

# Predictors of Childhood Vaccination Uptake in England: An Explainable Machine Learning Analysis of Longitudinal Regional Data (2021–2024)

Amin Noroozi<sup>a</sup>, Sidratul Muntaha Esha<sup>a</sup>, and Mansoureh Ghari<sup>b</sup>

<sup>a</sup> School of Engineering, Computing & Mathematical Sciences, University of Wolverhampton, Wolverhampton, WV1 1LY, UK

<sup>b</sup> School of Pharmacy, University of Wolverhampton, Wolverhampton, WV1 1NA, UK

## Corresponding Author:

Amin Noroozi

Room 148, Alan Turing Building, School of Engineering, Computing & Mathematical Sciences, University of Wolverhampton, Wolverhampton, WV1 1LY, UK

Email: a.noroozifakhabi@wlv.ac.uk

## Summary

**Background:** Childhood vaccination is a cornerstone of public health, yet disparities in vaccination coverage persist across England. These disparities are shaped by complex interactions among various factors, including geographic, demographic, socioeconomic, and cultural (GDSC) factors. While previous studies have investigated these predictors, most rely on static, cross-sectional data and traditional statistical approaches that assess individual or limited sets of variables in isolation. Such methods may fall short in capturing the dynamic and multivariate nature of vaccine uptake.

**Methods:** We conducted a longitudinal machine learning analysis of childhood vaccination coverage across 150 districts in England from 2021 to 2024. Using vaccination data from NHS records, we applied hierarchical clustering to group districts by vaccination coverage into low- and high-coverage clusters, using two, three, and six clusters to capture varying levels of disparity. A CatBoost classifier was then trained to predict districts' vaccination clusters using their GDSC data. Finally, the SHapley Additive exPlanations (SHAP) method was used to identify and interpret the most important predictors of vaccination disparities.

**Findings:** The optimal clustering involved two clusters, for which the CatBoost classifier achieved high accuracies of 92.1, 90.6, and 86.3 in predicting districts' vaccination clusters for the years 2021–2022, 2022–2023, and 2023–2024, respectively. SHAP analysis revealed that geographic, cultural, and demographic variables, particularly rurality, English language proficiency, percentage of foreign-born residents, and ethnic composition, were the most influential predictors of vaccination coverage. Contrary to common assumptions, rural districts were significantly more likely to have higher vaccination rates. Additionally, districts with lower vaccination coverage had significantly higher populations whose first language was not English, who were born outside the UK, or who were from ethnic minority groups. Surprisingly, socioeconomic variables, such as deprivation and employment, had consistently lower importance, especially in 2023–2024.

**Interpretation:** Vaccination disparities in England are primarily driven by geographic, demographic, and cultural factors rather than socioeconomic ones. Machine learning with explainable outputs offers actionable insights for public health planning, particularly for targeting vulnerable communities.

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**Keywords:** Childhood vaccination, Machine learning, Longitudinal vaccination analysis, Geographic and Demographic Disparities, Public health

# INTRODUCTION

## Background

Childhood vaccination is a cornerstone of public health, significantly reducing the incidence of infectious diseases and preventing outbreaks that can have severe consequences for children and communities alike (1). Vaccination programs are among the most effective interventions for disease prevention, yet disparities in vaccine coverage persist globally and within nations (2-5). In England, while overall childhood immunization rates have been relatively high, regional disparities have raised concerns about inequalities in vaccine uptake and the potential risks associated with suboptimal coverage (6, 7). These disparities are influenced by a complex interplay of geographic, demographic, socioeconomic, and cultural (GDSC) factors, making it crucial to analyze vaccination trends over time and identify the key predictors of vaccine uptake (8-10).

## Importance

Understanding the determinants of vaccination coverage is fundamental for effective public health planning and policymaking. Several studies have highlighted key predictors of vaccine uptake, including parental education (11), household income (12, 13), healthcare accessibility (14), and community trust in medical institutions (15, 16). Socioeconomic factors, in particular, have been shown to play a critical role, as lower-income households often face greater barriers to healthcare access, contributing to disparities in immunization rates (13, 17). Moreover, vaccine hesitancy, driven by misinformation, cultural beliefs, and concerns about vaccine safety, has emerged as a significant challenge in maintaining high vaccination rates (18). Geographic disparities in vaccine coverage add another layer of complexity to immunization programs. For example, some studies have reported lower vaccination rates in rural areas, primarily due to limited access to healthcare services, while urban centres often exhibit heterogeneous vaccination patterns, influenced by cultural and socioeconomic diversity (19, 20). These disparities highlight the need for targeted interventions and region-specific strategies to improve immunization coverage and reduce public health risks.

Current research predominantly relies on static, cross-sectional data, which restricts our ability to capture the dynamic nature of vaccination trends over time. Additionally, most studies focus on individual predictors or diseases, failing to provide a comprehensive comparison of the relative importance of various factors influencing different diseases' vaccination coverage. To overcome these limitations, a holistic, data-driven approach is essential for integrating multiple determinants and diseases and supporting targeted public health interventions.

Machine learning has emerged as a powerful tool in epidemiological research, enabling researchers to uncover hidden patterns in vaccination trends (21-23). Machine learning methods can process large-scale high-dimensional data more accurately than traditional statistical techniques, making them reliable options for addressing the problems mentioned above in vaccination research (22, 24). However, despite its potential, the application of machine learning to longitudinal vaccination coverage trends remains underexplored.

## Goals of This Study

This study aims to bridge this gap by investigating childhood vaccination disparities across a broad range of diseases in England between 2021 and 2024, using a machine learning framework. To achieve this, we first apply hierarchical clustering to group districts based on their vaccination coverage levels and analyse how these clusters evolve over time. We then train a CatBoost (CB) classifier to predict districts' vaccination clusters using their GDSC factors. Finally, we employ SHapley Additive exPlanations (SHAP) (25) to interpret the model and identify the most influential predictors contributing to vaccination coverage disparities across England.

## METHODS

### Study Setting and Data

Two types of data from three consecutive years, 2021–2022, 2022–2023, and 2023–2024, were collected for this study. Each study year runs from 1 April to 31 March of the following year, in alignment with the NHS national statistics format (26), which is published each September. The first dataset includes 14 types of vaccination data sourced from the NHS Immunization Statistics (26–29), providing annual records of immunization rates at the Upper-Tier Local Authority (UTLA) level for 150 districts across England with a focus on early vaccinations for children under 5 years old. The second dataset used in this study contains GDSC variables, grouped into nine categories. For simplicity, we refer to these nine categories collectively as GDSC data throughout this paper. The data were collected from statistics provided by the UK government, including the English Indices of Multiple Deprivation (IMD) (30), census data (31), and Rural-Urban Classification (32). Table 1 shows the abbreviations used for the data in the first and second datasets in this study and the corresponding descriptions.

As can be seen from Table 1, coverage rates of 14 vaccinations have been included in our analysis to ensure the comprehensiveness of the analysis, concentrating on early childhood immunizations that are part of the UK’s routine immunization schedule. These vaccinations cover 13 unique diseases, including Diphtheria, Tetanus, Pertussis (Whooping Cough), Polio, Haemophilus influenzae type B (Hib), Hepatitis B, Meningococcal Disease (Group B), Meningococcal Disease (Group C), Measles, Mumps, Rubella, Pneumococcal Disease, and Rotavirus Disease.

For the second dataset, “IMD-Average score”, “IMD-Proportion deprived”, “Long-term unemployed”, “Routine occupations”, and “No qualifications” primarily represent the socioeconomic condition of the population. The variables “Born Outside the UK” and “Ethnic Minority” can be classified as demographic factors, while “Rurality” captures the geographic characteristics of each district. Additionally, both “Ethnic Minority” and “English Proficiency” can be considered cultural variables, as research indicates that cultural elements associated with different ethnic groups, such as beliefs, traditions, and levels of trust in healthcare systems, can significantly affect attitudes toward vaccination (33). Moreover, since all GDSC factors are calculated separately for each district across England, the impact of geography is inherently included in their calculations, which in turn, impacts the vaccination disparities in respective regions (34).

### Machine Learning Analysis

The machine learning analysis in this study consisted of three steps, outlined as follows:

**Step 1:** Districts were clustered into two, three, and six clusters based on their vaccination rates extracted from the first dataset. In this step, a cluster label was assigned to each district, which served as the target variable for the next step. The assigned cluster reflects the district’s level of vaccination coverage. For example, if the districts are grouped into two clusters, one cluster would represent districts with high vaccination rates and the other those with low vaccination rates.

**Step 2:** In the second step, a CB classifier was employed to classify districts into their respective vaccination clusters using GDSC variables from the second dataset. This step is equivalent to predicting the cluster labels using the GDSC data, rather than the vaccination rates themselves.

**Step 3:** In this step, we used SHAP values derived from the CB model to evaluate the contribution of each of the nine GDSC factors in predicting the cluster labels assigned to districts in Step 2.

Clustering the districts in Step 1 using conventional methods is challenging, particularly when considering all vaccination rates from the first dataset (Table 1). Additionally, the optimal number of clusters is a hyperparameter that must be defined prior to running the clustering algorithm. To address these challenges, we employed a hierarchical clustering method, with the optimal number of clusters determined using a dendrogram (35). Hierarchical clustering is a method that creates a hierarchy of clusters in a tree-like structure known as a dendrogram. This approach is particularly useful in clinical

research involving heterogeneous data, as it allows for the exploration of similarities between observations and clusters, which can be visualized using dendrograms (35).

To classify data in step 2, we evaluated various methods, with the CB classifier demonstrating superior performance; consequently, it was selected for this research. Tree-based classifiers such as CB are renowned for their robustness and accuracy in classification tasks across diverse datasets (21, 36, 37). The CB algorithm, when combined with SHAP, provides a robust and interpretable approach for evaluating feature importance. This method enables the identification of the most influential predictors in the classification process by quantifying each feature's contribution to the model's predictions. (25, 38). This capability allows us to determine the key predictors influencing vaccination coverage rates across districts. Accordingly, we used this mechanism to extract feature importance values from the CB classifier and assess the contribution of the nine GDSC factors outlined in Table 1.

To ensure the robustness of our results, we implemented a five-fold cross-validation (CV) approach, which is a standard technique to enhance model generalizability and prevent overfitting (39-43). In this method, the dataset is initially partitioned into five equal folds. In each iteration, four folds are utilized for training, while the remaining fold serves for testing. This process is repeated five times, ensuring that each fold serves as the test set once. The final evaluation metrics and feature importance values were computed by averaging the results across all folds, ensuring a comprehensive assessment of the model's performance and the relevance of each feature.

**Table 1.** The abbreviations and descriptions of data used in this study.

	Abbreviation	Description
<b>First dataset</b> (vaccination rates)	DTaP_IPV_5y	4 in 1 vaccine (Diphtheria, tetanus, pertussis and polio) at 5 years
	DTaP_IPV_Hib_5y	5-in-1 vaccine (diphtheria, pertussis, tetanus, polio, Haemophilus influenzae type b) at 5 years
	DTaP_IPV_Hib_HepB_12m	6-in-1 vaccine (diphtheria, pertussis, tetanus, polio, Haemophilus influenzae type b, hepatitis B) at 12 months
	DTaP_IPV_Hib_HepB_24m	6-in-1 vaccine (diphtheria, pertussis, tetanus, polio, by Haemophilus influenzae type b, hepatitis B) at 24 months
	Hib_MenC_24m	Haemophilus Influenzae type b and meningococcal group C (Hib/MenC) at 24 months
	Hib_MenC_5y	Haemophilus Influenzae type b and meningococcal group C (Hib/MenC) at 5 years
	MenB_12m	Meningococcal disease (group b) at 12 months
	MenB_booster_24m	Meningococcal disease (group b) at 24 months
	MMR_24m	Measles mumps rubella (MMR) (1st dose at 24 months)
	MMR1_5y	Measles mumps rubella (MMR) (1st dose at 5 years)
	MMR2_5y	Measles mumps rubella (MMR) (2nd dose at 5 years)
	PCV_12m	Pneumococcal disease at 12 months
	PCV_24m	Pneumococcal disease at 24 months
	Rota_12m	Rotavirus at 12 months
<b>Second dataset</b> (GDSC data)	IMD-Average score	Represents the mean deprivation score across all Lower Layer Super Output Areas (LSOAs) within a given UTLA
	IMD-Proportion deprived	Refers to the percentage of LSOAs within a UTLA that fall into the most deprived 10% of all LSOAs in England
	Long-term unemployed	Percentage of individuals classified as long-term unemployed, derived from Census data
	Routine occupations	Percentage of people in routine occupation
	No qualifications	Percentage of people with no qualification
	English proficiency	Percentage of individuals whose primary language is not English
	Ethnic minority	Representation of ethnic minority populations within each UTLA
	Born outside UK	Percentage of residents born outside the UK
	Rurality	Categorical variable with 6 categories showing the proportion of the population living in rural areas, ranging from Urban with Major Conurbation (category 1) to Mainly Rural (category 6)

## RESULTS

### Districts' Longitudinal Vaccination Clusters

To identify patterns in vaccination coverage rates across districts, we initially employed hierarchical clustering and examined the resulting dendrograms to determine the optimal number of clusters for each study year: 2021–2022, 2022–2023, and 2023–2024. In all three years, the dendrograms indicated that

two clusters provided the best fit. However, to capture finer-grained disparities, we also conducted supplementary clustering using three and six clusters, offering a more detailed stratification of vaccination coverage levels. An example of the dendrogram used to derive the optimal number of clusters for the year 2023–2024 is provided in Figure W1 of the supplementary web appendix.

Figure 1 illustrates disparities in childhood vaccination coverage across England, using two, three, and six clusters for the years 2021–2022, 2022–2023, and 2023–2024. Table 2 presents the average vaccination rates for districts within each cluster. The complete list of districts grouped by cluster for each year can be found in Tables W1–W9 in the supplementary web appendix.

As shown in Figure 1(a), the overall pattern of vaccination disparities remained largely consistent between 2021–2022 and 2022–2023. However, a substantial shift is evident in 2023–2024, where district clustering patterns diverged markedly from the previous two years. In particular, several large and densely populated districts, including Birmingham, Manchester, Liverpool, Barnet, and Croydon, transitioned from the low-vaccination coverage cluster in 2021–2022 and 2022–2023 to the high coverage cluster in 2023–2024, indicating notable improvements in vaccine uptake. Conversely, two of England’s largest districts, Cambridgeshire and Cumbria, shifted from high to low vaccination coverage clusters in 2023–2024, suggesting a decline in performance. A more granular clustering with six groups, shown in Figure 1(c) and detailed in Tables W3, W6, and W9, reveals that Hackney consistently had the lowest vaccination coverage in the first two years. However, in 2023–2024, Haringey and Lambeth replaced Hackney in the lowest coverage cluster. Despite these changes, all three districts have consistently been among the lowest-performing areas in terms of childhood vaccination rates.

### **Classification**

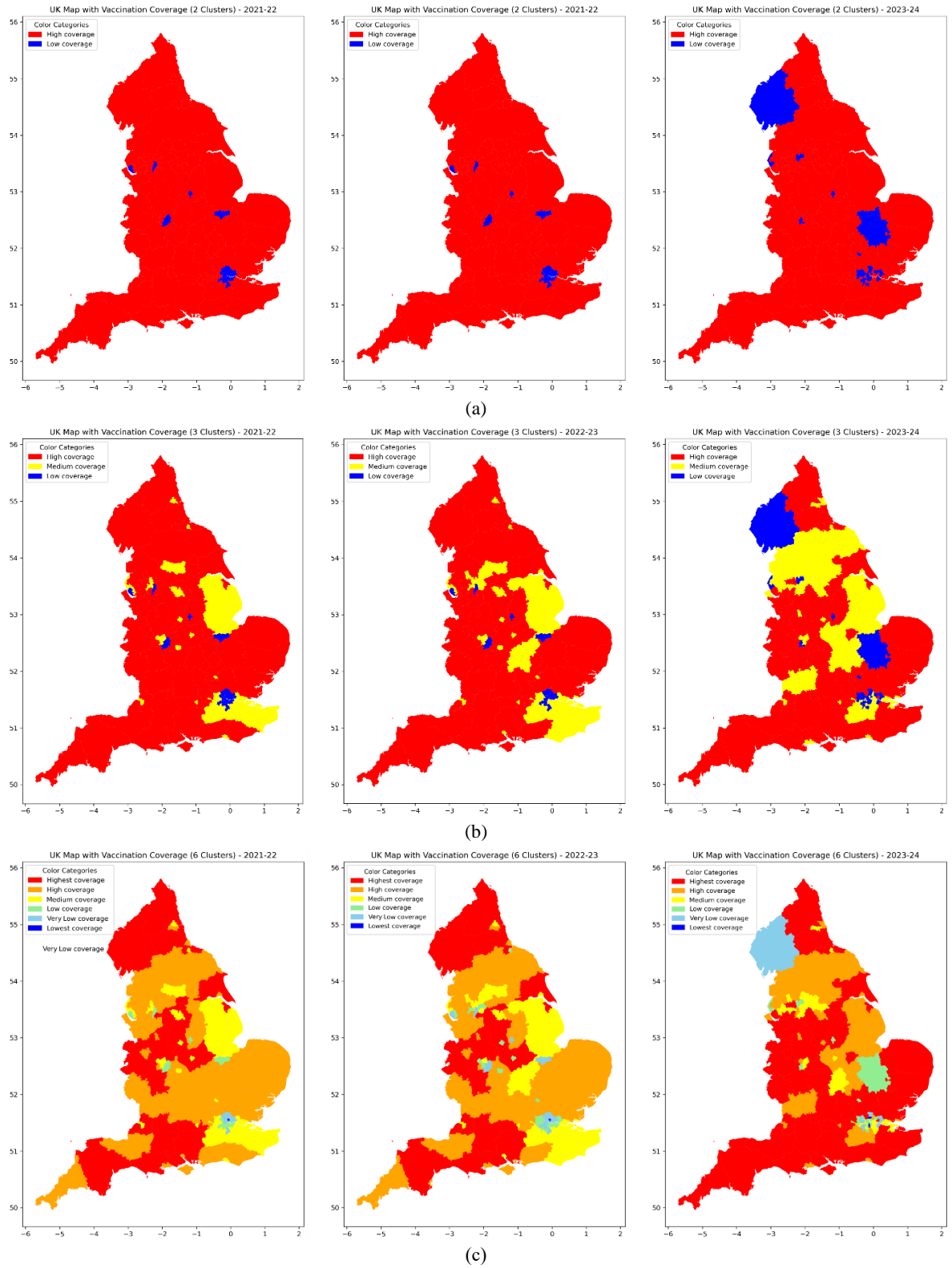
After clustering the districts based on their vaccination coverage and assigning cluster labels (as shown in Figure 1 and detailed in Tables W1–W9), we employed the CB classifier to predict these labels using the GDSC variables outlined in Table 1. Table 3 presents the classification performance metrics, including accuracy, precision, recall, and F1 score, across different clustering scenarios (two, three, and six clusters) and study years. These metrics were averaged across all classes and cross-validation folds. For detailed definitions of these evaluation metrics, please refer to (44).

Across all three years, the CB classifier demonstrated high predictive performance using two clusters, with accuracy consistently exceeding 86%. The highest accuracy was achieved in 2021–2022, reaching 92.1%. As expected, the classification accuracy declined with an increasing number of clusters, particularly when using six clusters. Nonetheless, performance remained acceptable under the three-cluster scenario. These results are consistent with the dendrogram analysis (Figure W1), which identified two as the optimal number of clusters based on hierarchical clustering.

### **The Most Important Predictors**

We used the trained CB classifiers to compute SHAP values, which are interpreted in this section as measures of feature importance. Figure 2 presents the feature importance results for the two-cluster configuration in the years 2021–2022 and 2022–2023. Results for the three- and six-cluster models are provided in Figure W2 in the web appendix. As illustrated, the features “Rurality,” “Born Outside UK,” “English Proficiency,” and “Ethnic Minority” consistently emerged as the most influential predictors across all years and clustering configurations.

Although the three demographic and cultural features, Born Outside UK, Ethnic Minority, and English Proficiency, may have relatively high intercorrelation, we retained all of them in our models. Empirical testing revealed that removing any one of these features resulted in a notable decline in model performance, suggesting that each contributes distinct and complementary information. One plausible explanation is that a significant portion of individuals may belong to an ethnic minority group or be born outside the UK but still speak English as their first language. The SHAP analysis supports this hypothesis, as all three features consistently demonstrated high importance scores, indicating they each capture unique aspects relevant to predicting vaccination coverage disparities.



**Figure 1.** Vaccination coverage rate maps for England using (a) two clusters, (b) three clusters, and (c) six clusters, from left to right, for the years 2021-2022, 2022-2023, and 2023-2024, respectively.

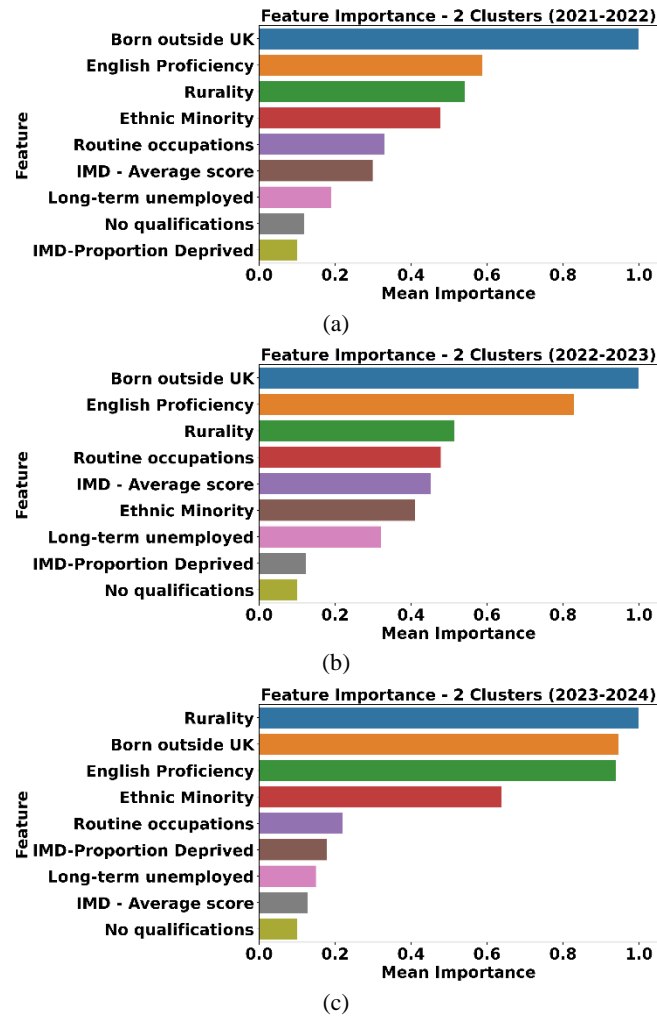
**Table 2.** Average vaccination rates for different diseases across England, grouped by two, three, and six clusters for the years 2021–2022, 2022–2023, and 2023–2024.

Year	Number of clusters	Cluster label	DTaP_IPV_5y	DTaP_IPV_Hib_5y	DTaP_IPV_Hib_HepB_12m	DTaP_IPV_Hib_HepB_24m	Hib_MenC_24m	Hib_MenC_5y	MenB_12m	MenB_booster_24m	MMR_24m	MMR1_5y	MMR2_5y	PCV_12m	PCV_24m	Rota_12m
2021-2022	2	L	69.9	89.2	85.2	86.3	78.8	84.6	84.8	76.8	79.0	87.1	72.6	87.6	79.4	82.9
		H	87.3	95.5	93.4	94.5	91.3	93.3	93.1	90.4	91.5	94.8	88.51	95.2	91.7	91.5
	3	L	69.9	89.3	85.2	86.3	78.8	84.6	84.8	76.8	79.0	87.1	72.6	87.7	79.4	82.9
		M	81.8	93.6	90.8	92.0	87.1	90.3	90.3	85.7	87.3	92.6	83.2	93.2	87.8	88.5
		H	89.5	96.3	94.4	95.5	93.0	94.5	94.3	92.4	93.2	95.7	90.7	96.0	93.3	92.8
	6	Ls	56.1	82.4	64.0	70.6	61.6	78.2	64.5	60.2	65.4	83.5	58.9	70.9	64.3	61.7
		VL	66.6	88.7	84.4	85.0	76.3	83.1	83.8	74.3	76.6	85.8	68.5	87.2	77.0	82.4
		L	73.4	90.2	87.3	88.5	81.9	86.2	86.9	79.8	81.8	88.3	76.9	89.1	82.3	84.8
		M	81.8	93.6	90.8	92.0	87.1	90.3	90.3	85.7	87.3	92.6	83.2	93.2	87.8	88.5
		H	88.4	95.9	93.6	94.9	91.9	93.8	93.4	91.2	92.1	95.2	89.5	95.4	92.2	91.8
		Hst	91.5	97.1	95.9	96.6	94.9	95.6	95.7	94.4	95.0	96.6	92.6	97.0	95.2	94.5
2022-2023	2	L	68.8	87.4	85.9	86.2	79.0	82.4	84.5	77.4	80.2	85.4	70.2	87.9	79.3	82.1
		H	85.6	94.1	92.9	93.7	90.4	91.7	92.2	89.3	90.9	93.7	86.8	94.7	90.1	89.9
	3	L	68.8	87.4	85.9	86.2	79.0	82.4	84.5	77.4	80.2	85.4	70.2	87.9	79.3	82.1
		M	81.3	92.0	90.9	91.6	87.3	88.9	89.8	85.6	88.0	91.5	82.7	93.0	86.5	87.2
		H	88.8	95.6	94.4	95.3	92.7	93.7	93.9	92.1	93.0	95.2	89.8	95.9	92.8	91.8
	6	Ls	62.2	81.1	67.8	77.7	66.7	74.6	68.5	64.0	69.5	80.2	62.7	75.0	68.3	64.9
		VL	66.4	84.8	84.1	86.2	77.8	79.0	83.3	75.8	78.2	81.9	66.2	87.0	77.3	81.6
		L	73.2	87.6	87.3	88.2	81.8	83.1	86.3	80.1	82.2	86.4	74.3	88.9	80.9	83.6
		M	78.9	91.2	88.9	90.6	85.5	87.5	88.1	83.7	86.1	90.2	80.5	91.6	84.7	85.6
		H	83.7	93.0	91.9	92.9	89.8	89.5	91.3	88.2	90.0	92.5	85.2	94.0	89.2	89.1
		Hst	88.7	95.5	94.6	95.4	93.0	93.5	94.2	92.2	93.2	95.2	89.7	96.0	92.8	92.3
2023-2024	2	L	70.1	86.2	84.8	86.8	79.3	81.1	84.0	77.5	79.9	84.4	70.8	87.2	78.8	81.5
		H	85.2	93.9	92.6	93.7	90.5	91.1	92.1	89.3	90.8	93.4	86.5	94.5	90.1	89.9
	3	L	70.1	86.2	84.8	86.8	79.3	81.1	84.0	77.5	79.9	84.4	70.8	87.3	78.8	81.5
		M	81.4	92.1	90.5	91.8	87.7	88.5	89.7	86.0	88.1	91.4	82.9	92.8	87.0	87.4
		H	88.7	95.5	94.6	95.4	93.0	93.5	94.2	92.2	93.2	95.2	89.7	96.0	92.8	92.3
	6	Ls	56.1	82.4	64.0	70.6	61.6	78.2	64.5	60.2	65.4	83.5	58.9	70.9	64.3	61.7
		VL	66.6	88.7	84.4	85.0	76.3	83.1	83.8	74.3	76.6	85.8	68.5	87.2	77.0	82.4
		L	73.4	90.2	87.3	88.5	81.9	86.2	86.9	79.8	81.8	88.3	76.9	89.1	82.3	84.8
		M	81.8	93.6	90.8	92.0	87.1	90.3	90.3	85.7	87.3	92.6	83.2	93.2	87.8	88.5
		H	88.4	95.9	93.6	94.9	91.9	93.8	93.4	91.2	92.1	95.2	89.5	95.4	92.2	91.8
		Hst	91.5	97.1	95.9	96.6	94.9	95.6	95.7	94.4	95.0	96.6	92.6	97.0	95.2	94.5

Ls: Lowest, VL: Very Low, L: Low, M: Medium, H: High, Hst: Highest

**Table 3.** Classification performance metrics (%), accuracy, precision, recall, and F1 score for predicting vaccination coverage clusters in England using GDSC data.

Year	Metric	2 cluster	3 cluster	6 cluster
2021-2022	Accuracy	92.1	77.3	48.7
	Precision	88.9	72.5	42.9
	Recall	86.5	71.9	45.5
	F1 score	86.2	71.4	42.1
2022-2023	Accuracy	90.6	76.0	42.7
	Precision	84.3	76.1	42.3
	Recall	77.0	71.8	41.8
	F1 score	77.9	72.1	40.6
2023-2024	Accuracy	86.3	64.6	49.3
	Precision	80.5	61.7	33.4
	Recall	70.0	59.8	32.8
	F1 score	70.4	59.9	31.6



**Figure 2.** Most important predictors of vaccination coverage rates in England, based on SHAP values from the two-cluster model for (a) 2021–2022, (b) 2022–2023, and (c) 2023–2024.

Although Rurality emerged as one of the most important determinants in the SHAP analysis, this does not imply that rural districts exhibit lower vaccination coverage. In fact, the data reveal the opposite trend. As shown in Tables W1, W4, and W7, only 2, 2, and 3 districts, respectively, within the low-coverage cluster had a rurality classification greater than 1. According to Table 1, a rurality level of 1 corresponds to urban areas, indicating that the majority of low-coverage districts are, in fact, highly urbanized.

To explore this relationship further, we examined the distribution of rurality levels across vaccination clusters for the two-cluster model in all study years, as depicted in Figure W3 of the supplementary web appendix. The visualizations confirm that most districts with a rurality level above 1, i.e., more rural areas, are clustered in the high-vaccination coverage group. However, it is important to note that rurality alone is not a sufficient predictor of vaccination coverage. A considerable number of urban districts (rurality level 1) appear in both high and low coverage clusters, suggesting that other factors are influencing coverage disparities within urban settings.

To better understand the distribution patterns of the four most influential features, we present their box plots by vaccination coverage cluster in Figures W4–W7 of the supplementary web appendix. These visualizations show that low-coverage districts tend to be highly urbanized and have higher proportions of residents whose primary language is not English, who were born outside the UK, or who belong to ethnic minority groups. To support these observations, we conducted hypothesis testing comparing the distributions of these features across the two vaccination coverage clusters. The results indicated that the differences were statistically significant ( $p < 0.05$ ) for all four features.



The socioeconomic factors presented in Figure 2 exhibit substantially lower SHAP importance values compared to the top four predictors, which are predominantly geographic, demographic, and cultural. With the exception of the two-cluster model for the year 2022–2023, where two socioeconomic variables, “Routine Occupation” and “IMD-Average Score”, showed importance values comparable to the leading features, the classification in all other years and clustering configurations was consistently dominated by Rurality, Born Outside UK, English Proficiency, and Ethnic Minority. This trend is particularly pronounced in the 2023–2024 model, where the relative contribution of socioeconomic variables is markedly lower than in previous years. These findings suggest that while socioeconomic conditions remain relevant, they are less predictive of vaccination coverage disparities compared to geographic, demographic, and cultural characteristics, especially in the most recent year of analysis.

The relatively low SHAP importance values associated with socioeconomic factors, as shown in Figure 2, suggest that these variables do not play a primary role in explaining the disparities in vaccination rates between rural and urban districts. Instead, the feature importance results indicate that the observed differences are predominantly driven by demographic and cultural factors, specifically, variations in the proportion of residents born outside the UK, levels of English proficiency, and ethnic composition between rural and urban areas.

## LIMITATIONS

The use of UTLA-level aggregated data in this study may restrict granularity and potentially mask important within-district variation. While the GDSC data are useful for national-level analyses, several studies suggest that individual-level predictors, such as parental attitudes, household composition, and vaccine confidence, may influence vaccination decisions (11, 15). Although some of these influences may be indirectly captured through demographic or socioeconomic proxies within the GDSC data, their effects are not explicitly modeled. Future research employing longitudinal, individual-level datasets would enhance the interpretability of predictive models and offer a more nuanced understanding of the behavioural and contextual drivers behind vaccination uptake.

This study did not include healthcare system variables such as GP density, service accessibility, or delivery logistics, which previous studies have found to be important (14, 34). While some of these factors may be indirectly reflected in certain GDSC variables, such as IMD, their individual contributions were not explicitly modeled. Future research could explore the relative impact of healthcare infrastructure variables alongside demographic and socioeconomic factors. Additionally, vaccine-specific concerns, such as hesitancy surrounding MMR or newer vaccines like MenB, were not captured in this study due to the absence of attitudinal data.

Finally, although model performance was validated through cross-validation, and SHAP analysis confirmed the relevance of retained features, the presence of correlated variables (e.g., ethnic minority status and language proficiency) may introduce redundancy and complicate interpretation. However, as demonstrated, removing any of these features significantly reduced model accuracy, suggesting each provides unique information.

Despite these limitations, the study provides a robust foundation for targeted policy and intervention design, and it highlights the utility of explainable machine learning in public health surveillance.

## DISCUSSION

This study provides a comprehensive longitudinal analysis of childhood vaccination coverage disparities across England from 2021 to 2024, using an interpretable machine learning approach. By leveraging SHAP values within a CB classifier, we identified that the most influential predictors of vaccine coverage disparities were consistently geographic, demographic, and cultural variables, specifically rurality, English proficiency, proportion of ethnic minorities, and foreign-born population, rather than traditional socioeconomic indicators. We also observed that districts with lower vaccination

rates tended to be more urban and had higher proportions of ethnic minority residents, foreign-born populations, and individuals whose first language was not English.

These findings align with prior research highlighting the significance of cultural and language barriers in vaccine uptake. For instance, one study (9) noted that vaccine confidence varied substantially across demographic groups, with minority and immigrant populations exhibiting greater hesitancy. Similarly, another study (18) emphasized the role of trust in healthcare systems and cultural beliefs as key contributors to vaccine acceptance or refusal. Our study adds to this literature by demonstrating, through quantitative feature importance, that these variables are more predictive of district-level disparities in England than socioeconomic factors like deprivation or employment status.

Our findings highlight the consistent and significant influence of ethnic minority representation on childhood vaccination coverage across all study years, as reflected in the SHAP importance values. Furthermore, as illustrated in Figure W7 of the supplementary web appendix, districts with higher proportions of ethnic minority populations were more likely to fall into the lower vaccination coverage clusters. This is consistent with previous research demonstrating that ethnic minority communities often face systemic barriers to vaccination, including reduced access to culturally appropriate health information, language barriers, and historical mistrust in healthcare systems (9, 33). Additionally, vaccine hesitancy may be more prevalent in some ethnic groups due to circulating misinformation, perceived discrimination, or negative healthcare experiences, which can undermine trust and reduce uptake (18). While the ethnic minority variable was correlated with other cultural and demographic features, such as English proficiency and foreign-born status, our model showed that each provided unique predictive value. This suggests that ethnic identity captures specific dimensions of community experience and cultural context that are not fully explained by language or migration status alone.

The association between English proficiency and vaccination uptake is especially noteworthy. Previous literature has emphasized that limited proficiency in the dominant language of a healthcare system can impair access to health information, reduce trust, and discourage vaccine-seeking behavior (11, 15). This highlights the importance of culturally competent communication and multilingual public health messaging in enhancing vaccine coverage among diverse communities.

Interestingly, our analysis found that rural districts generally had higher vaccination coverage than their urban counterparts, contrary to common assumptions that rurality correlates with reduced healthcare access (14, 45). This suggests that in the English context, urban complexity, diversity, and healthcare engagement dynamics may be more salient in shaping disparities than physical distance to services. This also mirrors the findings of (20), who reported heterogeneity within urban settings, particularly among low-income, diverse communities.

Furthermore, socioeconomic variables such as deprivation scores, unemployment rates, and educational attainment, which have historically been linked to health disparities, ranked lower in importance in our predictive models. This contrasts with earlier studies (8, 17) that identified a clear inverse relationship between deprivation and vaccine uptake. However, our findings may suggest a contextual shift in England, where universal access to NHS services has mitigated the direct impact of material deprivation on vaccination behaviour, while geographic, demographic, and cultural barriers have become more salient. Additionally, these results may reflect the effectiveness of policy interventions aimed at reducing access-related barriers for economically disadvantaged populations. This may suggest a shift in the relative influence of structural versus cultural predictors in contemporary England, possibly driven by widespread access to NHS vaccination services and evolving patterns of community engagement.

Notably, districts such as Birmingham, Manchester, and Liverpool showed marked improvement in vaccine coverage over the study period. These gains could reflect the successful implementation of targeted interventions, local outreach, or the impact of national campaigns. In contrast, formerly high-performing districts such as Cambridgeshire and Cumbria experienced declining coverage, echoing concerns raised by (6) about fluctuating local uptake despite overall national efforts.

By integrating machine learning with interpretable outputs, this study offers actionable insights for policymakers and public health practitioners. The findings support the need for localized, culturally informed strategies that address language proficiency, ethnic representation, and community trust as key levers for improving childhood immunization coverage. For example, multilingual outreach, collaboration with trusted local leaders, and culturally sensitive education campaigns could address low coverage in ethnically diverse urban areas. Additionally, the observed variation over time supports the need for adaptive strategies that respond to changing local conditions rather than static national policies.

### Contributors

Amin Noroozi conceived and designed the study, developed the methodology, supervised the analysis, validated the results, and wrote the original draft. Sidratul Muntaha Esha contributed to data curation, formal analysis, project administration, validation, and visualization. Mansoureh Ghari contributed to the investigation, formal analysis, and manuscript review and editing.

### Declaration of interests

No competing interests declared.

### Data sharing

Upon acceptance, the data and code used in this study will be made available via Dr Amin Noroozi's GitHub repository: <https://github.com/AminNoroozi/>

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The authors used ChatGPT (OpenAI, GPT-4) to assist with language editing and proofreading. Prompts were limited to requests for clarity, grammar correction, and academic tone refinement. All content was reviewed and verified by the authors

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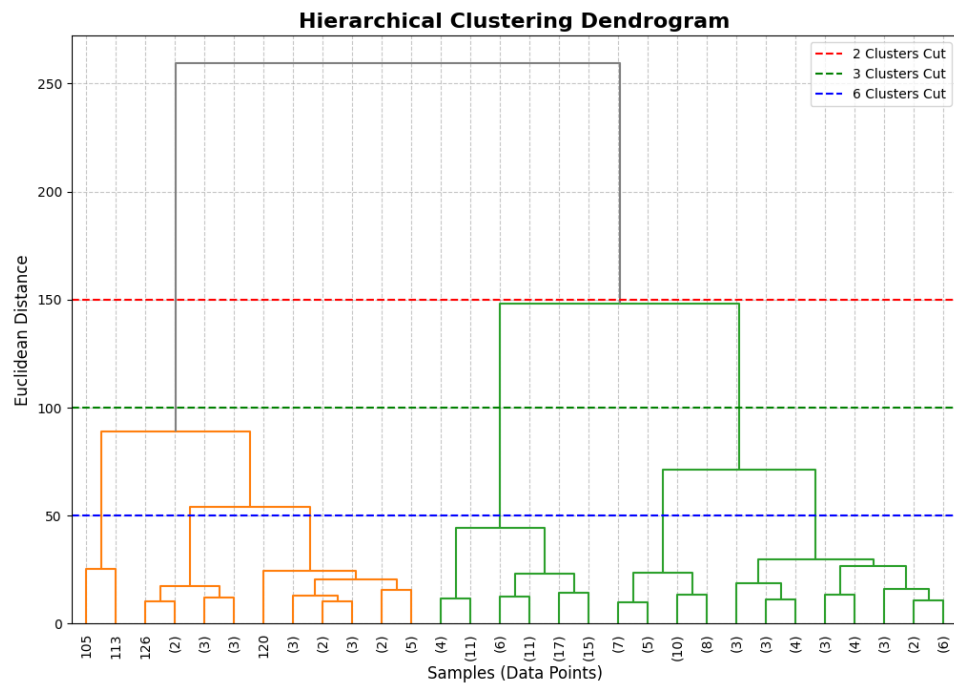
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## “Supplementary Web Appendix”

### Hierarchical Clustering Dendrogram



**Figure W3.** Hierarchical clustering dendrogram for vaccination rates in England in 2023-2024.

## Districts List by Vaccination Cluster

**Table W4.** List of districts in different vaccination coverage clusters for 2021-22 using two clusters

High					Low
Hartlepool	Thurrock	Bury	Kirklees	Nottinghamshire	Nottingham
Middlesbrough	Medway	Oldham	Leeds	Oxfordshire	Peterborough
Redcar and Cleveland	Bracknell Forest	Rochdale	Wakefield	Somerset	Manchester
Stockton-on-Tees	West Berkshire	Salford	Gateshead	Staffordshire	Liverpool
Darlington	Reading	Stockport	Bexley	Suffolk	Birmingham
Halton	Slough	Tameside	Bromley	Surrey	Barking and Dagenham
Warrington	Windsor and Maidenhead	Trafford	Ealing	Warwickshire	Barnet
Blackburn with Darwen	Wokingham	Wigan	Harrow	West Sussex	Brent
Blackpool	Milton Keynes	Knowsley	Havering	Worcestershire	Camden
Kingston upon Hull	Brighton and Hove	St Helens	Hillingdon	Rutland	Croydon
East Riding of Yorkshire	Portsmouth	Sefton	Hounslow		Enfield
North East Lincolnshire	Southampton	Wirral	Kingston upon Thames		Greenwich
North Lincolnshire	Isle of Wight	Barnsley	Sutton		Hackney
York	County Durham	Doncaster	Cambridgeshire		Hammersmith and Fulham
Derby	Cheshire East	Rotherham	Cumbria		Haringey
Leicester	Cheshire West and Chester	Sheffield	Derbyshire		Islington
Herefordshire	Shropshire	Newcastle upon Tyne	Devon		Kensington and Chelsea
Telford and Wrekin	Cornwall	North Tyneside	East Sussex		Lambeth
Stoke-on-Trent	Wiltshire	South Tyneside	Essex		Lewisham
Bath and North East Somerset	Bedford	Sunderland	Gloucestershire		Merton
Bristol	Central Bedfordshire	Coventry	Hampshire		Newham
North Somerset	Northumberland	Dudley	Hertfordshire		Redbridge
South Gloucestershire	Bournemouth, Christchurch and Poole	Sandwell	Kent		Richmond upon Thames
Plymouth	Dorset	Solihull	Lancashire		Southwark
Torbay	Buckinghamshire	Walsall	Leicestershire		Tower Hamlets
Swindon	North Northamptonshire	Wolverhampton	Lincolnshire		Waltham Forest
Luton	West Northamptonshire	Bradford	Norfolk		Wandsworth
Southend-on-Sea	Bolton	Calderdale	North Yorkshire		Westminster

**Table W5.** List of districts in different vaccination coverage clusters for 2021-22 using three clusters

<b>High</b>				<b>Medium</b>		<b>Low</b>
Hartlepool	Southampton	Doncaster	Lancashire	Middlesbrough	Hillingdon	Nottingham
Redcar and Cleveland	Isle of Wight	Rotherham	Leicestershire	North Lincolnshire	Hounslow	Peterborough
Stockton-on-Tees	County Durham	North Tyneside	Norfolk	Derby	Kingston upon Thames	Manchester
Darlington	Cheshire East	South Tyneside	North Yorkshire	Leicester	Sutton	Liverpool
Halton	Cheshire West and Chester	Sunderland	Nottinghamshire	Bristol	Kent	Birmingham
Warrington	Shropshire	Dudley	Oxfordshire	Luton	Lincolnshire	Barking and Dagenham
Blackburn with Darwen	Cornwall	Solihull	Somerset	Thurrock	Surrey	Barnet
Blackpool	Wiltshire	Calderdale	Staffordshire	Medway		Brent
Kingston upon Hull	Bedford	Kirklees	Suffolk	Reading		Camden
East Riding of Yorkshire	Central Bedfordshire	Wakefield	Warwickshire	Slough		Croydon
North East Lincolnshire	Northumberland	Gateshead	West Sussex	Brighton and Hove		Enfield
York	Bournemouth, Christchurch and Poole	Cambridgeshire	Worcestershire	Bury		Greenwich
Herefordshire	Dorset	Cumbria	Rutland	Salford		Hackney
Telford and Wrekin	Buckinghamshire	Derbyshire		Knowsley		Hammersmith and Fulham
Stoke-on-Trent	North Northamptonshire	Devon		Sefton		Haringey
Bath and North East Somerset	West Northamptonshire	East Sussex		Sheffield		Islington
North Somerset	Bolton	Essex		Newcastle upon Tyne		Kensington and Chelsea
South Gloucestershire	Oldham	Gloucestershire		Coventry		Lambeth
Plymouth	Rochdale	Hampshire		Sandwell		Lewisham
Torbay	Stockport	Hertfordshire		Walsall		Merton
Swindon	Tameside			Wolverhampton		Newham
Southend-on-Sea	Trafford			Bradford		Redbridge
Bracknell Forest	Wigan			Leeds		Richmond upon Thames
West Berkshire	St Helens			Bexley		Southwark
Windsor and Maidenhead	Wirral			Bromley		Tower Hamlets
Wokingham	Barnsley			Ealing		Waltham Forest
Milton Keynes				Harrow		Wandsworth
Portsmouth				Havering		Westminster



**Table W6.** List of districts in different vaccination coverage clusters for 2021-22 using six clusters

Highest		High		Medium		Low	Very Low	Lowest
Redcar and Cleveland	Hampshire	Hartlepool	Rochdale	Middlesbrough	Hillingdon	Nottingham	Barking and Dagenham	Hackney
Stockton-on-Tees	Leicestershire	Darlington	Tameside	North Lincolnshire	Hounslow	Peterborough	Barnet	
East Riding of Yorkshire	Staffordshire	Halton	Trafford	Derby	Kingston upon Thames	Manchester	Camden	
North East Lincolnshire	Worcestershire	Warrington	Wigan	Leicester	Sutton	Liverpool	Croydon	
Bath and North East Somerset	Rutland	Blackburn with Darwen	St Helens	Bristol	Kent	Birmingham	Enfield	
North Somerset		Blackpool	Wirral	Luton	Lincolnshire	Brent	Haringey	
South Gloucestershire		Kingston upon Hull	Doncaster	Thurrock	Surrey	Greenwich	Islington	
Plymouth		York	Dudley	Medway		Hammersmith and Fulham	Kensington and Chelsea	
Torbay		Herefordshire	Solihull	Reading		Lambeth	Newham	
Bracknell Forest		Telford and Wrekin	Calderdale	Slough		Lewisham	Redbridge	
West Berkshire		Stoke-on-Trent	Kirklees	Brighton and Hove		Merton	Waltham Forest	
Wokingham		Swindon	Gateshead	Bury		Richmond upon Thames	Westminster	
Portsmouth		Southend-on-Sea	Cambridgeshire	Salford		Southwark		
County Durham		Windsor and Maidenhead	East Sussex	Knowsley		Tower Hamlets		
Shropshire		Milton Keynes	Essex	Sefton		Wandsworth		
Wiltshire		Southampton	Gloucestershire	Sheffield				
Northumberland		Isle of Wight	Hertfordshire	Newcastle upon Tyne				
Dorset		Cheshire East	Lancashire	Coventry				
Stockport		Cheshire West and Chester	Norfolk	Sandwell				
Barnsley		Cornwall	North Yorkshire	Walsall				
Rotherham		Bedford	Nottinghamshire	Wolverhampton				
North Tyneside		Central Bedfordshire	Oxfordshire	Bradford				
South Tyneside		Bournemouth, Christchurch and Poole	Somerset	Leeds				
Sunderland		Buckinghamshire	Suffolk	Bexley				
Wakefield		North Northamptonshire	Warwickshire	Bromley				
Cumbria		West Northamptonshire	West Sussex	Ealing				
Derbyshire		Bolton		Harrow				
Devon		Oldham		Havering				

**Table W7.** List of districts in different vaccination coverage clusters for 2022-23 using two clusters

<b>High</b>					<b>Low</b>
Hartlepool	Luton	Buckinghamshire	Sandwell	Gloucestershire	Nottingham
Middlesbrough	Southend-on-Sea	North Northamptonshire	Solihull	Hampshire	Peterborough
Redcar and Cleveland	Thurrock	West Northamptonshire	Walsall	Hertfordshire	Manchester
Stockton-on-Tees	Medway	Bolton	Wolverhampton	Kent	Liverpool
Darlington	Bracknell Forest	Bury	Bradford	Lancashire	Birmingham
Halton	West Berkshire	Oldham	Calderdale	Leicestershire	Barking and Dagenham
Warrington	Reading	Rochdale	Kirklees	Lincolnshire	Barnet
Blackburn with Darwen	Slough	Salford	Leeds	Norfolk	Brent
Blackpool	Windsor and Maidenhead	Stockport	Wakefield	North Yorkshire	Camden
Kingston upon Hull, City of	Wokingham	Tameside	Gateshead	Nottinghamshire	Croydon
East Riding of Yorkshire	Milton Keynes	Trafford	Bexley	Oxfordshire	Enfield
North East Lincolnshire	Brighton and Hove	Wigan	Bromley	Somerset	Hackney
North Lincolnshire	Portsmouth	Knowsley	Ealing	Staffordshire	Hammersmith and Fulham
York	Southampton	St. Helens	Greenwich	Suffolk	Haringey
Derby	Isle of Wight	Sefton	Harrow	Surrey	Islington
Leicester	County Durham	Wirral	Havering	Warwickshire	Kensington and Chelsea
Herefordshire, County of	Cheshire East	Barnsley	Hillingdon	West Sussex	Lambeth
Telford and Wrekin	Cheshire West and Chester	Doncaster	Hounslow	Worcestershire	Lewisham
Stoke-on-Trent	Shropshire	Rotherham	Kingston upon Thames	Rutland	Merton
Bath and North East Somerset	Cornwall	Sheffield	Sutton		Newham
Bristol, City of	Wiltshire	Newcastle upon Tyne	Cambridgeshire		Redbridge
North Somerset	Bedford	North Tyneside	Cumbria		Richmond upon Thames
South Gloucestershire	Central Bedfordshire	South Tyneside	Derbyshire		Tower Hamlets
Plymouth	Northumberland	Sunderland	Devon		Waltham Forest
Torbay	Bournemouth, Christchurch and Poole	Coventry	East Sussex		Wandsworth
Swindon	Dorset	Dudley	Essex		Westminster

**Table W8.** List of districts in different vaccination coverage clusters for 2022-23 using three clusters

<b>High</b>			<b>Medium</b>		<b>Low</b>
Hartlepool	Portsmouth	Dudley	Middlesbrough	Doncaster	Nottingham
Redcar and Cleveland	Isle of Wight	Solihull	Blackburn with Darwen	Sheffield	Peterborough
Stockton-on-Tees	County Durham	Kirklees	Kingston upon Hull, City of	Newcastle upon Tyne	Manchester
Darlington	Cheshire East	Wakefield	North Lincolnshire	Coventry	Liverpool
Halton	Cheshire West and Chester	Gateshead	Derby	Sandwell	Birmingham
Warrington	Shropshire	Cambridgeshire	Leicester	Walsall	Barking and Dagenham
Blackpool	Cornwall	Cumbria	Bristol, City of	Wolverhampton	Barnet
East Riding of Yorkshire	Wiltshire	Derbyshire	Luton	Bradford	Camden
North East Lincolnshire	Bedford	Devon	Southend-on-Sea	Calderdale	Croydon
York	Central Bedfordshire	Essex	Thurrock	Leeds	Enfield
Herefordshire, County of	Northumberland	Gloucestershire	Medway	Bexley	Hackney
Telford and Wrekin	Bournemouth, Christchurch and Poole	Hampshire	Reading	Brent	Hammersmith and Fulham
Stoke-on-Trent	Dorset	Hertfordshire	Slough	Bromley	Haringey
Bath and North East Somerset	Buckinghamshire	Lancashire	Milton Keynes	Ealing	Islington
North Somerset	Bolton	Leicestershire	Brighton and Hove	Greenwich	Kensington and Chelsea
South Gloucestershire	Stockport	Norfolk	Southampton	Harrow	Merton
Plymouth	Trafford	North Yorkshire	North Northamptonshire	Havering	Newham
Torbay	Wigan	Nottinghamshire	West Northamptonshire	Hillingdon	Redbridge
Swindon	St. Helens	Oxfordshire	Bury	Hounslow	Richmond upon Thames
Bracknell Forest	Wirral	Somerset	Oldham	Kingston upon Thames	Tower Hamlets
West Berkshire	Barnsley	Staffordshire	Rochdale	Lambeth	Waltham Forest
Windsor and Maidenhead	Rotherham	Suffolk	Salford	Lewisham	Wandsworth
Wokingham	North Tyneside	Warwickshire	Tameside	Southwark	Westminster
Rutland	South Tyneside	West Sussex	Knowsley	Sutton	
	Sunderland	Worcestershire	Sefton	East Sussex	
				Kent	
				Lincolnshire	
				Surrey	

**Table W9.** List of districts in different vaccination coverage clusters for 2022-23 using six clusters

<b>Highest</b>	<b>High</b>		<b>Medium</b>		<b>Low</b>	<b>Very Low</b>	<b>Lowest</b>
Stockton-on-Tees	Hartlepool	Trafford	Blackburn with Darwen	Calderdale	Middlesbrough	Nottingham	Hackney
East Riding of Yorkshire	Redcar and Cleveland	Wigan	Kingston upon Hull, City of	Leeds	Derby	Peterborough	
North East Lincolnshire	Darlington	St. Helens	North Lincolnshire	Bromley	Leicester	Manchester	
Bath and North East Somerset	Halton	Wirral	Bristol, City of	East Sussex	Luton	Liverpool	
North Somerset	Warrington	Rotherham	Southend-on-Sea	Kent	Oldham	Birmingham	
South Gloucestershire	Blackpool	Dudley	Thurrock	Lincolnshire	Salford	Barking and Dagenham	
Plymouth	York	Solihull	Medway	Surrey	Knowsley	Barnet	
West Berkshire	Herefordshire, County of	Kirklees	Reading		Coventry	Camden	
County Durham	Telford and Wrekin	Wakefield	Slough		Sandwell	Croydon	
Shropshire	Stoke-on-Trent	Gateshead	Milton Keynes		Wolverhampton	Enfield	
Wiltshire	Torbay	Cambridgeshire	Brighton and Hove		Bexley	Hammersmith and Fulham	
Northumberland	Swindon	Essex	Southampton		Brent	Haringey	
Dorset	Bracknell Forest	Gloucestershire	North Northamptonshire		Ealing	Islington	
Stockport	Windsor and Maidenhead	Hertfordshire	West Northamptonshire		Greenwich	Kensington and Chelsea	
Barnsley	Wokingham	Lancashire	Bury		Harrow	Merton	
North Tyneside	Portsmouth	Norfolk	Rochdale		Havering	Newham	
South Tyneside	Isle of Wight	North Yorkshire	Tameside		Hillingdon	Redbridge	
Sunderland	Cheshire East	Nottinghamshire	Sefton		Hounslow	Richmond upon Thames	
Cumbria	Cheshire West and Chester	Oxfordshire	Doncaster		Kingston upon Thames	Tower Hamlets	
Derbyshire	Cornwall	Somerset	Sheffield		Lambeth	Waltham Forest	
Devon	Bedford	Suffolk	Newcastle upon Tyne		Lewisham	Wandsworth	
Hampshire	Central Bedfordshire	Warwickshire	Walsall		Southwark	Westminster	
Leicestershire	Bournemouth, Christchurch and Poole	West Sussex	Bradford		Sutton		
Staffordshire	Buckinghamshire						
Worcestershire	Bolton						
Rutland							

**Table W10.** List of districts in different vaccination coverage clusters for 2023-24 using two clusters

<b>High</b>					<b>Low</b>
Hartlepool	Thurrock	Bolton	Bradford	Lancashire	Nottingham
Middlesbrough	Medway	Bury	Calderdale	Leicestershire	Peterborough
Redcar and Cleveland	Bracknell Forest	Manchester	Kirklees	Lincolnshire	Luton
Stockton-on-Tees	West Berkshire	Oldham	Leeds	Norfolk	Rochdale
Darlington	Reading	Salford	Wakefield	North Yorkshire	Sefton
Halton	Slough	Stockport	Gateshead	Nottinghamshire	Dudley
Warrington	Windsor and Maidenhead	Tameside	Barking and Dagenham	Oxfordshire	Bexley
Blackburn with Darwen	Wokingham	Trafford	Barnet	Somerset	Brent
Blackpool	Milton Keynes	Wigan	Bromley	Staffordshire	Camden
Kingston upon Hull	Brighton and Hove	Knowsley	Croydon	Suffolk	Ealing
East Riding of Yorkshire	Portsmouth	Liverpool	Greenwich	Surrey	Enfield
North East Lincolnshire	Southampton	St Helens	Hammersmith and Fulham	Warwickshire	Hackney
North Lincolnshire	Isle of Wight	Wirral	Hounslow	West Sussex	Haringey
York	County Durham	Barnsley	Islington	Worcestershire	Harrow
Derby	Cheshire East	Doncaster	Lewisham	Rutland	Havering
Leicester	Cheshire West and Chester	Rotherham	Merton		Hillingdon
Herefordshire	Shropshire	Sheffield	Newham		Kensington and Chelsea
Telford and Wrekin	Cornwall	Newcastle upon Tyne	Tower Hamlets		Kingston upon Thames
Stoke-on-Trent	Wiltshire	North Tyneside	Waltham Forest		Lambeth
Bath and North East Somerset	Bedford	South Tyneside	Derbyshire		Redbridge
Bristol	Central Bedfordshire	Sunderland	Devon		Richmond upon Thames
North Somerset	Northumberland	Birmingham	East Sussex		Southwark
South Gloucestershire	Bournemouth, Christchurch and Poole	Coventry	Essex		Sutton
Plymouth	Dorset	Sandwell	Gloucestershire		Wandsworth
Torbay	Buckinghamshire	Solihull	Hampshire		Westminster
Swindon	North Northamptonshire	Walsall	Hertfordshire		Cambridgeshire
Southend-on-Sea	West Northamptonshire	Wolverhampton	Kent		Cumbria

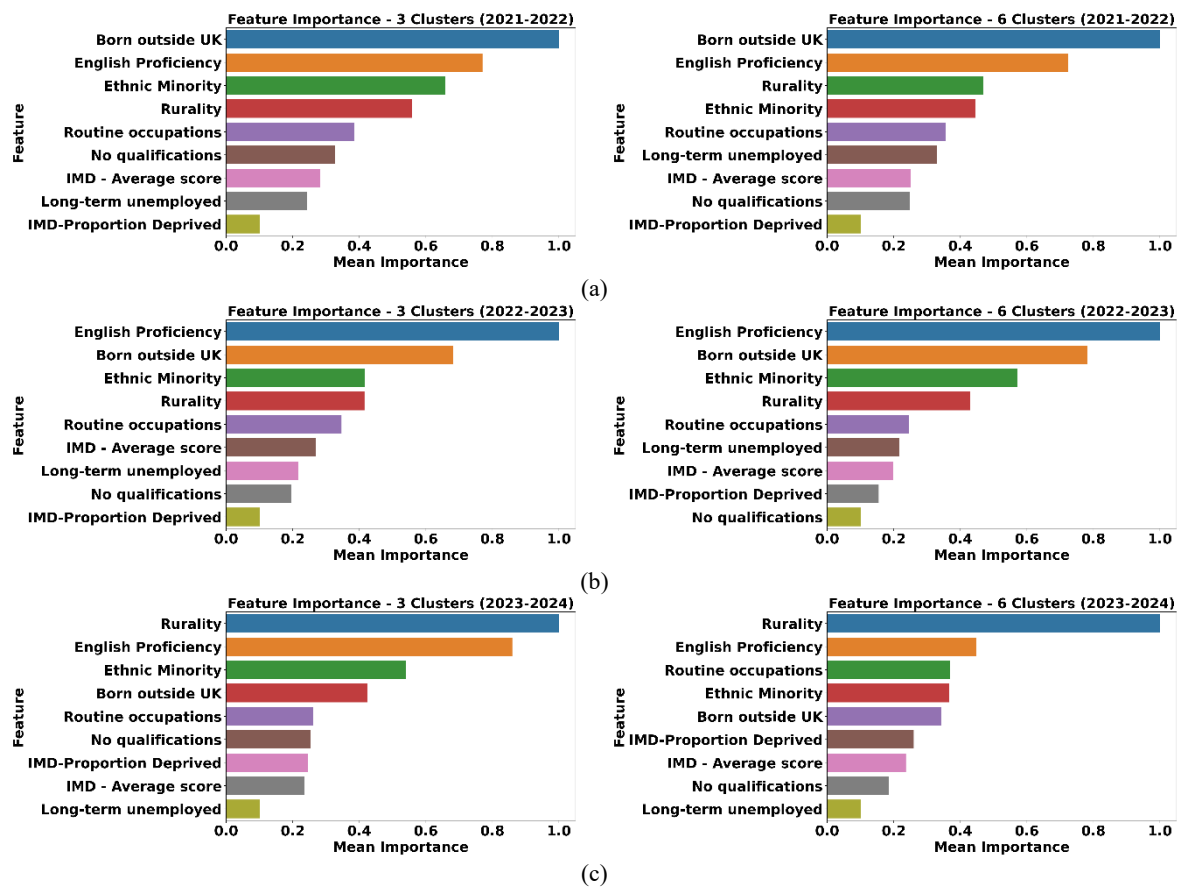
**Table W11.** List of districts in different vaccination coverage clusters for 2023-24 using three clusters

<b>High</b>			<b>Medium</b>			<b>Low</b>
Hartlepool	Shropshire	Hampshire	Middlesbrough	Wirral	Islington	Nottingham
Redcar and Cleveland	Cornwall	Hertfordshire	Blackburn with Darwen	Barnsley	Lewisham	Peterborough
Stockton-on-Tees	Wiltshire	Kent	Blackpool	Sheffield	Merton	Luton
Darlington	Central Bedfordshire	Norfolk	Kingston upon Hull	North Tyneside	Newham	Rochdale
Halton	Northumberland	Nottinghamshire	North Lincolnshire	South Tyneside	Tower Hamlets	Sefton
Warrington	Dorset	Oxfordshire	Derby	Sandwell	Waltham Forest	Dudley
East Riding of Yorkshire	Buckinghamshire	Somerset	Leicester	Walsall	Gloucestershire	Bexley
North East Lincolnshire	Bolton	Staffordshire	Stoke-on-Trent	Wolverhampton	Lancashire	Brent
York	Bury	Suffolk	Bristol, City of	Bradford	Leicestershire	Camden
Herefordshire	Trafford	Warwickshire	Southend-on-Sea	Calderdale	Lincolnshire	Ealing
Telford and Wrekin	Knowsley	West Sussex	Thurrock	Kirklees	North Yorkshire	Enfield
Bath and North East Somerset	Liverpool	Worcestershire	Medway	Leeds	Surrey	Hackney
North Somerset	Doncaster	Rutland	Reading	Wakefield		Haringey
South Gloucestershire	Rotherham		Slough	Gateshead		Harrow
Plymouth	Newcastle upon Tyne		Milton Keynes	Bromley		Havering
Torbay	Sunderland		Brighton and Hove	Croydon		Hillingdon
Swindon	Birmingham		Bedford	Greenwich		Kensington and Chelsea
Bracknell Forest	Coventry		Bournemouth, Christchurch and Poole	Hammersmith and Fulham		Kingston upon Thames
West Berkshire	Solihull		North Northamptonshire	Hounslow		Lambeth
Windsor and Maidenhead	Barking and Dagenham		West Northamptonshire			Redbridge
Wokingham	Barnet		Manchester			Richmond upon Thames
Portsmouth	Derbyshire		Oldham			Southwark
Southampton	Devon		Salford			Sutton
Isle of Wight	East Sussex		Stockport			Wandsworth
County Durham	Essex		Tameside			Westminster
Cheshire East			Wigan			Cambridgeshire
Cheshire West and Chester			St Helens			Cumbria

**Table W12.** List of districts in different vaccination coverage clusters for 2023-24 using six clusters

Highest			High		Medium	Low	Very Low	Lowest
Hartlepool	Cornwall	Nottinghamshire	Blackpool	North Yorkshire	Middlesbrough	Nottingham	Bexley	Haringey
Redcar and Cleveland	Wiltshire	Oxfordshire	Kingston upon Hull	Surrey	Blackburn with Darwen	Peterborough	Ealing	Lambeth
Stockton-on-Tees	Central Bedfordshire	Somerset	North Lincolnshire		Leicester	Luton	Enfield	
Darlington	Northumberland	Staffordshire	Derby		Thurrock	Rochdale	Hackney	
Halton	Dorset	Suffolk	Stoke-on-Trent		Medway	Sefton	Harrow	
Warrington	Buckinghamshire	Warwickshire	Bristol		Slough	Dudley	Havering	
East Riding of Yorkshire	Bolton	West Sussex	Southend-on-Sea		West Northamptonshire	Brent	Kingston upon Thames	
North East Lincolnshire	Bury	Worcestershire	Reading		Oldham	Camden	Richmond upon Thames	
York	Trafford	Rutland	Milton Keynes		Salford	Hillingdon	Cumbria	
Herefordshire	Knowsley		Brighton and Hove		Stockport	Kensington and Chelsea		
Telford and Wrekin	Liverpool		Bedford		Tameside	Redbridge		
Bath and North East Somerset	Doncaster		Bournemouth, Christchurch and Poole		Wigan	Southwark		
North Somerset	Rotherham		North Northamptonshire		St Helens	Sutton		
South Gloucestershire	Newcastle upon Tyne		Manchester		Barnsley	Wandsworth		
Plymouth	Sunderland		Wirral		Sandwell	Westminster		
Torbay	Birmingham		Sheffield		Walsall	Cambridgeshire		
Swindon	Coventry		North Tyneside		Calderdale			
Bracknell Forest	Solihull		South Tyneside		Kirklees			
West Berkshire	Barking and Dagenham		Wolverhampton		Gateshead			
Windsor and Maidenhead	Barnet		Bradford		Bromley			
Wokingham	Derbyshire		Leeds		Greenwich			
Portsmouth	Devon		Wakefield		Hammersmith and Fulham			
Southampton	East Sussex		Croydon		Hounslow			
Isle of Wight	Essex		Waltham Forest		Islington			
County Durham	Hampshire		Gloucestershire		Lewisham			
Cheshire East	Hertfordshire		Lancashire		Merton			
Cheshire West and Chester	Kent		Leicestershire		Newham			
Shropshire	Norfolk		Lincolnshire		Tower Hamlets			

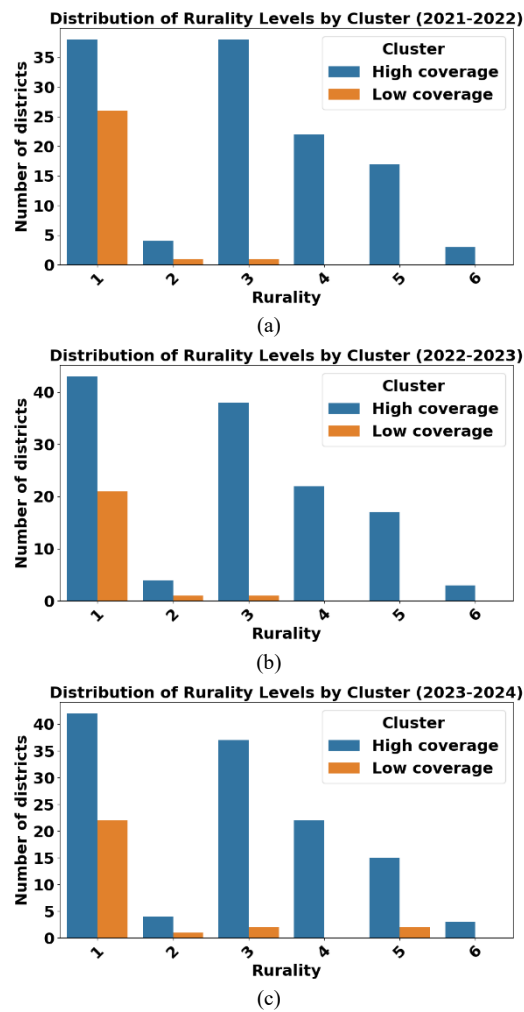
## Feature Importance for 2022-2023 and 2023-2024



**Figure W4.** The most important determinants of the vaccination coverage rate in England using three and six clusters for (a) 2021-2022, (b) 2022-2023, and (c) 2023-2024.

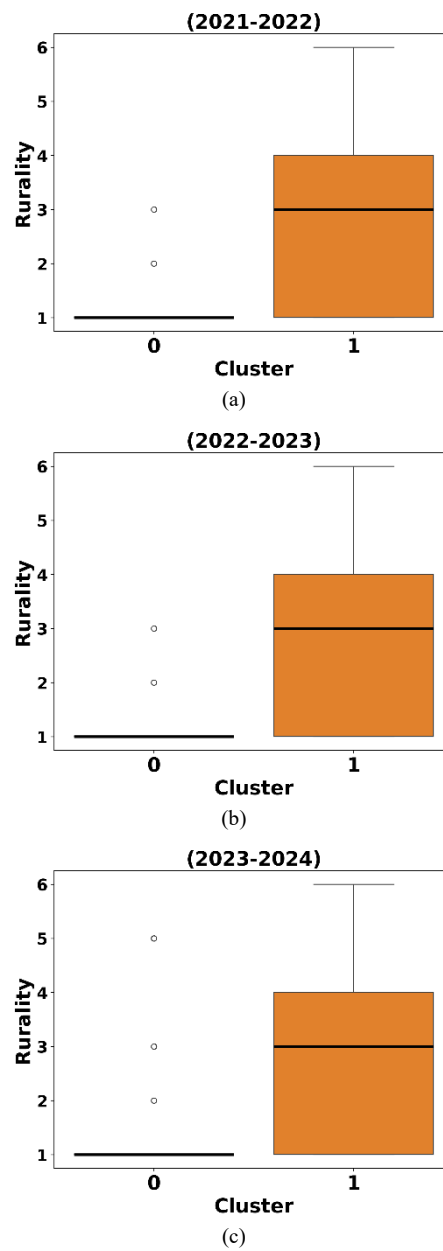


## Distribution of Rurality Level by Vaccination Cluster



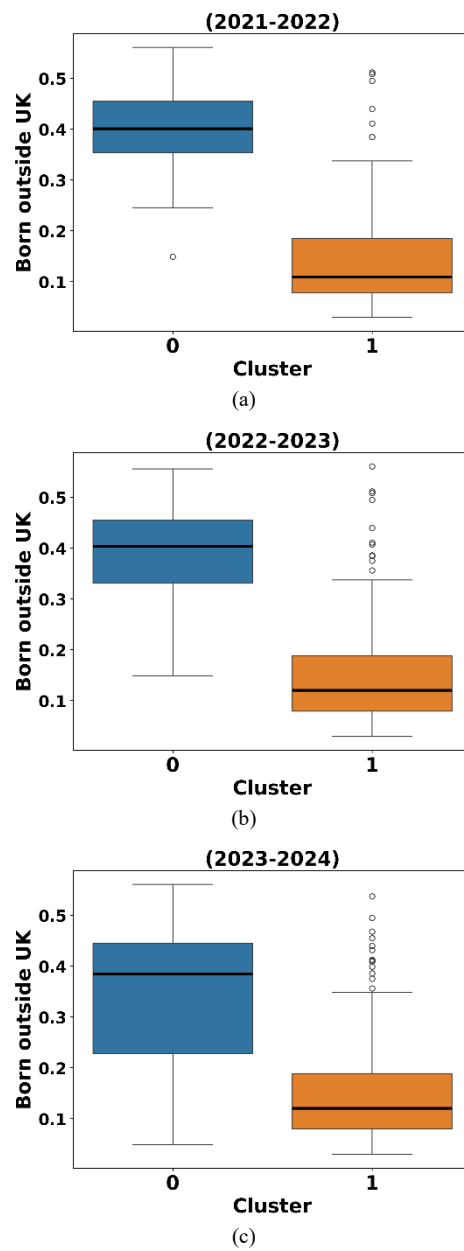
**Figure W5.** Distribution of rurality levels among districts by vaccination coverage cluster for (a) 2021–2022, (b) 2022–2023, and (c) 2023–2024, based on the two-cluster classification.

## Rurality by Vaccination Coverage Cluster



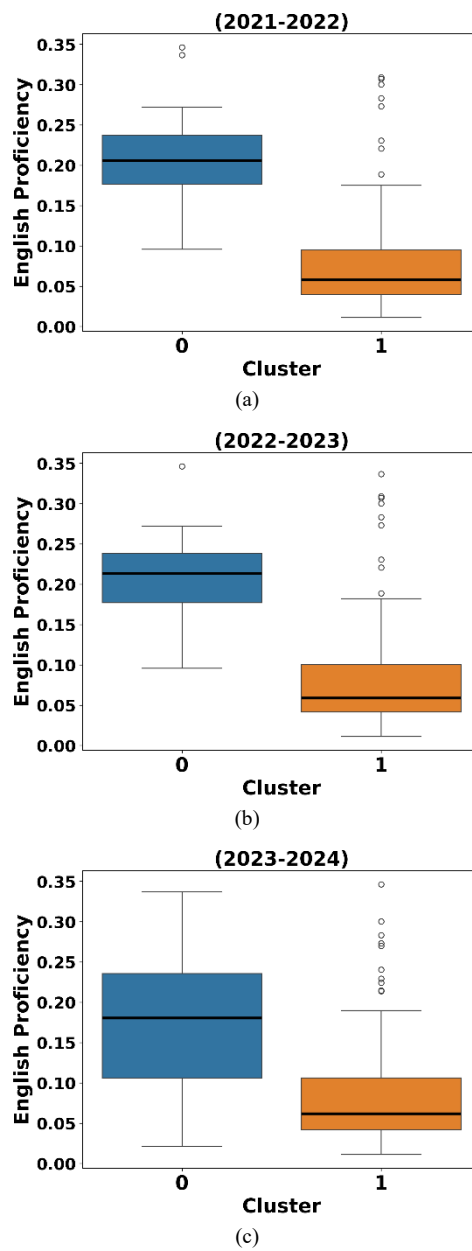
**Figure W6.** Box plot of Rurality by vaccination coverage cluster for (a) 2021-2022, (b) 2022-2023, and (c) 2023-2024, where 0 and 1 show the low and high vaccination coverage clusters, respectively.

## Born outside UK by Vaccination Coverage Cluster



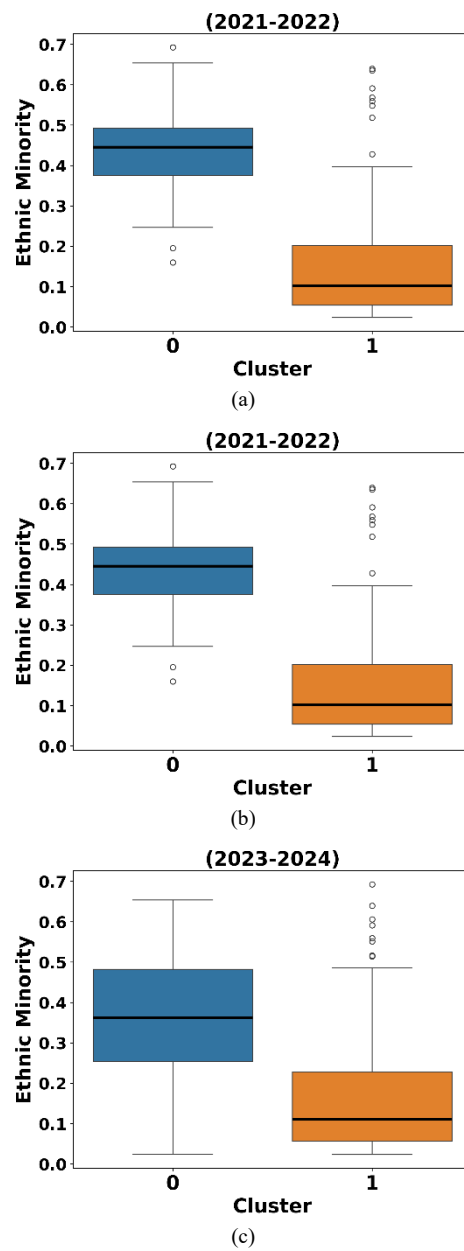
**Figure W7.** Box plot of Born outside UK by vaccination coverage cluster for (a) 2021-2022, (b) 2022-2023, and (c) 2023-2024, where 0 and 1 show the low and high vaccination coverage clusters, respectively.

## English Proficiency by Vaccination Coverage Cluster



**Figure W8.** Box plot of English Proficiency by vaccination coverage cluster for (a) 2021-2022, (b) 2022-2023, and (c) 2023-2024, where 0 and 1 show the low and high vaccination coverage clusters, respectively.

## Ethnic Minority by Vaccination Coverage Cluster



**Figure W9.** Box plot of Ethnic Minority by vaccination coverage cluster for (a) 2021-2022, (b) 2022-2023, and (c) 2023-2024, where 0 and 1 show the low and high vaccination coverage clusters, respectively.