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Artificial Intelligence in determining optimal questions in assessing social socio-economic status of individuals for routine immunisation services in Tanzania

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Abstract

Background: Accurate determination of socio-economic status (SES) is crucial for equitable access to immunization services. Existing SES assessment tools, like the DHS wealth index, are comprehensive but impractical for routine clinical settings due to their length.

Objective: To identify the minimum number of questions that can validly determine SES using artificial intelligence (AI), and to assess their validity compared to the standard DHS wealth index.

Methods: This study applied Principal Component Analysis (PCA), Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN) using the DHS wealth index as the gold standard. Data were collected from routine RCH clinics in Tanzania. CNN was used to extract weights for each question, and ANN was trained to validate different subsets of questions.

Results: Eight questions were identified as optimal for assessing household SES, achieving a sensitivity of 76.9% and specificity of 94.2%. The correlation between the derived SES score and the DHS standard wealth index was $R^2 = 0.76$. The study demonstrates that CNN can be an effective method for selecting valid SES indicators in healthcare.

Conclusion: AI models, particularly CNNs, can identify a small set of questions with strong predictive validity for SES, enabling practical and accurate equity assessments in immunization programs. Integrating such tools into the Tanzania Immunization Registry (TImR) may enhance targeting and improve vaccine coverage. This study was approved by the ethical review board of MUHAS.

Keywords: Artificial Intelligence, Socioeconomic status, PCA, ANN, CNN

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(You et al., 2010). However, to be effective, all eligible infants must be immunized, and a 90-95% immunization coverage, as dictated by the World Health Organization (WHO), is adequate in eliciting herd immunity (Funk et al., 2019). The trend in global vaccine coverage has been variable across the regions, but it 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 the first dose of Measles-Containing Vaccine (MCV1) of 86%, but MCV2 was still very low at 54% in countries that were offering the second dose in the second year of life (Peck, 2019).

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(Vaughan et al., 2020). 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% (Peck, 2019).

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(Semali, 2010) (Blue, 2018)(Magodi et al., 2019). At the same time, some health facility factors 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(Magodi et al., 2019).

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 stockouts, and inadequate outreach services, which would otherwise ensure populations in remote settings have access (Magodi et al., 2019; Oku et al., 2017; Akwataghibe et al., 2019).

Historically, data on routine immunization coverage have 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 into 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) has been 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 (Kalolo et al., 2021). These birth cohorts can then be followed up and analysed for various outcomes.

The Tanzanian EIR, termed 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 the 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(Carnahan et al., n.d.). 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 are low, and this compromises the overall effectiveness of the 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

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occupation, has been linked with immunization uptake and completion. There are known challenges in the measurement of SES, particularly when the scales may have different meanings for rural versus urban clients. Therefore, when populating the TImR questionnaire, it was crucial to ensure that the scale adopted would best measure the SES of the entire population (Ramesh Masthi et al., 2013). 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 it 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 times have 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 manuscript only presents the results of the methods used to select and validate the questions against those of the DHS wealth index using Artificial Intelligence (AI). Although there are existing studies for optimisation of different aspects in healthcare using AI, none of them has focused on healthcare and leveraging the weights distribution of CNN(Lyon et al., 2021a; Nihi & Forkuo, n.d.)(Lyon et al., 2021b), apart from the existing large number of literature which has applied CNN in non-image data, including gene expression and time series data (Kiranyaz et al., n.d.; Sharma et al., 2019). 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.

METHODOLOGY

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 lowest optimal questions that could accurately determine the socio-economic status (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.

Study Population

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

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 the 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 the Morogoro municipal council, and Mvomero health centre in Mvomero for the rural setting.

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 (Howe et al., 2008). 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 the 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 the 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 the level of poverty

N = population size

DEFF=Design effect was set at 2.0, hence the sample

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

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 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 residents in one of the villages served by the respective health facility. All participants signed a written consent form.

Exclusion criteria: None

Data collection

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Data were collected using a structured standard questionnaire, which consisted 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 the validity and reliability of the data collection tool, the measurement tool needed to carry the same wording in Swahili as its English version. In our study, this was ensured by the tool being translated from English to the Swahili language and back translated to English. Swahili 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 that may not give a true reflection of the wealth index estimate.
The data collection tool was tested among members of the 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 coronavirus disease of 2019.

Data management procedures

Data collection was conducted electronically with tablets using the 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 prohibits 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.

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 case) to preserve the variability among them. This also led to the selection of questions that are not correlated with each other. To this end, we were not sure whether the non-correlated questions or the correlated ones would capture the socioeconomic 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 socioeconomic status. The two methods captured both ends: the correlated and the uncorrelated questions. They were then compared to find which one could identify the most significant questions. To validate the questions, we developed and trained an ANN algorithm; its score on classifying individuals was compared against that of the DHS wealth index.

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 the 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 values 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), an initial PCA analysis was done to generate eigenvalues for the DHS adopted wealth index questions segregated by residence (rural or urban). These eigenvalues of the DHS wealth index questions were subsequently used to generate a wealth score for each of the participants. The participants/household wealth scores were then sorted into quintiles as a reference to 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 socio-economic categories).

Model training

A Convolutional Neural Network (CNN) was developed and trained by using five-fold cross-validation. CNN is a deep learning model that uses the concepts of neural networks. During the training of a CNN model, random weights were initialized in the filters/patches of the model. The randomly initialized weights were multiplied by the incoming data to form feature maps through 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 the question's weight. 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 measures 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 metrics, 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 (Straube & Krell, 2014). Classification accuracy is the ratio of the number of correctly classified examples to the total number of classified examples (Novaković et al., 2017).

Weight extraction

To understand the weight of each question's contribution to the socioeconomic 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.

$$W_f = \sum_{q=0}^{q=W_l} W(f,q)$$ (Mzurikwao et al., n.d.). *(2)*

where $0 \leq f < 32$ 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.

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 as having higher significance in classifying induvial 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 the DHS wealth index for validation purposes. This was aimed at validating the selected questions

The best-performing CNN model had an average accuracy of 87% with a standard deviation of 2% across 5-fold cross-validation. There is no clear-cut acceptable classification accuracy for machine learning, and its acceptance depends on the problem. A study (Valverde-Albacete & Peláez-Moreno, 2014) 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 (Peck, 2019), other performance metrics were also assessed to determine the optimal model (Semali, 2010). 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.

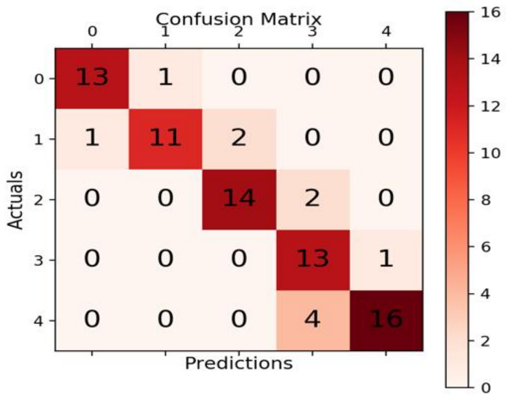

Figure 1: Confusion metrics of the Convolutional Neural Network (CNN)on 5 classes with 49 questions.

RESULTS

Participants' Demographics

A total number of 778 participants were recruited with a 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.

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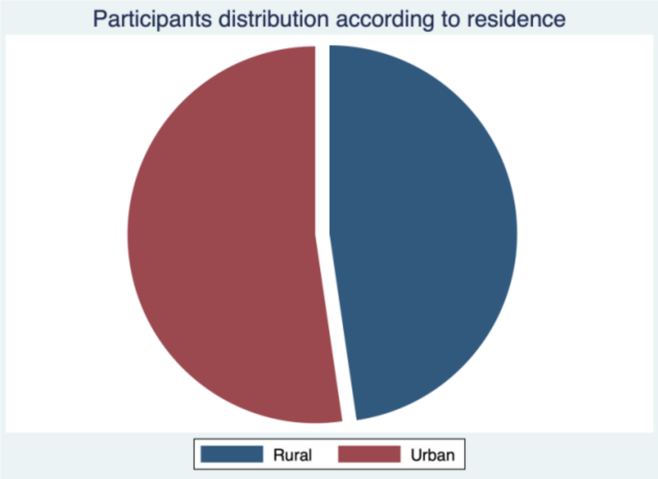

Figure 2: Participants Rural (47.7%) = Mvomero – Morogoro and Komkonga- Tanga, and Urban (52.3%) = Sabasaba – Morogoro, Mikanjuni – Tanga

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 areas and is summarized in 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 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)**

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Table 3: The CNN model performance (Accuracy) under different weight contributions of each question to the score of the SES

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

Table 3 above shows the model performance under different numbers of questions selected based on their weights as extracted from a trained CNN.
As the number of questions decreased with an 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.

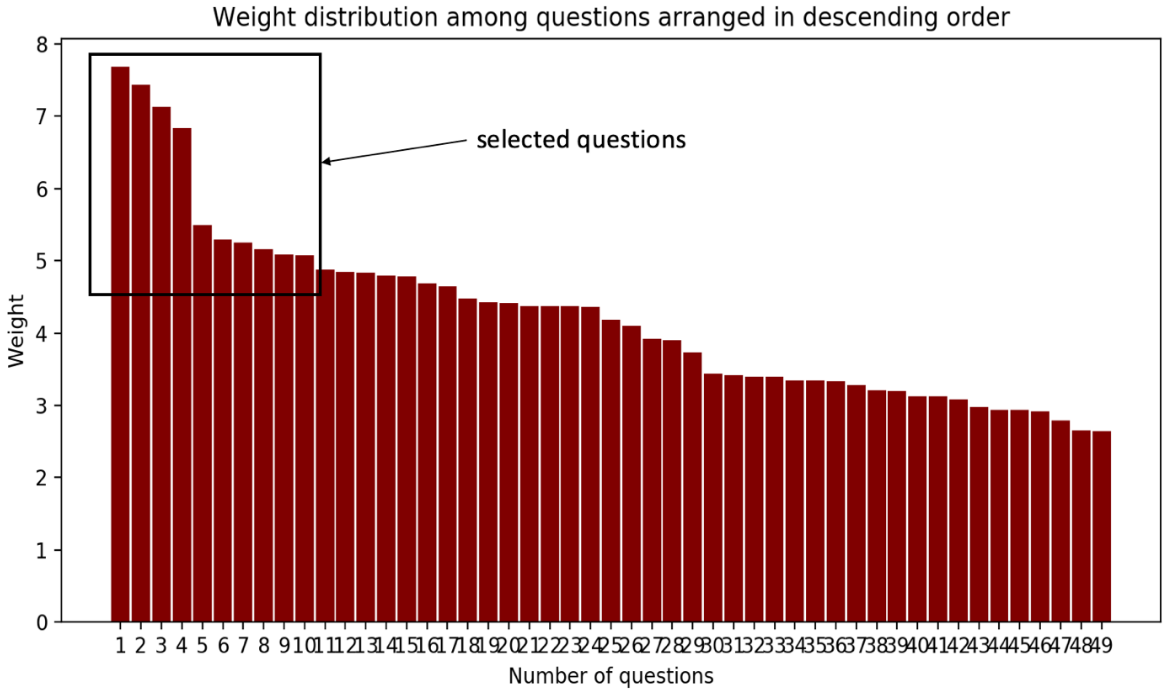

Figure 3: Weight distribution among questions arranged in descending order

Table 4: List of the top ten questions that contribute the 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

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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 in 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 eigenvalues, 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).

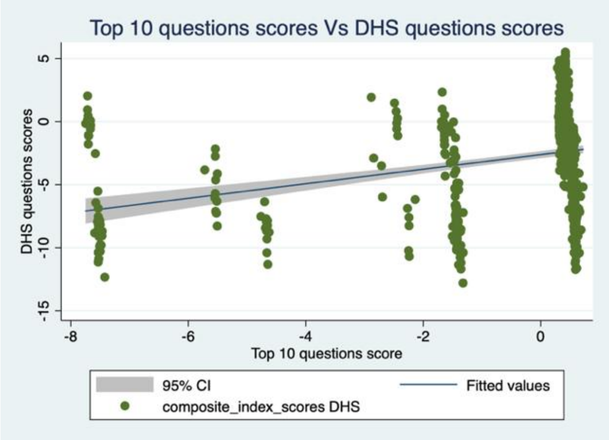

Figure 4: The R2 =0.08 for the top 10 questions Vs DHS questions score.

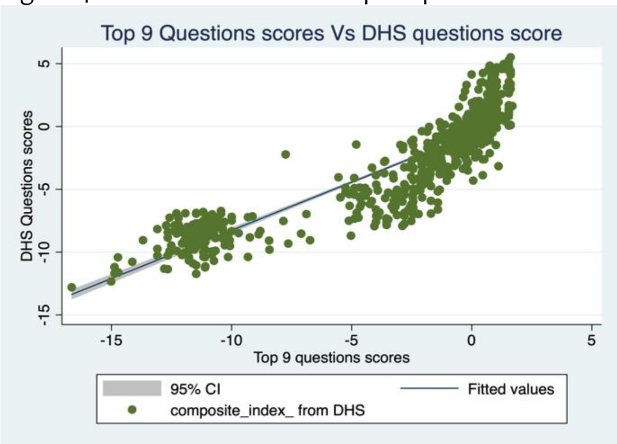

Figure 5: The R2 =0.80 for the top 9 questions Vs DHS questions score.

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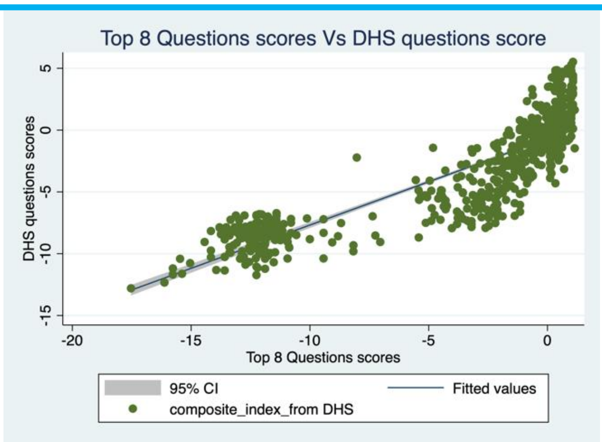

Figure 6: The R2 =0.76 for the top 8 questions Vs DHS questions score.

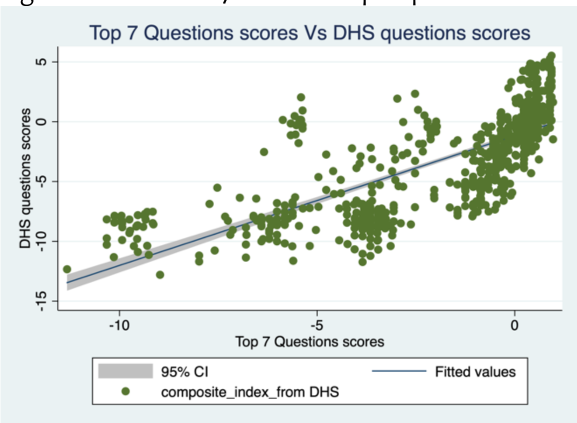

Figure 7: The R2 =0.56 for the top 7 questions Vs DHS questions score.

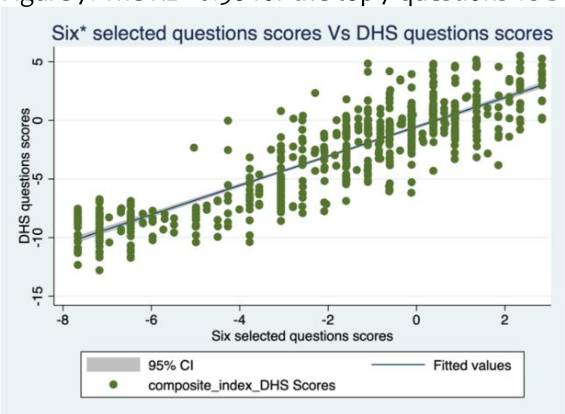

Figure 8: The R2 =0.79 for the top 6 questions Vs DHS questions score.

To assess the reliability of our model performance, 95% confidence intervals were calculated for accuracy, sensitivity, specificity, and precision across the five cross-validation folds. The CNN model achieved an accuracy of 0.98 (95% CI: 0.972–0.988), while the ANN and logistic regression models had accuracies of 0.91 (95% CI: 0.887–0.933) and 0.88 (95% CI: 0.873–0.887), respectively. Similarly, precision and sensitivity values for all models fell within narrow confidence bounds, indicating consistency across the folds. A chi-square test was performed to assess the association between participants' education level and geographic location (urban vs. rural), revealing a statistically significant difference (χ^2, $p < 0.0001$). Furthermore, the correlation between actual and predicted SES scores for the ANN model yielded an R^2 of

0.76, with the corresponding Pearson correlation being statistically significant ($p < 0.0001$), supporting the robustness of the model's predictive capability.

DISCUSSION AND CONCLUSION

We have attempted to create an 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 is 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 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.

Several studies support the findings presented in this manuscript regarding the application of artificial intelligence (AI) to optimize socioeconomic status (SES) assessment tools for immunization equity monitoring. For instance, Lyon et al., 2021c) demonstrated how AI can streamline healthcare processes by optimizing diagnostic workflows, a concept aligned with this study's use of CNN and ANN models to reduce redundant SES questions. Similarly, (Ramesh Masthi et al., 2013) highlighted the challenges of applying conventional SES scales in varied settings, underscoring the need for adaptive and context-specific tools, which this AI-driven approach effectively addresses.

Another study further emphasized methodological limitations in wealth index construction in low-income countries, reinforcing the value of innovative approaches like AI for improving equity measurement(Howe et al., 2008). In addition, recent work on electronic immunization registries in Tanzania and Zambia demonstrates the growing importance of digital innovations for improving immunization service delivery, complementing this study's focus(Carnahan et al., n.d.). Collectively, these studies validate the relevance and potential of AI in enhancing the accuracy, efficiency, and contextual relevance of public health monitoring tools.

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