low at 54% in countries which were offering the second dose in the second year of life [3].

In Tanzania, the vaccination coverage trends have been almost similar with as high as 91% for BCG and OPV0, 91% for DPT1, 89% for DPT3, 88% for MCV1 and much lower, 68% for MCV2 reported in 2018[4]. Hence, the Global Vaccine Action Plan of 2011-2020 was initiated and endorsed by the World Health Assembly as a framework to ensure equitable access to vaccines in all countries to reach national vaccine coverage and completion of >90% [3].

Several factors have been found to influence the access, coverage, and completion of the vaccination package. In Tanzania for example, these include individual factors such as low levels of education of the caregivers, low socio-economic status, gender dynamics, language barrier and lack of knowledge on the importance of immunization and the age for vaccinating against MCV1 and MCV2 [5, 6, 7, 8]. At the same time, there are some health facility factors that have been shown to deter coverage including: distance from access points, time spent at the facility waiting for vaccination services and inadequate advocacy regarding immunization days/schedules within the community [6, 8]. Policy factors that have been shown to equally influence vaccination uptake include lack of political will, poor governance in ensuring adequate funding of the supply chain to avoid stock outs, and inadequate outreach services which would otherwise ensure populations in remote settings have access [8, 9, 10].

Historically, data on routine immunization coverage has been obtained from tally sheets which are completed at the facility level. These are then aggregated into the monthly immunization summary books which are compiled at the district level and entered the Vaccine Information Management System (VIMS). The VIMS was designed to capture information on routine immunization, cold chain equipment (CCE) and in-country supply chain data at district and regional levels. However, since 2014, the Tanzanian Electronic Immunization System (EIS) was adopted. It consists of two components which are the VIMS and the Electronic Immunization Registry (EIR). The latter is used to register children from birth and automatically generate immunization schedules and reports [11]. These birth cohorts can then be followed up and analysed for various outcomes.

The Tanzanian EIR termed as the Tanzania Immunization Registry (TImR) was started off as a small project to digitize data collected at facilities offering immunization, which was then rolled out and is currently in use in other 11 regions. The Tanzanian Electronic Immunization Registry/System (EIR/EIS) was adopted through the Better Immunization Data (BID)-an initiative with the objective of enabling data-driven decision-making. Tanzania has been selected to spearhead the utilization of data from the digital systems (TImR) to summarize common immunization barriers, and to determine the EIR features that help respond to these challenges [12]. The current TImR doesn’t capture the SES of individuals/their families attending the clinics. Despite having relatively high coverage for immunization on initial vaccine doses, the uptake and completion of subsequent doses is low, and this compromises the overall effectiveness of immunization program in Tanzania. This decrease in completion rate can be attributed to the fact that the initial doses are given immediately after birth at the health facilities. The missed opportunities in subsequent doses must be evaluated to understand contributory factors and therefore design interventions to mitigate them. The SES of clients accessing immunization services whether assessed by level of income, education level or occupation, has been linked with immunization uptake and completion. There are known challenges in the measurement of SES particularly when the scales may mean different for rural versus urban clients. Therefore, when populating the TImR questionnaire, it was crucial to ensure that the scale adopted will best measure the SES of the entire population [13]. This requires the tool to be validated against the standard wealth index used in the DHS. The DHS wealth index tool contains various SES assessment elements but is lengthy and is best administered in community-based research settings. Therefore, there was a need to develop a shorter SES assessment tool, that gives comparable outcomes to the DHS wealth index, but which is feasible to administer in a busy immunization clinic setting, where long waiting time has been shown to deter uptake.

Therefore, before populating the TImR with the SES questionnaire, the Ministry of Health, Community Development, Gender, Elderly and Children (MoHCDGEC) under the department of Immunization and Vaccine Development Program (IVDP), United Nations Children's Fund (UNICEF), PATH (PATH (formerly known as the Program for Appropriate Technology in Health), Muhimbili University of Health and Allied Sciences and partners conducted this research to analytically pick, validate, optimize and test the feasibility of administering the SES questionnaire in the routine Reproductive and Child Health (RCH) clinic setting.

This paper only present results of the methods used to select and validate the questions against that of DHS wealth index. Therefore, the findings from this study will be pertinent in devising the optimal SES questionnaire that will be adopted into the TImR for routine immunization equity assessment.

2. METHODOLOGY

2.1. Study Design

Part of the study presented in this paper employed a quantitative method. This method was adopted because the objective of this part was to determine the optimal questions that could accurately determine the SES score of the participants and determine their validity. Quantitative method was used to formulate the questionnaire for determining the SES score of the participants. Its objectives were to assess the validity of the SES questionnaire in accurately measuring the SES of participants when compared to the standard DHS wealth index. The research team compiled a selection of DHS standard questions from the wealth index, combined with additional questions from other SES evaluation scales from the literature and used these to obtain data from the participants.

2.2. Study Population

The study population were caregivers of children attending routine RCH clinics for immunization services.

2.3. Study Site

This study was conducted in selected representative health facilities in Tanzania mainland; two rural and two urban RCH clinics in Morogoro and Tanga regions. Health facilities in these regions were selected based on their current high-performance in utilization of the TImR for implementation of the IVDP and for a better urban-rural heterogeneity of participants. In Tanga region, the urban health facility was Mikanjuni health centre, in Tanga City and for the rural health facility Komkonga dispensary in Handeni district was selected. In Morogoro, Sabasaba health centre represented the urban setting in Morogoro municipal council and Mvomero health centre in Mvomero for the rural setting.

2.4. Sample Size and Sampling

The minimum sample size for testing the validity of the SES in the field was obtained through the following formula of a known proportion. In this case, the known proportion of persons living below the poverty line was 26.4% which was documented in 2018 [15]. The proportion of people living below the poverty line was used because our study aimed at assessing the validity of the SES questionnaire in accurately identifying the poor (those below poverty line) as compared to others in the standard wealth index.

The sample size calculated was powered at 95.6% to detect a 10% difference in immunization coverage between the poor and least poor, shown in Table 1.

Therefore, in this study the level of poverty was approximated to be 30%.

n = sample size
d = level of confidence 95%
E = margin of error
P = hypothesized proportion of outcome factor which is level of poverty
N = population size
DEFF=Design effect was set at 2.0 hence the sample

$$n = \frac{DEFF \cdot Np(1-p)}{d^2/Z^2{}_{1-\alpha/2} \cdot (N-1) + p \cdot (1-p)} \quad (1)$$

The estimated sample size was 646 and to cater for a 10 % non-response rate, the final estimated sample size was 717.

Sampling

The sample size was divided into four thus Sabasaba, Mvomero, Komkonga and Mikanjuni health facilities. All caregivers of children under the age of 5 years attending routine RCH clinics on the day of the study were consecutively recruited until the required sample size was reached or unless they declined consent.

Table 1: Power calculation

Two sided-confidence intervals (%)	95
Number of Exposed	215
Prevalence/Coverage among Exposed (%)	80
Number of non-exposed	502
Prevalence/Coverage among Non-exposed (%)	90
Prevalence/Coverage Ratio	0.89
Prevalence Difference (%)[1]	-10
Power based on:	
Normal approximation	95.58%
Normal approximation with continuity correction	94.29%

[1] Prevalence Difference = Prevalence in Exposed - Prevalence in Non-exposed.

Inclusion criteria: All caregivers of children under the age of 5 years attending routine RCH clinics during the study period. Caregivers must be a resident in one of the villages served by the respective health facility. All participants signed a written consent form.

Exclusion criteria: None

2.5. Data Collection

Data were collected using a structured standard questionnaire which comprised of four sections: demographic characteristics, accessibility to vaccination services, religious and cultural beliefs and household wealth. The demographic and household characteristics were adopted from the Tanzania Demographic and Health Survey 2015/16 data collection tool. To ensure validity and reliability of the data collection tool, it was very important that the measurement tool carried the same wording in Swahili as its English version. In our study this was ensured by the tool being translated from English to Swahili language and back translated to English. Swahili language is the national language, that participants comprehended. Information pertaining to the asset ownership was obtained from the participants and verified by their respective hamlet leader and/ or the village healthcare worker where appropriate. Validation was necessary because interviews were conducted at the healthcare facility where observation of some of the wealth items could not be done. The rationale behind this was to avoid desirable responses which may not give a true reflection of the wealth index estimate.

The data collection tool was tested among members of research team not involved in designing it. piloted at MUHAS in a classroom setting, because piloting at Muhimbili National Hospital at the paediatrics and child health department was not possible due to the then ongoing second wave of corona virus disease of 2019.

2.6. Data Management Procedures

Data collection was collected electronically with tablets using Online Data Kit (ODK). Data were backed up to a password-protected cloud storage system daily; for safety and to allow for real time data monitoring. The cloud service was managed by a data manager at MUHAS. Data transmission was done over a secure and private connection or Virtual Private Network (VPN) through the regular cellular phone network. This VPN prohibited data access by outside users during data transmission. The participants' unique identification (ID) number was entered in the ODK at the beginning of the interview.

To minimize data entry errors, questions in the ODK had prompts and checks for data validation and correction of identified errors. The tablets used for data collection and the databases were all password-protected.

Following each day of data collection, the tablets were connected to a wireless network to upload data to a password protected, encrypted, and backed up cloud service.

2.7. Data Analysis

The provided questions were used to score the SES of the participants by using DHS SES score values and scales, which are country specific as documented in the DHS Program wealth index construction [14]. This enabled the researchers to categorize the participants into SES quintiles (i.e., poorest, very poor, poor, less poor and least poor).

The Principal Component Analysis (PCA) and the Convolutional Neural Network (CNN), which uses the concepts of Artificial Neural Networks (ANN) were used to determine optimal questions as described in detail below. The PCA assessed the correlation between variables (questions in our cases) to preserve the variability among them. This also led to selection of questions which are not correlated to each other. To this end, we were not sure whether the non-correlated questions or the correlated ones will capture the social economic status of an individual. On the other hand, CNN investigated the contributions of each variable (questions in this case) to the final score, which is the social economic status. The two methods captured both ends: the correlated and the not correlated questions. They were then compared to find which one could identify the more significant questions. To validate the questions, we developed and trained an ANN algorithm, its score on classifying individuals were compared against that of DHS wealth index.

2.8. Data Pre-Processing

To prepare the data for machine learning training, a further pre-processing step was done on the data. This included the dropping of non-numeric columns like the name of the data collector and names of the participants. Other non-numeric data were encoded into numbers, with reference to their significance to the wealth index of an individual. The location of the health centre was also converted to reflect rural and urban and converted into numeric as 0 for rural and 1 for urban. We only kept the questions that were common for all participants. To generate five reference wealth quintiles (poorest, very poor, poor, less poor and least poor), initial PCA analysis was done to generate eigen values for the DHS adopted wealth index questions segregated by residence (rural or urban). These eigen values of DHS wealth index questions were subsequently used to generate wealth score for each of the participants. The participants/household wealth scores were then sorted into quintiles as reference the SES categories. In the end, our data set contained 778 rows/instances with 50 columns in which 49 were for features (questions asked) and the last column was for quintile labels (the five social-economic categories).

2.9. Model Training

A Convolutional Neural Network (CNN) was developed and trained by using five-fold cross-validation. CNN is a deep learning model, which uses the concepts of neural networks. During the training of a CNN model, random weights were initiated in the filters/patches of the model. The randomly initialized weights were multiplied with the incoming data to form feature maps trough a convolution process. These weights were adjusted during the learning process, and features with higher contribution to the output scores were assigned higher weights. As the aim was to be able to find the weight of each question's contribution to the SES score of an individual, a 1 by 10 filter for the CNN was selected to avoid mixing up weights of the questions. During the training of the CNN model, 80% of the dataset was used for training, 10% for validation to monitor the model's performance and the remaining 10% was used for testing. We used accuracy, specificity, sensitivity, and precision as the performance measure of the model. Several parameters of the model were tested fine-tuned to find the best performing one, this included the number of hidden layers of the architecture, the number of neurons in each layer, the number of fully connected layers, the number of training iterations, and the number of filters. The best-performing architecture had two hidden layers, with 32 filters in the first layer and 64 filters in the second layer. Together with other performance metrices, we chose prediction accuracy which was also included as the performance metric measure of our model as we had a balanced dataset, and it is a classification problem [16]. Classification accuracy is the ratio of the number of correctly classified examples according to the total number of classified examples [17].

2.10. Weight Extraction

To understand the weight of each question's contribution to the social-economic status score of an individual, we extracted the weights of the trained CNN model. This was done by extracting weights from the feature maps formed in the first convolution layer. The weights were calculated using the formula below. W_l stands for filter length, which is 10 in our case and W_f stands for the number of filters which is 32 in the first layer.

$$W_f = \sum_{q=0}^{q=W_l} W(f,q) \text{ [19].} \qquad (2)$$
$$where 0 \leq f < 32 \text{ and } 0 \leq q < W_l$$

From the extracted weights, we arranged the weights in descending order, which reflects the order of significance of the questions.

2.11. Finding the Optimal and Valid Questions

Based on the weights extracted from a trained CNN, different batches of questions were prepared in descending order of the weights. The questions with higher weights were regarded to have higher significance in classifying individuals in different wealth indexes. To obtain the lowest possible optimal questions and their validity, we trained an ANN on these batches of questions. The model performance was monitored in different batches and compared against that of DHS wealth index for validation purpose. This was aimed to validate the selected questions

The best performing CNN model had an average accuracy of 87% with a standard deviation of 2% across 5 folds cross validation. There is no clear-cut acceptable classification accuracy for machine learning and its acceptance depends on the problem. A study [18] regarded 100% classification accuracy as harmful, and 50% accuracy will be considered as tossing some dice. As it is regarded that, high classification accuracy is not necessarily an indicator of high classifier performance [3], other performance metrices were also assessed to determine the optimal model [4,5,6]. Sensitivity of 86%, Specificity of 96% and Precision of 87% were obtained from our optimal model. A confusion matrix of one of the five folds of the optimal model is shown in Figure (1) below. In the confusion matrix only seven subjects were misclassified out of the 78 test subjects.

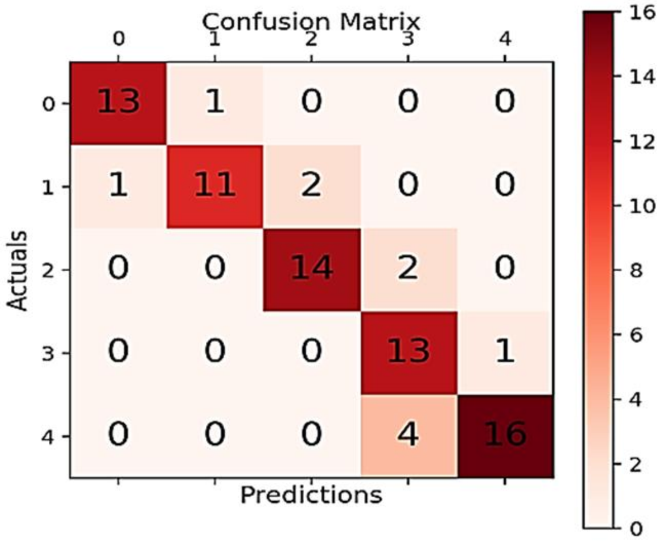

Figure 1: Confusion metrics of the Convolutional Neural Network (CNN)on 5 classes with 49 questions.

3. RESULTS

3.1. Participants Demographics

A total number of 778 participants were recruited with mean (SD) age of 26.6 years. Each recruitment site reached its estimated sample size; for urban (Sabasaba, n (%) =181(23.3), and Mikanjuni, n (%) =226(29.1)) for rural (Mvomero n (%) = 181(23.3) and Komkonga n (%) = 190 (24.4)) with no difference in representative proportion between the two populations (Figure 1). The mean number of children in each household was 2.3, ranging from 1 to 9 children.

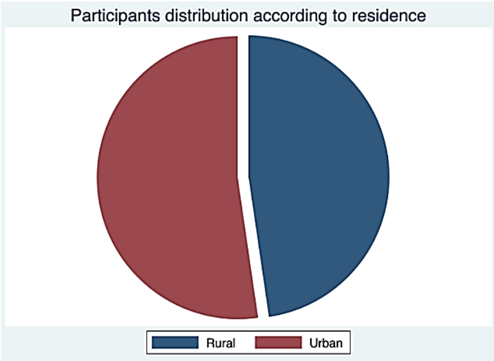

Figure 2: Participants Rural (47.7%) = Mvomero – Morogoro and, Komkonga- Tanga and Urban (52.3%) = Sabasaba – Morogoro, Mikanjuni – Tanga

The marital status of participants in the households was single for n/N (%) = 139/778 (17.9) (defined as living alone, divorced, widowed or never married) and married for n/N (%) = 639/778 (82.1) (defined as living with a partner whether married officially or cohabiting). The head of the household was the father of the child for n/N (%) = 630/778 (81%) participants, and only in n/N (%) = 43/778 (5.5%) households, the head of the household was someone else other than the mother or the father e.g., grandparent of the child. The difference in education level of the parent/caregivers interviewed was statistically significant between rural and urban and is summarized in the table 2 below. In the rural setting, more participants had no education compared to urban, n/N (%) 113/371(30.5) vs n/N (%) 14/407 (3.4) p = 0.000, but in both rural and urban settings more than 50% of the participants had primary school education in both rural and urban settings.

Table 2: Education level of participants by residence

Education level	**Rural n (%)**	**Urban n (%)**	**Total**
None	113 (30.5)	14 (3.4)	127 (16.3)
Pre-primary	1 (0.3)	1(0.3)	2 (0.3)
Primary	209 (56.3)	241 (59.2)	450 (57.8)
Post-primary	1 (0.3)	3 (0.7)	4 (0.5)
Secondary (o level)	35 (9.4)	108 (26.5)	143 (18.4)
Post -Secondary	4 (1.1)	0 (0.0)	4 (0.5)
Secondary (A-level)	4 (1.1)	11 (2.7)	15 (1.9)
Post- Secondary	1 (0.3)	0 (0.0)	1 (0.1)
University	3 (0.8)	29 (7.1)	32 (4.1)
Total	**371 (100.0)**	**407 (100.0)**	**778 (100.0)**

Table 3: The CNN model performance (Accuracy) under different

No of questions	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	Standard deviation
49	0.87	0.87	0.90	0.88	0.85	0.87	0.02
20	0.70	0.72	0.69	0.71	0.72	0.71	0.01
10	0.69	0.70	0.70	0.69	0.67	0.69	0.01
9	0.69	0.70	0.71	0.69	0.69	0.70	0.01
8	0.67	0.68	0.68	0.69	0.68	0.68	0.01
7	0.63	0.62	0.59	0.63	0.64	0.62	0.02
6	0.60	0.65	0.64	0.66	0.66	0.64	0.02
5	0.63	0.64	0.66	0.62	0.66	0.64	0.02
4	0.60	0.66	0.66	0.66	0.64	0.64	0.03

Weights contribution of each question to the score of the SES

The table 3 above shows the model performance under different number of questions selected based on their weights as extracted from a trained CNN.

As the number of questions decreased with increase in their weights, the model's performance decreased. The decrease in the accuracy of the model might also be affected by the decrease in the amount of training data. This is because the performance of the machine learning models is also affected by the amount of training data. Therefore, our CNN model was only used to determine the order of weight contribution of each question to the score of the social-economic status of an individual. The top ten questions, shown in Table 3 and Figure 3, were selected based on their weights for further analysis.

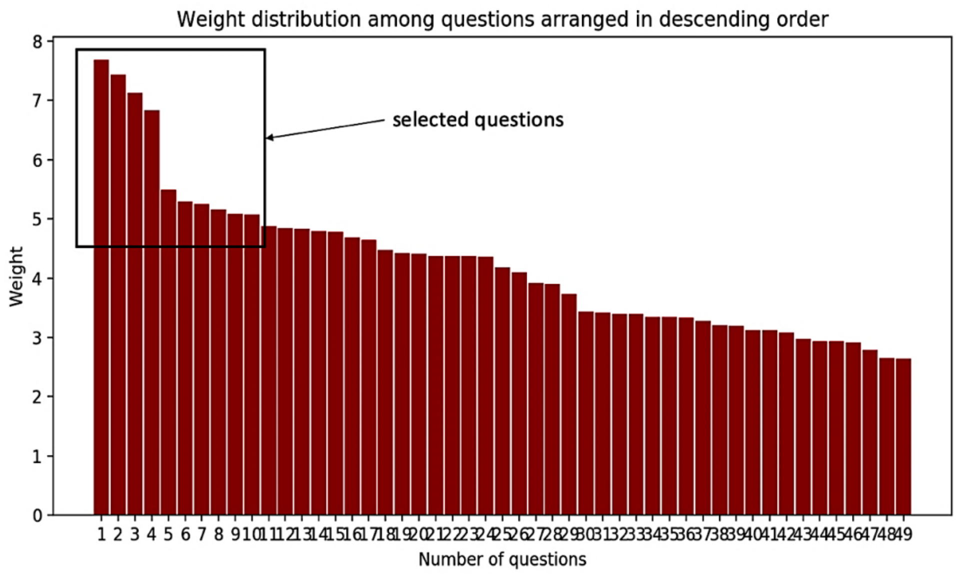

Figure 3: Weight distribution among questions arranged in descending order

Table 4: List of top ten questions that contribute most weight in the final wealth

No	**Questions**	**Weights (Units)**
1	Ability to read and write (Father)	7,69
2	How long does it take for you to reach this health facility	7,44
3	Ability to read and write (Mother)	7,13
4	Does your household have Electricity that is connected	6,84
5	Highest level of school attended (Father)	5,50
6	Marital Status	5,30
7	What is the main roofing material at your household?	5,25
8	What is the main wall material at your household?	5,16
9	Does your household have A television in working condition	5,09
10	Ability to read and write (Head of household)	5,08

3.2. Correlation of SES Allocation Between Standard DHS vs Optimal Questions

Using PCA, the performance of the selected questions was tested by generating their eigen values, and subsequent scoring of participants according to the top ten selected (Table 3). Then a regression model was fitted assessing the correlation of the scores generated by the top ten questions vs the standard reference scores generated from the DHS questions. The R2 value was then assessed as we subsequently removed the least weighing questions one after the other from the top ten weighing questions. The R2 value ranged from 0.08 to 0.80. (Figure 4, Figure 5, Figure 6 and Figure 7).

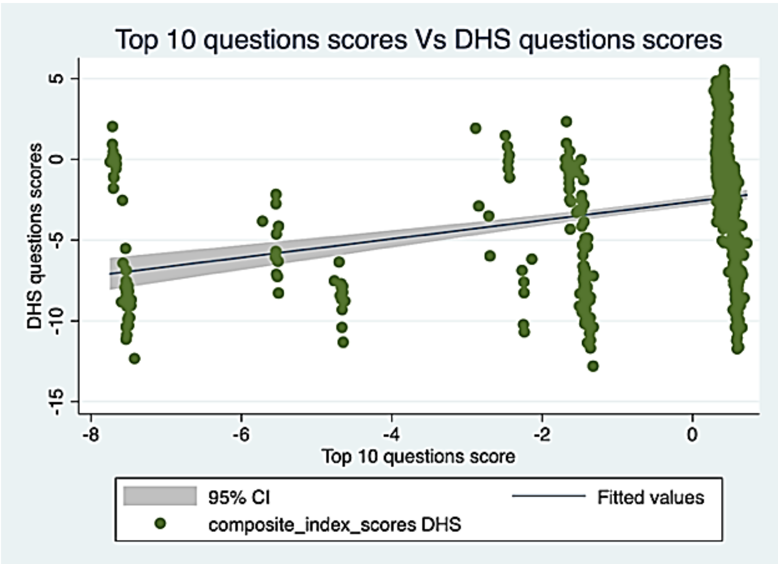

Figure 4: The R2 =0.08 for top 10 questions Vs DHS questions score.

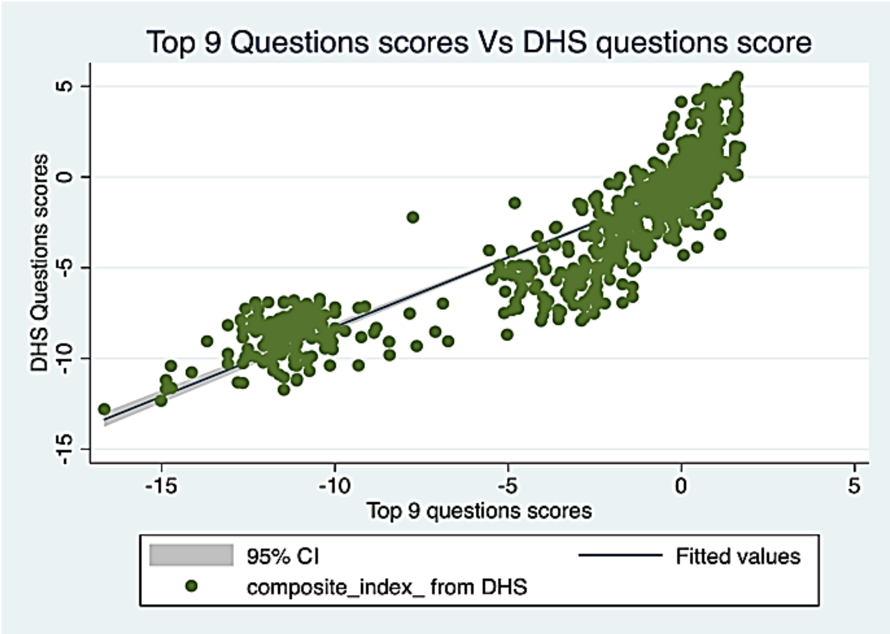

Figure 5: The R2 =0.80 for top 9 questions Vs DHS questions score.

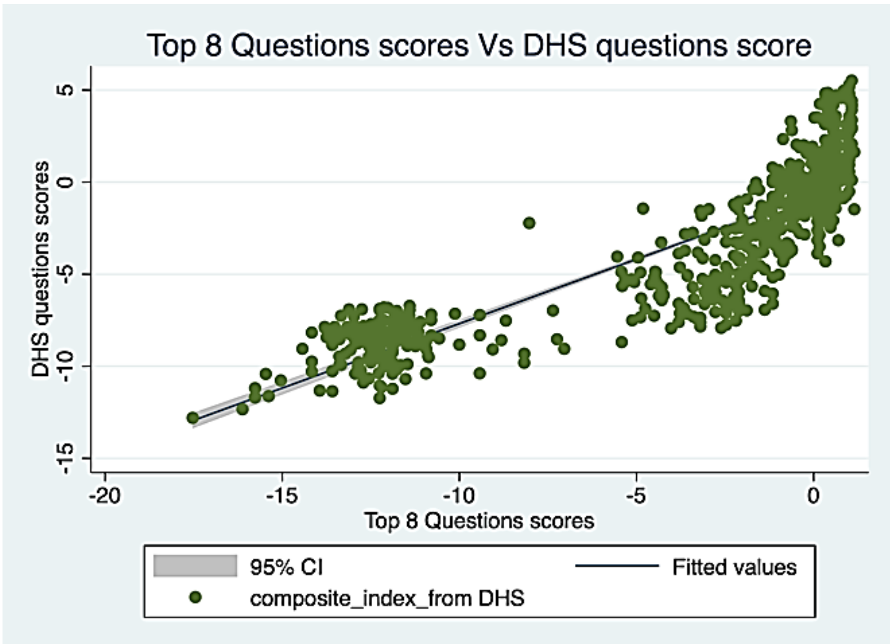

Figure 6: The R2 =0.76 for top 8 questions Vs DHS questions score.

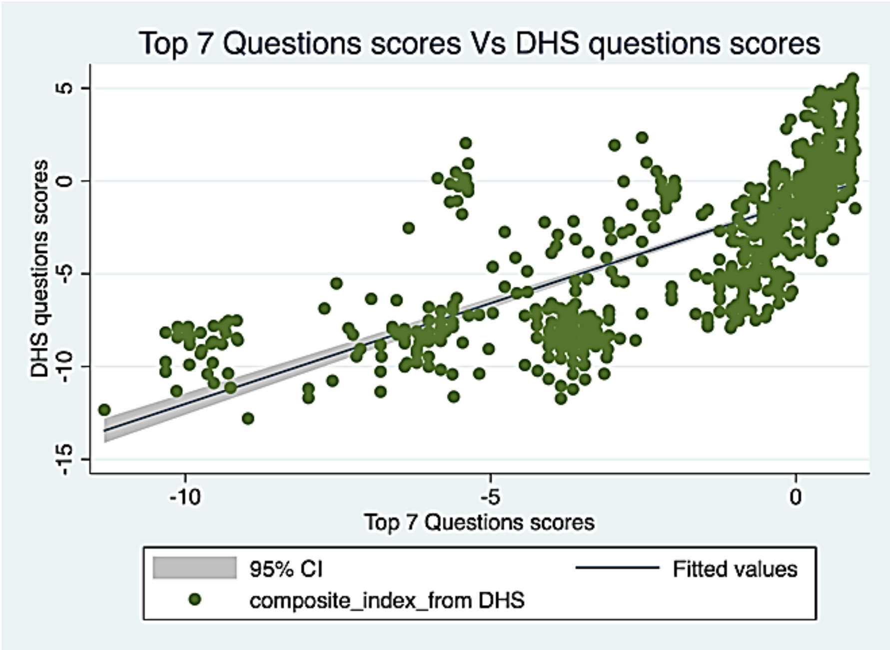

Figure 7: The R2 =0.56 for top 7 questions Vs DHS questions score.

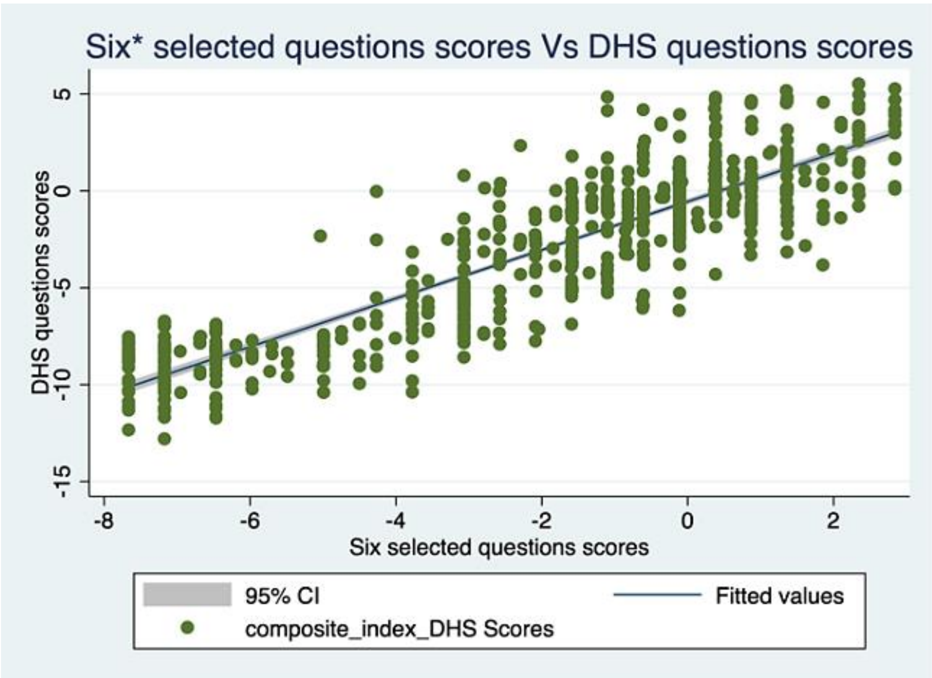

Figure 8: The R2 =0.79 for top 6 questions Vs DHS questions score.

4. Discussion and Conclusion

We have attempted to create a SES index that closely represents what more comprehensive SES tools such as the DHS would provide. Optimization of the SES questions in the questionnaire was done using PCA, whereby weighting was done for various items on a larger assessment tool. Artificial neural networking (ANN) is another modality used to weight variables and determine scores by training a neural network. The key behind neural networking to determine the weights assigned to each parameter (questions in our case) and then analyse the extracted weights that can be used to determine significant questions that measure the SES score. Contracting such a broad construct into only eight questions comes at a cost. Another limitation is minimal sensitivity to sudden changes of social or economic status, especially for the poorest. In case of recent loss of income, i.e., when one loses a job or has a very sick relative and needs to spend resources to care for their loved one. These economic shocks are hard to capture in this model. The limitation of several questions if broadened, questions regarding occupation can be included, and this will mitigate some of the limitations stated above; however, the tool is reasonably accurate for the intended use. This study has demonstrated on how AI can be used to develop a simplified tool for SES assessment which is fairly accurate and representative, and this can be administered in a clinic setting.

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