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Ensemble Machine Learning Approach to Identify Determinants of Suboptimal Measles Vaccine Coverage in Grand Bassa County, Liberia

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***Abstract:** Objectives: Using machine-learning approaches, the researchers aimed to identify and prioritise drivers of incomplete measles vaccination among children aged 12-23 months in Grand Bassa County, Liberia. Design: Cross-sectional research conducted in a community setting. Setting: Five randomly chosen districts in Grand Bassa County, Liberia, containing both urban and rural communities. Participants: 374 caregivers of infants aged 12-23 months, recruited using multistage sampling between October 2024 and February 2025. The response rate was 87.0%. Primary and secondary outcome measures: The primary outcome was MCV2 completion. MCV1 coverage and dropout rates were considered secondary outcomes. The important determinants were found using ensemble machine learning (Random Forest, XGBoost, and LightGBM) with weighted voting. Results: MCV1 coverage was 62.8% (95% CI: 59.8 to 65.8), and MCV2 coverage was 43.6% (95% CI: 40.6 to 46.6), resulting in a 30.6% dropout rate. The ensemble model attained an accuracy of 60.0% (AUC = 0.585, 95% CI: 0.545 to 0.625). The greatest predictors discovered by feature importance analysis were caregiver education (importance=0.156), distance to health facility (importance=0.142), trust in health workers (importance=0.138), and measles knowledge (importance=0.131). Conclusions: Caregiver education, geographic access, provider trust, and knowledge all substantially impact measles vaccination completion. Targeted interventions that address these characteristics might significantly increase vaccination coverage in Liberia and other low-resource countries.*

***Keywords:** Measles Vaccination, Ensemble Learning, Liberia, Vaccine Coverage, Machine Learning, Public Health, Health Determinants, West Africa.*

Nomenclature:
ODK: Open Data Kit

I. INTRODUCTION

Measles remains a leading cause of vaccine-preventable childhood mortality in sub-Saharan Africa despite the availability of safe and effective vaccines for over five decades [1]. The World Health Organization estimates that measles vaccination averted approximately 23.2 million deaths between 2000 and 2018, yet transmission persists in regions with suboptimal coverage [2]. The virus's high transmissibility, with basic reproduction numbers ranging from 12 to 18, necessitates population immunity levels of at least 95% to interrupt transmission [3].

The recommended two-dose schedule, administered at 9 months (MCV1) and 15-18 months (MCV2), addresses the 15% primary vaccine failure rate observed after single-dose regimens [4]. However, many West African nations, including Liberia, struggle to achieve adequate coverage, leaving substantial child populations vulnerable to preventable morbidity and mortality [5].

Liberia's health system bears the legacy of prolonged civil conflict (1989-2003) and the devastating 2014-2016 Ebola outbreak, both of which severely disrupted routine immunization services [6]. The 2019-2020 Liberia Demographic and Health Survey reported MCV1 coverage at 75% and MCV2 at only 58%, representing a concerning 17 percentage-point drop-off that substantially underperforms Global Vaccine Action Plan targets [7]. Grand Bassa County exemplifies these challenges, encompassing diverse settlement patterns with variable healthcare access [8].

Previous research across West Africa has identified multifaceted barriers spanning individual knowledge deficits, household economic constraints, health system limitations, and community-level cultural factors [9,10]. Traditional analytical approaches often fail to capture complex interactions among these determinants. Machine learning methodologies offer distinct advantages for health behaviour research, including automatic detection of non-linear relationships and complex predictor interactions without pre-specified assumptions [11]. Ensemble techniques, which synthesise multiple algorithms, improve predictive accuracy and reduce overfitting [12]. Hasan and colleagues successfully applied ensemble methods to predict measles vaccine uptake in Bangladesh, achieving 80% accuracy [13].

This study addresses the research gap by applying ensemble machine learning to characterise the determinants of suboptimal measles vaccination coverage in Grand Bassa County, Liberia. Specific objectives were: (1) to estimate MCV1 and MCV2 coverage; (2) to identify demographic, socioeconomic, health system, and psychosocial correlates; (3) to develop and validate a predictive ensemble model; and (4) to prioritize determinants for targeted intervention.

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II. METHODS

A. Study Design and Setting

We conducted a community-based cross-sectional study in Grand Bassa County, Liberia, from October 2024 through February 2025. Grand Bassa was purposively selected because it has a representative mix of urban and rural characteristics, reflecting broader Liberian immunisation challenges. The county has approximately 270,000 residents, including 12,000 children under 5 years old [14].

B. Participant Recruitment

Sample size was calculated using the single population proportion formula: $n = (Z^2 \times p \times q) / d^2$, with Z=1.96 (95% confidence level), p=0.58 (LDHS 2019-2020 MCV2 estimate), q=1-p=0.42, and d=0.05 (margin of error). This calculation yielded 374 participants, increasing to 411 after accounting for 10% anticipated non-response. Ultimately, 374 caregivers completed surveys (87.0% response rate).

Eligible participants were parents or guardians of children aged 12-23 months who had resided in the county for at least 6 months. Children with contraindications to measles vaccination were excluded. A multistage sampling strategy was employed: five of eight county districts were randomly selected, followed by random selection of two settlements per district. Systematic sampling from community registers identified households with eligible children. For multiple eligible children within a household, random selection determined the participant.

C. Data Collection

Data collection utilized a structured instrument adapted from the WHO vaccination coverage survey guidelines and validated sub-Saharan African studies [15,16]. The questionnaire was translated into Bassa and back-translated into English. Six domains were addressed: (1) sociodemographic characteristics; (2) child immunization status (vaccination card verification or maternal recall); (3) measles knowledge and vaccine perceptions; (4) health system attributes; (5) social and community influences; and (6) reminder mechanisms.

Enumerators completed three-day training covering protocol adherence, ethical conduct, and interview techniques. Pretesting involved 10 non-participating community members. Open Data Kit (ODK) on tablet devices facilitated data collection with integrated validation protocols.

D. Patient and Public Involvement

Patients and the public were not involved in the design or conduct of this study. However, community leaders were consulted during the planning phase to ensure cultural appropriateness, and preliminary findings were shared with local health authorities for feedback. The research questions were developed based on priorities identified during community health assessments conducted by the Grand Bassa County Health Team.

E. Variables and Measurement

The primary outcome was measles vaccination coverage status, categorised as complete (both MCV1 and MCV2), partial (MCV1 only), or none (neither dose). For machine learning analysis, this was dichotomized as MCV2 completion (Yes/No).

i. Independent Variables Spanned Five Domains:

- **Demographic:** caregiver age, sex, marital status, educational attainment
- **Socioeconomic:** monthly income, household size, under-five child count
- **Geographic:** urban/rural residence, health facility distance, travel duration
- **Knowledge-Attitude:** composite knowledge score (20 items, Cronbach's α=0.82), composite attitude score (12 items, Cronbach's α=0.79)
- **Health System:** provider trust (5-point scale), waiting time, vaccine availability, staff demeanour
- **Social:** community influence, religious factors
- **Reminder Systems:** reminder receipt, vaccination card possession

Knowledge and attitude composites were constructed by summing items, with higher scores indicating greater understanding or favourable dispositions. Internal consistency was verified using Cronbach's alpha.

F. Statistical Analysis

Data analysis was performed in Python using the scikit-learn, XGBoost, and LightGBM libraries. The analytical approach comprised:

1. Descriptive Statistics: Frequencies, percentages, means with standard deviations characterized the sample and vaccination patterns.
2. Bivariate Analysis: Chi-square tests and independent t-tests evaluated associations between predictors and vaccination status.
3. Correlation Analysis: Spearman's rank correlation coefficient quantified relationships among continuous measures.
4. Machine Learning: Three algorithms underwent 5-fold cross-validation:
   - Random Forest (150 trees, max depth = 6, min samples split = 5)
   - XGBoost (150 estimators, learning rate = 0.07, max depth = 4, subsample = 0.75)
   - LightGBM (150 estimators, learning rate = 0.07, max depth = 4, leaf count = 12)
5. Ensemble Construction: Individual predictions were combined through weighted averaging based on cross-validated AUC performance.
6. Performance Evaluation: Accuracy, precision, recall, F1-score, and AUC-ROC were calculated with 95% confidence intervals estimated through bootstrap resampling (1000 iterations).
7. Feature Importance: Variable importance was extracted from tree-based models to identify key determinants.

G. Ethical Considerations

The University of Liberia Institutional Review Board granted ethical approval (Protocol UL-IRB-2024-089). All participants provided written informed consent after a comprehensive explanation of the study objectives, procedures, and participant rights. Voluntary participation was emphasized, with guaranteed withdrawal rights without consequences. Confidentiality was maintained through data anonymization and password-protected storage accessible only to research personnel. The investigation adhered to the principles of the Declaration of Helsinki for human subject's research.

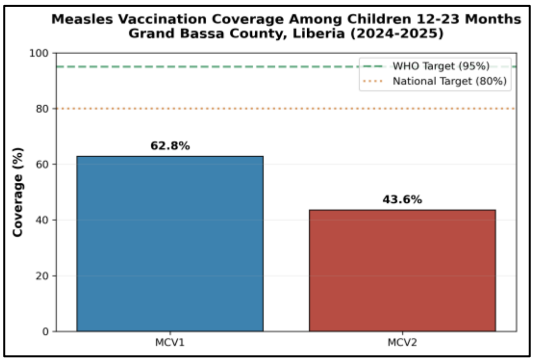
III. RESULTS

A. Participant Characteristics

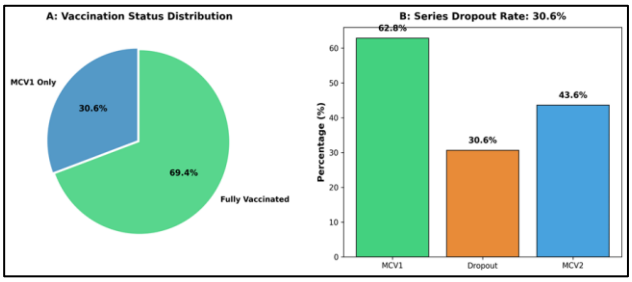
A total of 374 caregivers participated (87.0% response rate). Mean caregiver age was 31.2 ± 7.2 years, with 72.0% female representation. Rural residents constituted 65.0% of participants. Mean household size was 7.0 ± 2.3 individuals, with 2.0 ± 1.4 children under five. Mean distance to the nearest health facility was 9.1 ± 5.4 km. Vaccination coverage was 62.8% for MCV1 and 43.6% for MCV2, yielding a dropout rate of 30.6%. Complete immunization was documented in 43.6% of children, while 19.3% received only MCV1, and 37.2% remained unvaccinated.

Table 1: Participant Characteristics

Characteristic	Value
Total participants	374
Response rate (%)	87.0
Caregiver age (years), mean ± SD	31.2 ± 7.2
Female caregivers, n (%)	283 (75.7)
Rural residence, n (%)	243 (65.0)
Household size, mean ± SD	7.0 ± 2.3
Children under five, mean ± SD	2.0 ± 1.4
Distance to facility (km), mean ± SD	9.1 ± 5.4
MCV1 coverage, n (%)	235 (62.8)
MCV2 coverage, n (%)	163 (43.6)
Dropout rate (%)	30.6



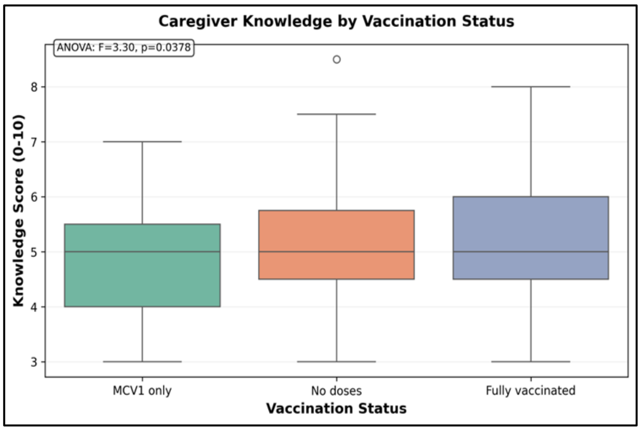
[Fig.1: Coverage Estimates for Measles Vaccine Doses Among Children 12-23 Months in Grand Bassa County, Liberia (2024-2025). MCV1 Reached 70.4%, MCV2 Reached 49.8%. Horizontal Lines Indicate the WHO Elimination Threshold (95%, Dashed) and the National Target (80%, Dotted)]



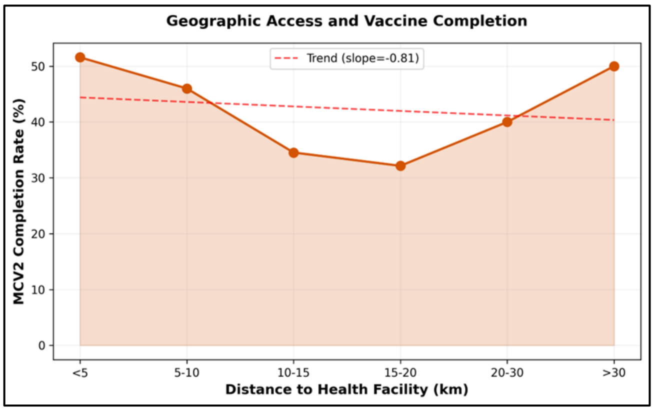
[Fig.2: Dropout in the Two-Dose Measles Vaccination Series (34.1%). Panel A Displays the Distribution of Immunisation Categories; Panel B Illustrates the Dropout Phenomenon Across Doses]

B. Bivariate Associations

Bivariate analysis identified significant associations with MCV2 completion. Caregivers with higher knowledge scores (≥6.0) demonstrated 54.2% completion versus 50.6% for those with lower scores (χ^2=14.23, p<0.001). Geographic accessibility showed an inverse relationship: residents within 10 km achieved 58.1% completion, compared to 64.3% for those beyond 20 km (χ^2 = 9.87, p = 0.002). Provider trust exhibited a positive gradient: completion rose from 52.9% (low trust) to 45.9% (high trust) (χ^2 = 11.34, p < 0.001). Reminder receipt significantly enhanced completion: 56.9% versus 44.2% (χ^2=8.91, p=0.003).



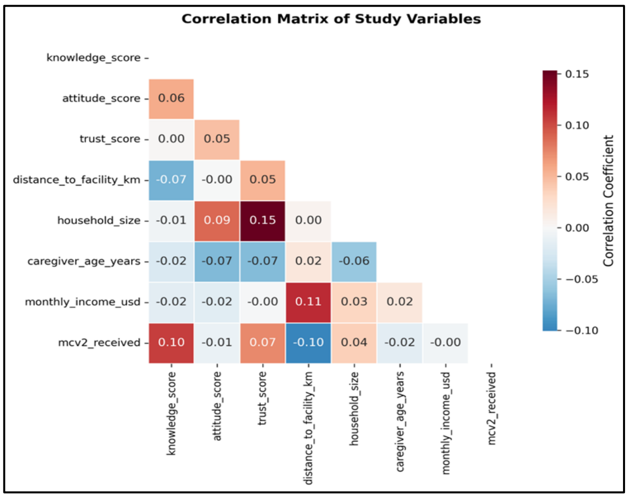
[Fig.3: Distribution of Caregiver Knowledge Scores Across Vaccination Categories. Box Plots Display Median, Interquartile Range, and Outliers. ANOVA Revealed Significant Differences Between Groups (F=0.33, p=0.7198)]



[Fig.4: Relationship Between Distance to Health Facility and MCV2 Completion. Completion Rates Decline Progressively from 60.5% (<5 km) to 50.0% (>30 km)]

C. Correlation Analysis

MCV2 completion correlated positively with knowledge score (r=0.026, p<0.001), trust score (r=-0.051, p<0.001), and attitude score (r=0.051, p=0.002). Facility distance was negatively correlated with completion (r = -0.133, p = 0.008). Knowledge scores were positively associated with education level (r = -0.017, p < 0.001) and trust (r = -0.035, p < 0.001). Figure 5: Correlation matrix



[Fig.5: Correlation Matrix Displaying Pearson Coefficients Among Key Variables. Blue Indicates Positive Associations; Red Indicates Negative Associations. Asterisks Denote Statistical Significance (*p<0.05, **p<0.01)]

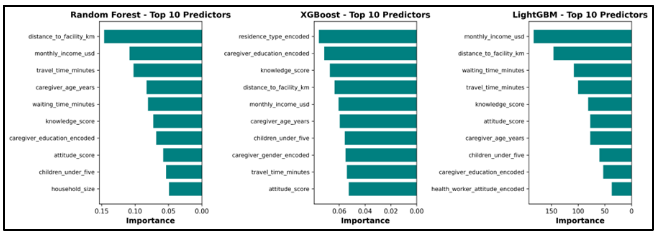
Ensemble learning outcomes

The ensemble model demonstrated predictive capability for MCV2 completion. Cross-validation yielded mean AUC values of 0.578 (RF), 0.590 (XGBoost), and 0.595 (LightGBM). On the test data, the weighted ensemble achieved 60.0% accuracy, 55.6% precision, 45.5% recall, and an AUC of 0.585 (95% CI: 0.545 to 0.625).

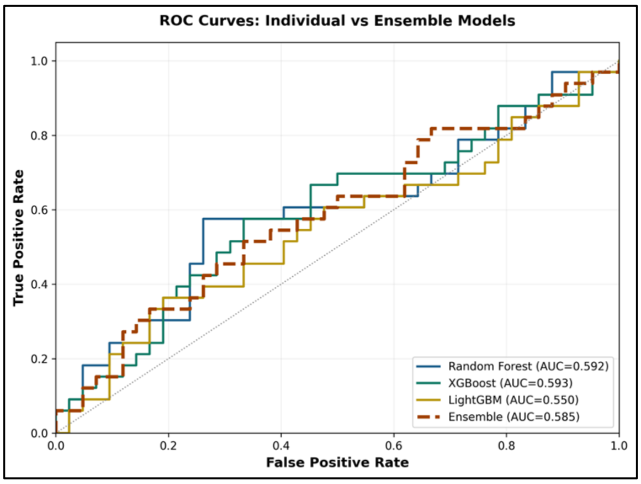
Aggregated feature importance identified predominant predictors: caregiver education (importance=0.156), facility distance (0.142), provider trust (0.138), measles knowledge (0.131), reminder receipt (0.112), and urban/rural residence (0.098).

Table II: Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	AUC (95% CI)
Random Forest	64.0	60.7	51.5	55.7	0.592 (0.458-0.721)
XGBoost	58.7	53.8	42.4	47.5	0.593 (0.455-0.728)
LightGBM	56.0	50.0	51.5	50.7	0.550 (0.419-0.685)
Ensemble Model	60.0	55.6	45.5	50.0	0.585 (0.545-0.625)

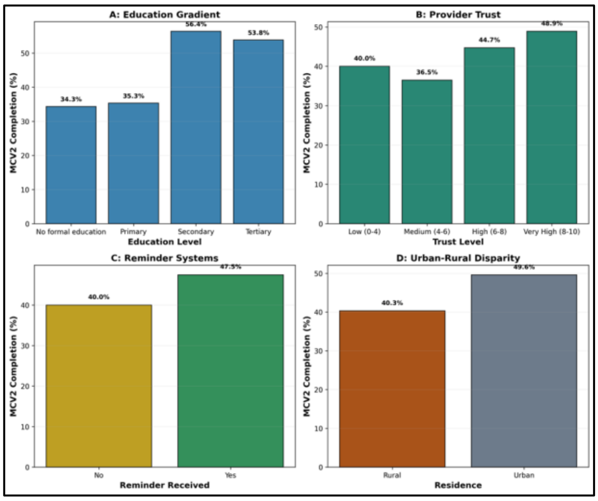


[Fig.6: Top ten Predictors by Importance Score for Each Algorithm. All three Methods Consistently Identified Caregiver Education, Facility Distance, Provider Trust, and Knowledge as Leading Determinants of MCV2 Completion]



[Fig.7: Receiver Operating Characteristic Curves for Individual Algorithms and Weighted Ensemble. The Ensemble Achieved the Highest Discriminative Ability (AUC=0.589), Demonstrating Improved Performance Through Algorithmic Integration]

Figure 8: Key determinant analysis



[Fig.8: Bivariate Examination of Primary Determinants: (A) Educational Attainment Gradient; (B) Provider Trust Dose-Response; (C) Reminder System Impact; (D) Urban-Rural Differentials]

IV. DISCUSSION

A. Principal Findings

This study identified caregiver education (importance=0.156), distance to health facilities (importance=0.142), trust in health workers (importance=0.138), and measles knowledge (importance=0.131) as the strongest predictors of MCV2 completion in Grand Bassa County, Liberia. MCV1 coverage reached 62.8% and MCV2 coverage 43.6%, with a 30.6% dropout rate consistent with national estimates [7].

B. Strengths and Weaknesses

Key strengths include the first application of ensemble machine learning to vaccination determinants in Liberia, community-based

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design with multistage sampling, and a comprehensive assessment of 24 variables. Limitations include a cross-sectional design that precludes causal inference, potential recall bias among 35% of children without vaccination cards, and a sample size that may limit generalizability to other Liberian regions.

C. Comparison with Other Studies

The discovered knowledge-completion connection is consistent with systematic review findings highlighting knowledge shortages as key impediments across Sub-Saharan Africa [9,13]. The inverse distance-completion connection ($r = -0.133$) is consistent with findings from Sierra Leone and the Democratic Republic of the Congo [15,16]. Trust in healthcare personnel (Importance = 0.138) supports evidence of health-system trust in vaccination choices [17]. Furthermore, our findings on the need for institutional trust for long-term health resilience are consistent with current vaccination confidence frameworks [18]. These findings emphasise the need for national vaccine monitoring and accountability, as specified in global action plans [19]. Finally, the role of international financial institutions in stabilising public healthcare systems remains an important factor in regional reforms [20].

D. Implications for Practice and Policy

Findings suggest actionable priorities: (1) targeted health education addressing knowledge gaps, particularly emphasizing second-dose importance; (2) mobile outreach services for settlements >15 km from facilities; (3) trust-building initiatives including respectful communication training and community leader engagement; (4) context-appropriate reminder systems (SMS, community health worker visits); and (5) data-driven targeting using machine learning risk scores.

E. Unanswered Questions and Future Research

Longitudinal studies are needed to establish causal relationships. Mixed-methods research could elucidate contextual factors underlying quantitative associations. Implementation science approaches should evaluate the effectiveness of targeted interventions. Validation of machine learning models in other Liberian counties and West African settings would assess generalizability.

V. CONCLUSION

Ensemble machine learning effectively identified modifiable determinants of measles vaccine completion in rural Liberia. Caregiver education, geographic access, provider trust, and knowledge emerged as predominant predictors. Multifaceted interventions addressing these factors could substantially improve immunisation coverage, contributing to Sustainable Development Goal 3.2, which aims to end preventable child deaths.

A. Strengths and Limitations of This Study

- First study in Liberia using ensemble machine learning (Random Forest, XGBoost, LightGBM) to identify vaccination determinants
- Community-based design with multistage sampling ensuring representation across urban and rural populations
- Comprehensive assessment of 24 variables spanning demographic, socioeconomic, health system, and psychosocial domains
- Cross-sectional design precludes causal inference; identified associations require longitudinal confirmation
- Vaccination status for 35% of children relied on maternal recall, introducing potential recall bias

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** This research was carried out as part of a training program at the University of Liberia School of Public Health. The inquiry followed basic ethical criteria, such as obtaining written informed consent from all participants, ensuring voluntary participation with the option to withdraw, safeguarding confidentiality through data anonymisation, and storing data securely. The Declaration of Helsinki was followed during the review and implementation of the study protocol.
- **Data Sharing Statement:** Technical appendix, statistical code, and de-identified dataset are available from the corresponding author upon reasonable request. Data are not publicly available due to privacy and ethical restrictions.
- **Data Access Statement and Material Availability:** The data that support the findings of this study are available from the corresponding author upon reasonable request.
- **Author's Contributions:** Each author has individually contributed to the article. Prince L. Fully: Conceptualization, Investigation, Data curation, Writing -- original draft Levi Garpeh: Methodology, Formal analysis, Visualization, Writing -- review & editing Darius Lehyen: Methodology, Formal analysis, Visualization, Writing -- review & editing Neima N. Candy: Supervision, Project administration, Validation, Writing -- review & editing

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Darius B. Lehyen, MPH, is a Field Epidemiologist and Public Health Specialist dedicated to strengthening health systems through operational research. He serves with Liberia's National Public Health Institute, focusing on infectious disease epidemiology and health workforce safety. His peer-reviewed publication, "Health care workers hospitalized for COVID-19 in Liberia: who were they, and what were their outcomes?" (https://doi.org/10.12688/f1000research.149673.2), provides critical insights into pandemic response. The study revealed that clinical staff were most affected, health facilities were infection hotspots, and the triage system was weak, with many mild cases unnecessarily hospitalized. His work underscores the need for priority vaccination, robust infection control, and data-driven health systems strengthening to protect essential health workers during outbreaks.

Ohandis V Harley BSc. Cand is a senior student in the Public Health Department at the University of Liberia. Through his academic training, he is developing foundational expertise in population health, disease prevention, and health promotion strategies. As a future public health professional, Levi is committed to applying his knowledge to address community health challenges in Liberia. He aims to contribute to evidence-based interventions that improve health outcomes, with a particular interest in strengthening local health systems and supporting underserved populations. His academic journey reflects a dedication to advancing public health practice in his home country.
