Who Is left behind? Exclusion paradoxes and clusters in Kenya's private insurance market

Evidence from the 2024 FinAccess Survey

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Executive summary

Private insurance plays a central role in household risk management and economic resilience, yet coverage remains persistently low across many low- and middle-income countries. In Kenya, private insurance uptake has remained low despite sustained growth of the insurance sector, raising serious concerns that headline market indicators conceal deep, uneven, and structurally embedded patterns of exclusion. This study interrogates who is left behind in Kenya's private insurance market and whether exclusion is systematically shaped by demographic and socio-economic position, and geography in ways that are not visible in aggregate coverage statistics.

Drawing on nationally representative data from the 2024 FinAccess Household Survey, the analysis applies a three-stage diagnostic framework that integrates descriptive profiling, multilevel binomial logistic regression, and spatial diagnostics. This approach enables a granular examination of private insurance uptake alongside the two dominant dimensions of exclusion among the uninsured: affordability and awareness barriers. By moving beyond surface-level statistics to predictive and spatial analysis, the study exposes hidden dynamics of exclusion that conventional monitoring fails to detect.

Headline results reveal that only 6.3 percent of adults hold private insurance in their own name, with uptake sharply stratified by wealth, education, age, gender, and livelihood. Exclusion exceeds 90 percent across most demographic groups and is particularly pronounced among women, young adults, rural residents, casual workers, and households in lower wealth quintiles. Multilevel modelling demonstrates substantial county-level heterogeneity in both uptake and exclusion barriers, indicating that place-based factors account for a meaningful share of variation beyond individual demographic and socio-economic characteristics. Once these characteristics are controlled for, urban residents are significantly less likely to hold private insurance, revealing a form of hidden urban exclusion that is masked by descriptive averages. A further paradox emerges in relation to awareness barriers: older adults, who appear more excluded in descriptive statistics, are in fact less constrained by awareness once socio-economic differences are accounted for. These paradoxes demonstrate that headline statistics can be misleading and that reliance on aggregate indicators risks obscuring the true structure of exclusion.

Affordability dynamics emerge as more complex than simple inability to pay. Affordability barriers increase with higher levels of education, suggesting that reported cost constraints also reflect scepticism about value for money, trust in insurance providers, and perceptions of fairness and transparency in insurance products. This indicates that low uptake is driven not only by limited resources but also by weak consumer confidence and misalignment between product design and peoples lived realities. Addressing affordability therefore requires more than pricing adjustments; it demands credible improvements in product transparency, consumer protection, and the perceived relevance and fairness of insurance offerings.

Spatial diagnostics further show that exclusion is geographically structured rather than randomly distributed. Low uptake and high affordability and awareness barriers cluster in specific counties, with entrenched pockets of exclusion across western and northern Kenya and more localised hotspots of inclusion in parts of central Kenya and in the hinterland of Nairobi. These spatial patterns indicate that where people live significantly shapes their likelihood of insurance inclusion, reinforcing the need for geographically differentiated strategies rather than uniform national interventions.

These findings imply that strategies to expand private insurance coverage in Kenya cannot rely on aggregate sector growth or one-size-fits-all national approaches. Inclusive insurance requires a multidimensional policy response that integrates advanced data analytics into routine market monitoring, aligns insurance inclusion with broader social protection, education, and labour market strategies, tailors interventions to geographically clustered patterns of exclusion, strengthens transparency and consumer trust to address perceived affordability, and supports the development of innovative products that reflect people's everyday financial behaviours and constraints. Without such a shift, insurance expansion risks reinforcing existing inequalities rather than reducing them.

The study also points to clear directions for further research and policy innovation. Future work should incorporate granular household economic measures, including continuous income and dependency ratios, to sharpen vulnerability profiling. Behavioural and attitudinal factors such as trust, perceived value, and risk preferences should be integrated to capture non-economic constraints on uptake. Longitudinal data, combined with advanced analytics such as Bayesian spatial models and machine learning, would enable tracking of exclusion dynamics over time, improve predictive accuracy, and support early warning systems for emerging pockets of exclusion. Finally, deeper sub-county analysis is needed to move beyond county averages and generate actionable insights for highly localised intervention design.

Using predictive analytics and spatial diagnostics, this study reveals who is truly left behind in Kenya's private insurance market, uncovering the paradoxes and geographic clusters that headline statistics obscure. These hidden patterns highlight that inclusive insurance policy interventions must be evidence-based, targeted, and context-sensitive. This approach ensures that private insurance reaches excluded populations, turning inclusion from aspiration into measurable impact. The adoption of advanced data analytics is central to designing responsive and innovative policy solutions that close persistent gaps in access and ensure that no one is left behind. These exclusion patterns have important, gendered dimensions, with women disproportionately affected by barriers related to income insecurity, informal employment, and limited awareness of insurance products. The findings are therefore directly relevant to women's financial inclusion efforts, including implementation of

the WE Finance Code[1], which emphasises the use of sex-disaggregated data and evidence-based action to expand women's access to financial services.

[1] *The WE Finance Code is a collaborative framework that mobilizes ecosystem actors serving women-led MSMEs to use sex-disaggregated data to identify gaps, commit to action, and improve women's access to financial services. Although commonly applied to lending, the Code also provides a relevant platform for advancing insurance and other non-credit services that support women's financial resilience and business sustainability.*

1. Introduction

1.1 Background

Insurance plays a central role in economic resilience by enabling households and firms to manage risk, smooth consumption, and invest in productive activities (Geneva Association, 2022). In low- and middle-income countries, access to insurance is increasingly recognised as a pillar of inclusive development, with established links to poverty reduction, health security, and climate resilience (Holliday, Remizova, & Stewart, 2021). Yet across Sub-Saharan Africa, private insurance coverage remains limited, with most adults uninsured despite increase in financial inclusion (Wrede, 2018).

In Kenya, private insurance coverage remains low, with only 6.3 percent of the population having private insurance in their own name in 2024 - a decline from 6.9 percent in 2021 (Insurance Regulatory Authority, 2025). This is despite steady expansion of the insurance industry, with gross written premiums reaching KES 397.1 billion in 2024 from KES 270.5 billion in 2021 (Insurance Regulatory Authority, 2024). This divergence between sector growth and persistently low insurance uptake raises a core policy problem: *aggregate indicators of market expansion coexist with widespread exclusion at the population level. Headline coverage statistics alone therefore provide an incomplete picture of who is being left behind and where exclusion is most entrenched.*

Evidence from the 2024 FinAccess Household Survey identifies affordability constraints and limited awareness as the most frequently reported barriers to private insurance uptake (Insurance Regulatory Authority, 2025). However, most policy-facing analysis of FinAccess data relies on descriptive statistics and bivariate comparisons across broad socio-economic groups. While useful for monitoring national trends, such summaries mask heterogeneity within groups and across space (i.e. where they live). They do not distinguish between exclusion driven by compositional differences associated with socio-economic characteristics of individuals and exclusion associated with place-based constraints. As a result, important patterns of exclusion remain analytically hidden in headline statistics.

Recent analytical work using FinAccess data has demonstrated the value of predictive modelling in identifying socio-economic correlates of insurance uptake (Yego, Kasozi, & Nkurunziza, 2021; Yego, Nkurunziza, & Kasozi, 2023). These studies show the value of moving beyond descriptive statistics toward predictive modelling. However, they have largely focused on explaining uptake at the individual level, with limited attention to diagnosing patterns of exclusion, spatial heterogeneity, and place-based constraints in insurance access. As a result, current evidence offers limited guidance on where exclusion is most entrenched and how exclusionary dynamics vary among individuals once compositional differences in population characteristics are considered, and across counties. These gaps constrain the

usefulness of existing evidence for policy design, particularly for targeting inclusive insurance interventions to excluded and underserved populations.

This paper addresses these gaps by conceptualising private insurance exclusion in Kenya as a multidimensional and spatially structured phenomenon that cannot be fully observed through descriptive statistics alone. By combining predictive modelling and geospatial diagnostics, it provides population-representative evidence on multiple forms of exclusion in Kenya's private insurance market. The analysis reveals hidden exclusion dynamics and spatial clustering that headline coverage statistics obscure, with direct implications for inclusive insurance policy interventions.

Insurance inclusion is increasingly recognized as a critical component of women's economic resilience, supporting households' ability to manage risk, smooth consumption, and recover from shocks. In Kenya, policy initiatives such as the WE Finance Code highlight the importance of understanding gendered barriers to financial and insurance access, and of deploying data-driven diagnostics to inform institutional commitments, product design, and accountability.

1.2 Study objectives

The objective of this paper is to provide population-representative evidence on private insurance inclusion and exclusion dynamics in Kenya, conceptualised as a multidimensional and spatially structured phenomenon. By applying predictive modelling and geospatial diagnostics to nationally representative survey data, the study seeks to move beyond descriptive statistics to reveal hidden exclusion dynamics that are not visible in headline coverage rates, including gendered dimensions of exclusion. The aim is to generate insights that can inform inclusive insurance policy interventions.

To achieve this overarching objective, the study pursues three specific objectives:

i) To profile private insurance uptake and barriers to uptake, identifying headline exclusion patterns and reported barriers.

ii) To identify who is left behind in Kenya's private insurance market after controlling for socio-demographic and socio-economic characteristics.

iii) To assess whether private insurance uptake and exclusion, including barriers, is geographically structured or random.

2. Methodology

2.1 Data source and study design

This study employs a multi-method diagnostic design using secondary data from the 2024 FinAccess Household Survey (https://finaccess.knbs.or.ke/reports-and-datasets). The survey was nationally representative, covering individuals aged 16 and above living in conventional households across all 47 counties. Stratification was applied by urban and rural domains in 45 counties, while Nairobi and Mombasa were treated as fully urban.

A total of 28,275 households were sampled from the Kenya Household Master Sample Frame, constructed from the 2019 Population and Housing Census and structured into 92 strata. One eligible respondent per household was selected using an automated Kish Grid embedded in the CAPI software, minimising interviewer discretion. Of these, 20,871 interviews were successfully completed, yielding an overall response rate of 84.6%, with higher participation in rural areas (87.6%) than in urban areas (79.4%).

For this analysis, the sample is restricted to individuals aged 18 and above, reflecting the minimum age for obtaining a national identity card, which is a prerequisite for accessing most formal financial services. All estimates are weighted using individual survey weights to ensure representativeness at both national and county levels. Spatial analysis uses a publicly available Kenya county shapefile reflecting the 47 constitutionally recognised counties under the 2010 constitution, providing consistent administrative boundaries for mapping insurance uptake and reported barriers.

2.2 Study variables

Three binary dependent variables were derived from the insurance module of the FinAccess survey:

- *Private insurance uptake* – whether a respondent has a private insurance policy registered in their own name.
- *Affordability barrier* – uninsured respondents citing don't have a regular income/job/too expensive/can't afford for not having insurance.
- *Awareness barrier* – uninsured respondents citing don't understand or know about insurance/don't know where to get it, for not having insurance.

The explanatory variables include gender, age group, education level, livelihood (i.e. main source of income), residence (urban/rural), and wealth quintile. All the explanatory variables are categorical. County of residence is used as the spatial unit for multilevel modelling and spatial diagnostics. Gender is included as a key explanatory variable, enabling the analysis to generate sex-disaggregated insights that are relevant for policy initiatives such as the WE Finance Code.

2.3 Analytical framework

This study applies a three-stage analytical framework to diagnose private insurance exclusion in Kenya using nationally representative data from the 2024 FinAccess Household Survey. The framework integrates descriptive profiling, multilevel binomial logistic regression analysis, and spatial diagnostics to move beyond headline coverage statistics and identify population groups and geographic areas that remain excluded from private insurance.

2.3.1 Descriptive analysis

Descriptive statistics were computed to profile private insurance uptake and reported barriers across socio-demographic variables (residence, sex, age, education), socio-economic variables (livelihood, wealth quintile), and county-level geographic variation. Cross-tabulations were used to summarize baseline patterns of coverage and exclusion.

2.3.2 Multilevel binomial logistic regression

Multilevel binomial logistic regression models with county-level random intercepts were estimated for three binary outcomes: (i) private insurance uptake, (ii) affordability barrier among uninsured respondents, and (iii) awareness barrier among uninsured respondents. The model was specified as:

$$\text{logit}(P_{ij}) = \beta_0 + \sum_{k=1}^{K} \beta_k X_{kij} + u_j$$

where:

P_{ij} was the probability that individual *i* in county *j* had private insurance or reported affordability or awareness barriers, depending on the model.

β_0 was the overall intercept representing the log-odds of insurance uptake or reporting affordability or awareness barriers for the reference categories of explanatory variables.

.X_{kij} was a vector of explanatory variables for individual *i* in county *j*, including socio-demographic (residence, sex, age, education) and socio-economic (livelihood, wealth quintile) characteristics.

β_k were fixed-effect coefficients measuring the association between each explanatory variable and the probability of insurance uptake or reporting affordability or awareness barriers.

$u_j$was the county-level random intercept capturing unobserved county-specific effects, with $u_j \sim N(0, \sigma^2_{\text{county}})$.

County-level clustering was quantified using the intraclass correlation coefficient (ICC):

$$ICC = \frac{\sigma^2_{\text{county}}}{\sigma^2_{\text{county}} + \pi^2/3}$$

where σ^2_{county} is the variance of the county-level random intercepts and $\frac{\pi^2}{3}$ is the fixed variance of the logistic distribution at the individual level. The ICC quantified the proportion of variance in insurance uptake attributable to county-level clustering.

Multicollinearity among explanatory variables was assessed using Variance Inflation Factors (VIF):

$$VIF_k = \frac{1}{1 - R_k^2}$$

where R_k^2 is the coefficient of determination from regressing explanatory variable *k* on all other explanatory variables. VIF values measured how much the variance of a regression coefficient was inflated due to collinearity, with values above 10 considered indicative of problematic multicollinearity.

The independence assumption was not tested because survey respondents were independent (one respondent was randomly selected per household). Linearity was also not tested because all explanatory variables were categorical.

All statistical inference was conducted at the 95% confidence level ($\alpha = 0.05$), with p-values reported to indicate statistical significance.

2.3.3 Spatial diagnostics

Spatial diagnostics were conducted using county-level prevalence of private insurance uptake and reported barriers. Spatial weights were defined using queen contiguity, where counties sharing a boundary were treated as neighbours.

Global spatial autocorrelation was assessed using Moran's I:

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \, (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2}$$

where:

I was the Moran's I statistic measuring global spatial autocorrelation.

N was the number of counties (47).

x_i was the county-level proportion of individuals with private insurance uptake or reported barriers in county *i*.

$\bar{x}$ was the national mean of the county-level proportions.

w_{ij} was the queen-contiguity spatial weight (1 if counties *i* and *j* shared a boundary, 0 otherwise).

$W = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}$ was the sum of all spatial weights.

The expected value under spatial randomness was:

$$E[I] = -\frac{1}{N-1}$$

Moran's I quantified whether insurance uptake or reported barriers were spatially clustered, dispersed, or random across counties.

Spatial clustering was assessed using Local Indicators of Spatial Association (LISA):

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_{j=1}^{N} w_{ij} (x_j - \bar{x})$$

where:

I_i was the local Moran's I statistic for county *i*, indicating the extent of local clustering or outlier status.

x_i was the county-level proportion of insured individuals or reported barriers in county *i*.

x_j was the corresponding proportion in neighbouring county *j*.

$\bar{x}$ was the national mean of the county-level proportions.

w_{ij} was the queen-contiguity spatial weight between counties *i* and *j*.

$m_2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2$ was the variance term used for standardization.

LISA identifies four types of spatial patterns: High–High clusters, Low–Low clusters, High–Low outliers, and Low–High outliers. Statistically significant clusters ($p < 0.05$) were visualized using county-level choropleth maps, highlighting areas of spatial concentration or divergence in insurance uptake and reported barriers.

3. Results

This section presents empirical results on private insurance uptake and exclusion using data from the 2024 FinAccess Household Survey. Findings are structured to move from headline descriptive patterns of uptake and reported barriers, to multilevel regression results that examine predictors of private insurance uptake and reported barriers, thereby identifying hidden exclusions, and finally to spatial diagnostics that assess geographic clustering of inclusion and exclusion.

3.1 Headline private insurance uptake and exclusion – Descriptive evidence

Private insurance uptake remains low nationally at 6.3 percent. Coverage is concentrated among men, older adults, respondents with higher levels of education, those in higher wealth quintiles, and respondents in formal employment or business ownership. In contrast, exclusion exceeds 95 percent among women, rural residents; individuals with no formal education and those with primary education; casual workers; dependents; individuals in the lowest, second and middle wealth quintiles; and among those aged 18-25 years. Uptake is highest among respondents aged 46–55 years (**Annexure 1: Private insurance uptake patterns**).

Within this headline exclusion, three additional dimensions of exclusion are observed. First, cost exclusion is dominant with 76 percent of uninsured respondents reporting inability to afford insurance as the primary reason for not taking up insurance. This barrier is more prevalent among women, respondents aged 46–55 years, urban residents, those with primary level of education, casual workers and those in the second wealth quintile. Second, informational exclusion is significant with 23 percent of uninsured respondents citing lack of awareness as the reason for not taking up insurance. Awareness gaps are highest among rural residents, women, older adults above 55 years, those with no formal education, those whose main source of income is agriculture, and those in the lowest wealth quintile (**Annexure 2: Barriers to insurance uptake**). Third, descriptive county-level patterns reveal geographic disparities in insurance uptake, with several counties recording exclusion rates above 98 percent (**Annexure 3: County-level uptake and exclusion statistics)**

These descriptive patterns demonstrate that private insurance exclusion is multidimensional, encompassing low overall coverage, affordability constraints, awareness gaps, and marked geographic disparities. However, descriptive statistics mask underlying patterns of exclusion once demographic and socio-economic characteristics, and geographic heterogeneity are accounted for. The sections hereafter therefore present predictive and spatial evidence on exclusion patterns across population groups and counties after accounting for demographic and socio-economic differences.

Note: For the predictive analysis, odds ratios (ORs) greater than 1 indicate higher odds of having private insurance relative to the reference category, while ORs less than 1 indicate lower odds. The reference categories are female (gender), rural (residence),

ages 18–25 (age), no education i.e. none (education level), lowest wealth quintile (wealth), and dependent (livelihood).

3.2 Hidden exclusion in private insurance uptake – Multilevel regression evidence

Multilevel binomial logistic regression results reveal significant county-level heterogeneity in private insurance uptake, with a county-level random intercept variance of 0.67 and an intraclass correlation coefficient (ICC) of 0.17, indicating that 17 percent of the variation in uptake is attributable to between-county differences (**Table 1**).

Uptake is strongly stratified by socio-economic position. Men are significantly more likely to have private insurance in their own name compared to women (OR = 2.35). The magnitude and significance of the gender coefficient suggest that women face structural barriers to insurance uptake beyond income and location, potentially linked to informal employment, lower and more volatile earnings, and limited access to tailored insurance products. The likelihood of uptake increases with age. Additionally, people with higher levels of education are more likely to have private insurance, especially those with tertiary education, who have much higher odds of uptake than those with no education (OR = 14.73). Insurance uptake is concentrated among the richest households with those in the highest wealth quintile having over 20 times higher odds of being insured than those in the lowest quintile (OR = 20.6).

Livelihood status also shapes access to private insurance. Individuals in formal employment and business ownership are more likely to be insured, while casual workers are substantially less likely to be insured compared to dependents (OR = 0.42); those in agriculture are also more likely to be insured compared to dependents (OR = 1.15).

A notable finding is the presence of a Simpson's paradox in insurance uptake among urban residents. While descriptive statistics indicate higher uptake in urban areas, the multilevel regression shows that, after controlling for age, gender, education, wealth quintile, and livelihood, urban residents are significantly less likely to have private insurance in their own name compared to rural residents (OR = 0.53). This finding is particularly relevant in urban contexts, where women engaged in informal economic activities may remain excluded despite proximity to financial service providers. Full regression estimates for private insurance uptake are reported in **Table 1.**

Table 1: Insurance uptake – Multi-level binomial logistic regression results

	Term	Coefficient	Std.Error	z.value	P-value	OR
	(Intercept)	-8.0214	0.1185	-67.6659	<0.001	0.0003
Age	26-35	1.1890	0.0031	386.6036	<0.001	3.2838
	36-45	1.7292	0.0033	523.4897	<0.001	5.6362
	46-55	1.8102	0.0037	495.3175	<0.001	6.1117
	Above 55	1.8982	0.0037	518.4174	<0.001	6.6740
Gender	Male	0.8549	0.0019	451.7766	<0.001	2.3511
Residence	Urban	-0.6433	0.0027	-241.1656	<0.001	0.5255
Education Level	Primary	1.4999	0.0079	189.4635	<0.001	4.4814
	Secondary	1.8462	0.0079	233.3504	<0.001	6.3355
	Tertiary	2.6896	0.0080	336.2778	<0.001	14.7254
Livelihood	Agriculture	0.1389	0.0034	40.9326	<0.001	1.1490
	Casual Worker	-0.8747	0.0038	-230.4728	<0.001	0.4170
	Employed	0.5119	0.0030	172.4483	<0.001	1.6685
	Own Business	0.3101	0.0030	101.7218	<0.001	1.3636
Wealth quintile	Second	0.7581	0.0059	128.7445	<0.001	2.1343
	Middle	1.2055	0.0056	213.5887	<0.001	3.3384
	Fourth	1.9222	0.0056	344.4317	<0.001	6.8359
	Highest	3.0241	0.0059	510.9767	<0.001	20.5748
	Variance components					
	Component	County Variance	ICC			
	County random intercept	0.6672	0.1686			

Source: 2024 FinAccess Household survey data

3.3 Dimensions of exclusion in private insurance uptake

3.3.1 Cost exclusion – Affordability barriers

Affordability constraints display significant county-level variation, with a random intercept variance of 0.52 and an intraclass correlation coefficient (ICC) of 0.14 (**Table 3**). This shows that about 14 percent variation in reporting affordability barriers is attributable to county of residence.

Men are less likely than women to report affordability as a barrier. Individuals aged 46–55 years face the highest odds of affordability barrier. The likelihood of reporting affordability as a barrier is higher among individuals with any level of education than among those with no education, with the highest odds (OR 1.71) observed among those with tertiary education. Affordability barriers are less commonly reported among those in formal employment (OR = 0.52), business ownership (OR = 0.48), and agriculture (0.66), while casual workers are slightly more likely (OR = 1.09) to report affordability constraints compared to dependents. After controlling for socio-economic and socio-demographic characteristics, urban residents exhibit higher odds of reporting affordability barriers than rural residents (OR = 1.28). The predictive

results on reporting affordability barrier among the various socio-economic and demographic groups are consistent with the descriptive results (**Annexure 2**). These barriers closely mirror constraints commonly faced by women, for whom affordability challenges are often compounded by income insecurity and for whom awareness gaps reflect broader information asymmetries and trust deficits in financial markets.

Full model estimates for affordability barriers are presented in **Table 2**

Table 2: Affordability barrier – Multi-level binomial logistic regression results

	Term	**Coefficient**	**std.error**	**z.value**	**p.value**	**OR**
	(Intercept)	1.0337	0.1027	10.0657	< 0.001	2.8114
Gender	Male	-0.1623	0.0012	-131.6252	< 0.001	0.8502
Age	26-35	0.2955	0.0016	181.0944	< 0.001	1.3438
	36-45	0.2660	0.0020	136.0974	< 0.001	1.3048
	46-55	0.4114	0.0024	168.8034	< 0.001	1.5089
	Above 55	0.1934	0.0022	87.2492	< 0.001	1.2133
Education level	Primary	0.4627	0.0023	203.3584	< 0.001	1.5884
	Secondary	0.4461	0.0025	178.7427	< 0.001	1.5622
	Tertiary	0.5377	0.0031	172.0959	< 0.001	1.7120
Residence	Urban	0.2483	0.0019	132.5898	< 0.001	1.2818
Livelihood	Agriculture	-0.4091	0.0019	-210.1711	< 0.001	0.6643
	Casual Worker	0.0870	0.0018	48.4719	< 0.001	1.0909
	Employed	-0.6481	0.0025	-263.6955	< 0.001	0.5230
	Own Business	-0.7405	0.0019	-384.5627	< 0.001	0.4769
Wealth quintile	Second	-0.1166	0.0019	-61.2464	< 0.001	0.8899
	Middle	-0.1891	0.0021	-91.1481	< 0.001	0.8277
	Fourth	-0.4317	0.0023	-184.5895	< 0.001	0.6494
	Highest	-0.5977	0.0029	-208.5431	< 0.001	0.5501
	Variance components					
	Component	County variance	ICC			
	County Random (Intercept)	0.5212	0.1368			

Source: 2024 FinAccess Household survey data

3.3.2 Informational exclusion – Awareness barriers

Awareness barriers exhibit meaningful county-level variation, with a random intercept variance of 0.70 and an intraclass correlation coefficient (ICC) of 0.17(**Table 3**). This indicates that around 17 percent of the variation in reporting awareness barriers is attributable to county of residence.

Reporting an awareness barrier varies across socio-economic and demographic groups. Men are slightly less likely than women to report awareness barriers (OR = 0.95).

Compared to youths aged 18–25, older age groups are less likely to report awareness barriers, with odds decreasing across age groups (ORs range from 0.80 to 0.91).

There are statistically significant differences in reporting awareness barriers by education level. Individuals with primary, secondary, and tertiary education are substantially less likely to report awareness barriers than those with no education, with progressively lower odds observed at higher levels of education (primary: OR = 0.45; secondary: OR = 0.28; tertiary: OR = 0.18). Urban residents are slightly less likely than rural residents to report awareness barriers (OR = 0.96).

Livelihood status is also associated with reporting awareness barriers. Compared to dependents, individuals in agriculture and business ownership are more likely to report awareness barriers (OR = 1.19 and OR = 1.20, respectively). Those in formal employment have the highest odds or reporting awareness barrier (OR = 1.90). Casual workers are slightly less likely to report awareness barriers than dependents (OR = 0.93).

There are statistically significant differences by wealth quintile in reporting awareness barriers. Individuals in higher wealth quintiles are less likely to report awareness barriers than those in the lowest quintile, with odds declining as wealth increases (second: OR = 0.82; middle: OR = 0.64; fourth: OR = 0.56; highest: OR = 0.47).

Notably, Simpson's paradox is observed for awareness barriers across age groups. Descriptive statistics suggest that awareness barriers increase with age; however, the multilevel regression analysis indicates that older respondents are less likely to report awareness barriers after controlling for other socio-demographic and socio-economic characteristics.

Full regression results on reporting awareness barrier are shown in **Table 3.**

Table 3: Awareness Barrier – Multi-level Binomial Logistic Regression Results

	Predictor	**coefficient**	**std.error**	**z.value**	**p.value**	**OR**
	(Intercept)	-0.0440	0.1217	-0.3616	>0.001	0.9569
Gender	Male	-0.0533	0.0013	-39.9316	< 0.001	0.9481
Age	26-35	-0.2217	0.0018	-122.8977	< 0.001	0.8012
	36-45	-0.2091	0.0021	-99.2570	< 0.001	0.8113
	46-55	-0.1965	0.0025	-78.2580	< 0.001	0.8216
	Above 55	-0.0943	0.0023	-40.8556	< 0.001	0.9100
Education	Primary	-0.8061	0.0022	-371.3420	< 0.001	0.4466
	Secondary	-1.2747	0.0025	-509.2676	< 0.001	0.2795
	Tertiary	-1.6895	0.0037	-457.7459	< 0.001	0.1846
Residence	Urban	-0.0436	0.0020	-21.7589	< 0.001	0.9574
Livelihood	Agriculture	0.1742	0.0020	85.9913	< 0.001	1.1903
	Casual Worker	-0.0776	0.0019	-40.7954	< 0.001	0.9253
	Employed	0.6438	0.0029	223.8771	< 0.001	1.9036
	Own Business	0.1864	0.0022	85.9113	< 0.001	1.2049
Wealth quintile	Second	-0.2045	0.0018	-112.5418	< 0.001	0.8150
	Middle	-0.4534	0.0021	-216.4535	< 0.001	0.6355

	Predictor	coefficient	std.error	z.value	p.value	OR
	Fourth	-0.5740	0.0025	-226.6178	< 0.001	0.5633
	Highest	-0.7638	0.0033	-230.7324	< 0.001	0.4659
	Component	Variance	ICC			
	County (Intercept)	0.6961	0.1746			

Source: 2024 FinAccess Household survey data

3.3.3 Geographic exclusion – Spatial diagnostic evidence

Spatial analysis using Moran's I confirms significant geographic clustering of insurance uptake under the Queen contiguity scheme. The results (Moran's I = 0.31, z = 3.47, analytical $p < 0.05$) indicates that insurance uptake is clustered rather than randomly distributed across counties. The clustering in uptake, identified using the Local Indicators of Spatial Association (LISA), further illustrates the spatial patterning of uptake, and identifies three distinct clusters across counties.

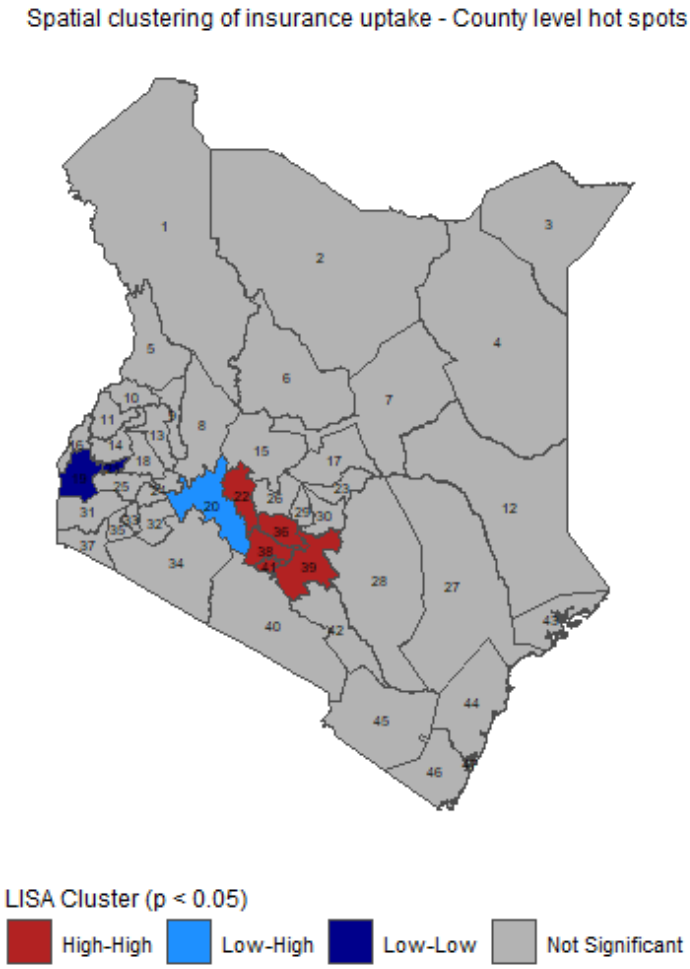
High-High clusters, where counties with relatively high insurance uptake are surrounded by neighbors with similarly high uptake, are identified in Nairobi, Kiambu, Murang'a, Machakos, and Nyandarua Counties. These counties form regional hotspots that reflect entrenched advantages in private insurance access.

Low-Low clusters, where counties with relatively low insurance uptake are surrounded by neighbors with similarly low uptake, are observed in Siaya and Vihiga Counties. Uptake in these counties falls below 5%, representing entrenched pockets of exclusion in which individuals are consistently disadvantaged.

A Low–High outlier is observed in Nakuru County, where uptake is comparatively low despite being surrounded by counties with higher uptake, highlighting localized disparities within the broader spatial pattern.

Counties outside these clusters show no significant spatial association ($p \geq 0.05$), indicating that their uptake rates do not exhibit spatial clustering. These results, together with insurance uptake across counties are illustrated in **Figure 1.**

Overall, these findings suggest that insurance uptake in Kenya is unevenly distributed, with clear regional clustering of high and low uptake, reflecting geographic exclusion in private insurance access.



ID	County	Uptake Rate (%)
1	Turkana	3.2
2	Marsabit	2.2
3	Mandera	8.1
4	Wajir	3.7
5	West Pokot	2.1
6	Samburu	5.9
7	Isiolo	7.8
8	Baringo	3.8
9	Elgeyo-Marakwet	7.3
10	Trans Nzoia	6.0
11	Bungoma	5.0
12	Garissa	7.2
13	Uasin Gishu	7.8
14	Kakamega	3.9
15	Laikipia	5.5
16	Busia	4.6
17	Meru	1.3
18	Nandi	4.5
19	Siaya	1.2
20	Nakuru	4.0
21	Vihiga	4.4
22	Nyandarua	8.9
23	Tharaka	5.4
24	Kericho	7.3
25	Kisumu	1.1
26	Nyeri	10.0
27	Tana River	3.3
28	Kitui	2.7
29	Kirinyaga	9.5
30	Embu	8.8
31	Homa Bay	1.6
32	Bomet	7.1
33	Nyamira	6.0
34	Narok	6.2
35	Kisii	7.2
36	Murang'a	11.3
37	Migori	3.3
38	Kiambu	12.0
39	Machakos	5.7
40	Kajiado	9.0
41	Nairobi	12.0
42	Makueni	4.1
43	Lamu	2.0
44	Kilifi	1.4
45	Taita Taveta	2.4
46	Kwale	5.7
47	Mombasa	4.1

.

Figure 1: Spatial clustering of insurance uptake

Source: 2024 FinAccess Household survey data

Further, spatial analysis of affordability barriers (cost exclusion) shows that counties with affordability barriers cluster together rather than being randomly distributed (Moran's I = 0.18; z = 2.14, analytical p < 0.05). The Local Indicators of Spatial Association (LISA) results identify three distinct cluster types for affordability barriers across counties.

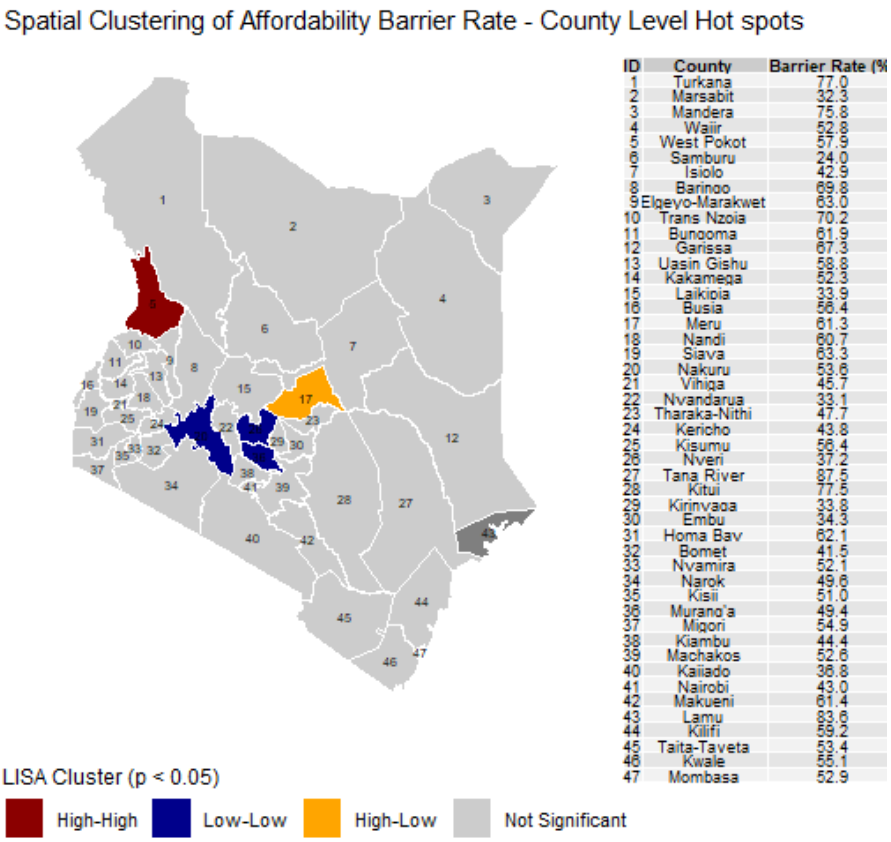
High–High clusters, where counties with high affordability barriers are surrounded by neighbours with similarly high affordability barriers, are concentrated in western Kenya, specifically West Pokot and surrounding counties.

Low–Low clusters, where counties with low affordability barriers are surrounded by neighbors with similarly low affordability barriers, are observed in Nakuru, Nyeri, and Murang'a.

A High–Low outlier is observed in Meru County, where, although it has high affordability barriers, it is surrounded by counties with lower affordability barriers.

Counties outside these clusters show no significant spatial association ($p \geq 0.05$), indicating that affordability barriers are not spatially patterned. The LISA results and affordability barriers across counties are summarized in **Figure 2**.

Overall, these clusters indicate that cost-related exclusion in insurance access varies across regions, creating localized pockets of disadvantage.



ID	County	Barrier Rate (%
1	Turkana	77.0
2	Marsabit	32.3
3	Mandera	75.8
4	Wajir	52.8
5	West Pokot	57.9
6	Samburu	24.0
7	Isiolo	42.9
8	Baringo	69.8
9	Elgeyo-Marakwet	63.0
10	Trans Nzoia	70.2
11	Bungoma	61.9
12	Garissa	67.3
13	Uasin Gishu	58.8
14	Kakamega	52.3
15	Laikipia	33.9
16	Busia	56.4
17	Meru	61.3
18	Nandi	60.7
19	Siaya	63.3
20	Nakuru	53.6
21	Vihiga	45.7
22	Nyandarua	33.1
23	Tharaka-Nithi	47.7
24	Kericho	43.8
25	Kisumu	56.4
26	Nyeri	37.2
27	Tana River	87.5
28	Kitui	77.5
29	Kirinyaga	33.8
30	Embu	34.3
31	Homa Bay	62.1
32	Bomet	41.5
33	Nyamira	52.1
34	Narok	49.6
35	Kisii	51.0
36	Murang'a	49.4
37	Migori	54.9
38	Kiambu	44.4
39	Machakos	52.6
40	Kajiado	36.8
41	Nairobi	43.0
42	Makueni	61.4
43	Lamu	83.6
44	Kilifi	59.2
45	Taita-Taveta	53.4
46	Kwale	55.1
47	Mombasa	52.9

Figure 2: Spatial clustering of cost exclusion
Source: 2024 FinAccess Household survey data

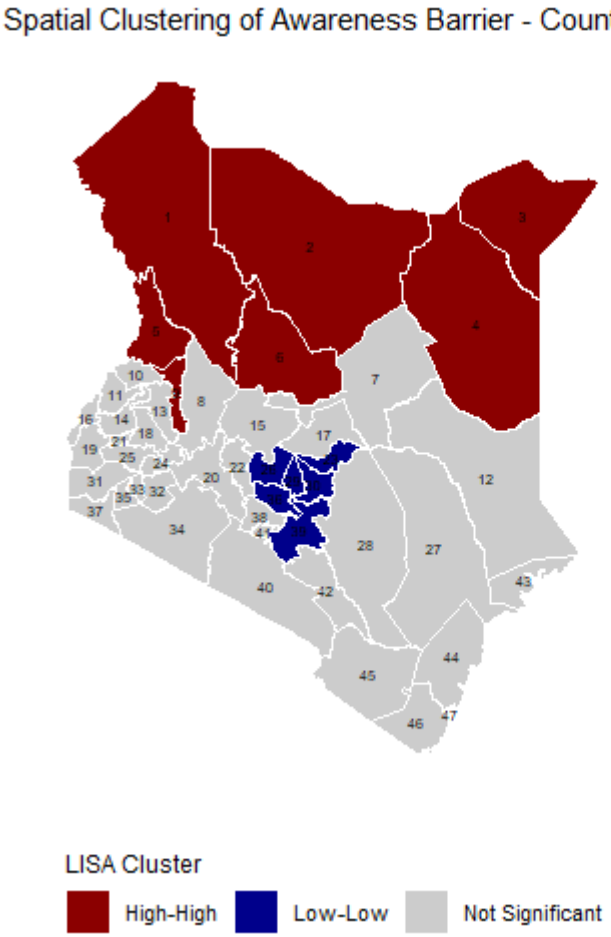
Spatial analysis of informational exclusion shows evidence of clustering (Moran's I = 0.57, z = 6.41, $p < 0.05$). Two distinct clusters were identified across counties using LISA analysis.

High-High clusters, where counties with high awareness barriers are surrounded by similar neighbours, are concentrated in northern Kenya (Turkana, Marsabit, Mandera, Wajir, West Pokot, Samburu, and Elgeyo-Marakwet).

Low-Low clusters, where counties with low barriers are surrounded by similar neighbours, occur in central and eastern regions (Tharaka-Nithi, Nyeri, Kirinyaga, Embu, Murang'a, and Machakos).

Counties outside these clusters show no significant spatial association ($p \geq 0.05$). The LISA results and awareness barriers across counties are summarized in **Figure 3.**

Overall, these patterns highlight geographic informational exclusion, creating localised pockets of disadvantage in accessing insurance.



ID	County	Barrier Rate (%
1	Turkana	56.8
2	Marsabit	50.7
3	Mandera	67.4
4	Wajir	51.2
5	West Pokot	45.0
6	Samburu	42.3
7	Isiolo	38.1
8	Baringo	26.9
9	Elgeyo-Marakwet	25.0
10	Trans Nzoia	57.5
11	Bungoma	9.9
12	Garissa	28.8
13	Uasin Gishu	18.0
14	Kakamega	17.3
15	Laikipia	10.5
16	Busia	15.9
17	Meru	3.8
18	Nandi	29.9
19	Siaya	11.0
20	Nakuru	15.0
21	Vihiga	23.1
22	Nyandarua	5.4
23	Tharaka-Nithi	9.7
24	Kericho	12.9
25	Kisumu	3.3
26	Nyeri	4.4
27	Tana River	19.6
28	Kitui	14.1
29	Kirinyaga	2.9
30	Embu	5.3
31	Homa Bay	16.4
32	Bomet	9.7
33	Nyamira	13.0
34	Narok	22.8
35	Kisii	16.6
36	Murang'a	9.9
37	Migori	29.6
38	Kiambu	5.3
39	Machakos	11.4
40	Kajiado	10.6
41	Nairobi	5.2
42	Makueni	3.8
43	Lamu	5.6
44	Kilifi	22.0
45	Taita-Taveta	5.9
46	Kwale	31.5
47	Mombasa	7.0

Figure 3: Spatial clustering of informational exclusion
Source: 2024 FinAccess Household survey data

3.3.4 Gendered Exclusion – County Level Evidence

Additional county-level analysis by gender (Annexure 4) confirms that while overall insurance uptake remains low across all counties, women consistently exhibit lower or at best equal levels of uptake compared to men, reinforcing the presence of gendered disparities within geographically clustered patterns of exclusion.

4. Discussions and implications for inclusive insurance policy interventions

4.1 Discussions

The analysis demonstrates that exclusion in Kenya's private insurance market is multidimensional, shaped by socio-demographic and socio-economic stratification, paradoxical dynamics, and spatial clustering. While descriptive statistics show informative headline results, predictive modelling reveals that apparent inclusions can mask deeper exclusions. This confirms that headline measures alone are insufficient, and deeper analytical approaches are required to expose the true nature of exclusion.

The findings also reveal significant disparities in private insurance uptake across socio-demographic, socio-economic, and geographic dimensions. Uptake is concentrated among males, individuals aged 46-55 years, those with higher education levels, formal employment or business livelihoods, and wealthier households. Conversely, exclusion from private insurance remains high, exceeding 90 percent in most demographic groups, with particularly high exclusion among women, youths (18–25), the uneducated, casual workers, rural residents, and lower wealth quintiles. These disparities highlight the persistence of structural inequalities that continue to shape insurance access in Kenya.

The paradoxes uncovered highlight the importance of advanced analysis. The Simpson's urban paradox on insurance uptake shows that urban residents, despite appearing better covered on surface figures, are less likely to hold insurance once socio-demographic and socio-economic differences are controlled. The Simpson's paradox in awareness barriers demonstrates that older adults, who seem more excluded descriptively, are less constrained once socio-demographic and socio-economic factors are accounted for. These findings underscore that headline statistics can mislead, and that granular analysis is essential to uncover the true dynamics of exclusion. Such paradoxes demonstrate that inclusive insurance policy must be informed by advanced diagnostics rather than surface-level statistics.

A further dimension of exclusion was revealed, relating to affordability barriers. Affordability concerns increase with higher education levels, suggesting that these barriers may not necessarily reflect cost alone. Instead, they may also capture perceptions of value for money and trust in insurance products. This indicates that exclusion is not only driven by ability to pay, but also by consumer confidence in the fairness and transparency of insurance offerings. Addressing affordability therefore

requires not only pricing reforms but also measures to strengthen product trust and transparency.

Spatial diagnostics further reveal that exclusion is geographically structured, with clusters of uptake, affordability and awareness barriers concentrated in specific areas. This structuring implies that inclusive insurance interventions must be tailored not only to socio-economic realities but also to geographic contexts. Geographic clustering underscores the need for spatially differentiated strategies that respond to localised patterns of exclusion.

Taken together, these findings provide a strong evidence base for advancing women's financial inclusion under initiatives such as the WE Finance Code. The use of granular diagnostics, predictive modelling, and spatial analysis aligns with the Code's emphasis on data-driven target setting, tailored product development, and ongoing monitoring of progress. By identifying where and why women are excluded from insurance markets, the study offers actionable insights for policymakers, regulators, and insurers seeking to translate commitment into measurable outcomes.

4.2 Policy interventions

i) **Institutionalise advanced data analytics and granular diagnostics**
The regulator to embed predictive modelling and spatial diagnostics into routine market monitoring. This will ensure in-depth insights to support evidence-based targeting. By institutionalising advanced analytics, the regulator can strengthen its supervisory role, generate deeper insights into exclusion dynamics, and design interventions that respond to both socio-economic and geographic realities.

ii) **Integrate insurance inclusion with social protection and labour market strategies**
Collaboration among relevant stakeholders to align insurance policy with broader social protection frameworks, education initiatives, and labour market reforms. Since uptake is tied to education, wealth, and livelihood stability, insurance inclusion cannot be pursued in isolation. Coordinated strategies will help address structural inequalities that drive exclusion and ensure insurance contributes meaningfully to Kenya's national development goals.

iii) **Design spatially differentiated interventions**
Develop county-specific and regional strategies to respond to insurance inclusion challenges across Kenya. Where exclusion is concentrated, regional programmes can be deployed; where exclusion is dispersed, county-level tailoring is required. This spatial differentiation ensures interventions match geographic realities rather than applying uniform national solutions, making inclusion more responsive and effective.

iv) **Strengthen product transparency, simplify products and processes, and build consumer trust**
Mandate clearer disclosure standards, fair pricing practices, and robust consumer protection mechanisms while encouraging insurers to simplify

product design, policy documentation, and customer-facing processes. Exclusion is not only about ability to pay but also about perceptions of product value, fairness, and the complexity of insurance products. Building trust through transparent, simple, and customer-centric insurance offerings will improve consumer understanding, reinforce confidence, and broaden participation in insurance.

v) **Support development of innovative affordable products based on people's realities**

Encourage and support insurers and Insurtechs operating in Kenya to design products and insurance solutions that reflect the lived realities of excluded groups. By aligning product features and insurance solutions with the financial behaviours and constraints of individuals, affordability can be enhanced not only through lower premiums but also through relevance and usability. This approach ensures that insurance solutions resonate with everyday experiences, making inclusion both practical and sustainable.

vi) **Strengthen awareness and literacy**

Strengthen awareness and financial literacy by ensuring that targeted communication and literacy campaigns respond to information gaps among diverse population groups in Kenya. Campaigns must be designed to reduce information asymmetries alongside affordability constraints, using context-sensitive messaging and delivery channels that resonate with everyday experiences.

vii) **Leverage the WE-Finance Code to advance women's insurance inclusion**

Policymakers and insurers should use sex-disaggregated data to set explicit targets for women's insurance uptake, promote innovation in products tailored to women's needs, and strengthen accountability for progress through regular reporting and monitoring.

In summary, inclusive insurance in Kenya requires a multidimensional policy approach. A strategic framework that combines advanced analytics, integration with social protection, spatially differentiated interventions, product transparency, and innovation grounded in people's realities will enable the private insurance market to evolve in ways that are equitable, context-sensitive, and responsive to the lived realities of excluded populations.

5. Limitations of the study

Three main limitations are worth noting. First, reliance on cross-sectional survey data limits the ability to capture changes in exclusion over time. Longitudinal data would be needed to track how inclusion and exclusion dynamics, and spatial clusters evolve.

Second, while predictive modelling improves inference, categorical household variables may obscure finer distinctions in vulnerability. Continuous measures such as income, household size, and dependency ratios would provide deeper insights. Behavioural and psychological dimensions of exclusion, including perceptions of insurance value, trust, and risk preferences, are not fully captured and call for complementary qualitative or experimental approaches.

Third, spatial diagnostics are conducted at the county level, which may mask important sub-county variation. Outlier clusters highlight divergence from neighbouring counties, but aggregation reduces the precision on small areas.

However, these limitations do not undermine the validity of the results. Instead, they highlight areas for methodological refinement and future research, reinforcing the value of the current findings as a foundation for policy and regulatory innovation in Kenya's insurance market.

6. Conclusion and direction for future research

This study demonstrates that exclusion in Kenya's private insurance market is multidimensional, systematically patterned, and geographically entrenched. Uptake is concentrated among advantaged groups, while affordability and awareness barriers disproportionately affect vulnerable populations. Predictive and spatial diagnostics reveal paradoxes and clusters of exclusion that are invisible in descriptive statistics, underscoring the need for advanced analytics to support evidence-based, targeted interventions.

The central contribution of this study lies in advancing evidence-based policy by moving beyond headline monitoring toward advanced analytics. Predictive models combined with descriptive methods provide regulators with a diagnostic lens for designing interventions that respond to both people's realities and geographic contexts. This shift from aggregate monitoring to targeted diagnosis marks a critical step in inclusive insurance policy.

Future research should extend this diagnostic approach in several directions. First, granular household economic measures, including continuous income and dependency ratios, would sharpen vulnerability profiles. Second, behavioural and attitudinal factors such as perceptions of value, trust, and risk preferences should be incorporated to capture non-economic constraints. Third, longitudinal models combined with advanced data analytics including Bayesian spatial models and machine learning would allow tracking of exclusion dynamics over time, enhance predictive accuracy, uncover non-linear relationships, and identify complex interaction effects that traditional methods may miss. Such models can strengthen early warning systems of exclusion and guide proactive regulatory responses. Finally, a dedicated deep dive study is needed to understand county-level dynamics in greater detail. Moving beyond county averages to explore small area variations would provide actionable insights for tailoring interventions to specific counties, particularly in those where outlier clusters of inclusion and barriers are detected. This approach would ensure strategies are responsive to local realities rather than uniform national templates.

This study provides a robust foundation for policy and regulatory innovation in Kenya's insurance market, positioning advanced data analytics as a cornerstone for inclusive insurance strategies. These insights also offer practical guidance for implementing the WE Finance Code, demonstrating how advanced data and diagnostics can support more inclusive insurance markets for women in Kenya.

Annexure 1: Private insurance uptake patterns

	Uptake rate within each group	Share of insured population	Share of total insured population	Share of total population
Gender				
Female	3.8%	31.1%	2.0%	51.5%
Male	8.9%	68.9%	4.3%	48.5%
Age				
18-25	2.2%	9.8%	0.6%	28.0%
26-35	7.7%	34.7%	2.2%	28.5%
36-45	8.5%	25.2%	1.6%	18.6%
46-55	9.0%	15.2%	1.0%	10.7%
Above 55	6.7%	15.2%	1.0%	14.3%
Residence				
Urban	8.7%	57.8%	3.6%	41.7%
Rural	4.6%	42.2%	2.7%	58.3%
Education				
None	1.0%	1.6%	0.1%	9.8%
Primary	2.9%	15.9%	1.0%	34.9%
Secondary	5.1%	30.6%	1.9%	38.0%
Tertiary	18.9%	52.0%	3.3%	17.3%
Livelihood				
Dependent	3.8%	13.5%	0.9%	22.3%
Casual Worker	1.8%	7.7%	0.5%	26.5%
Own Business	9.5%	25.2%	1.6%	16.7%
Agriculture	5.2%	14.7%	0.9%	17.9%
Employed	17.8%	37.4%	2.4%	13.2%
Other	2.7%	1.4%	0.1%	3.3%
Wealth Quintile				
Lowest	1.0%	3.0%	0.2%	18.9%
Second	1.9%	6.0%	0.4%	19.5%
Middle	3.4%	10.5%	0.7%	19.2%
Fourth	7.1%	23.7%	1.5%	21.1%
Highest	16.9%	56.8%	3.6%	21.2%

Source: 2024 FinAccess Household survey data

Annexure 2: Barriers to insurance uptake

Demographics	Barriers						
	Cannot afford	Don't understand/Not aware	Don't need	Brings bad luck	Don't trust insurance providers	Lacks requirements e.g ID	Others
	%	%	%	%	%	%	%
Gender							
Male	74.7	22.7	8.6	0.4	1.9	9.8	2.6
Female	77.3	24.0	6.6	0.5	1.5	7.4	2.9
Age							
18-25	74.1	21.0	6.8	0.4	1.1	21.0	2.4
26-35	77.7	22.1	7.9	0.3	2.2	1.8	3.3
36-45	77.2	23.9	8.2	0.8	2.3	1.1	3.0
46-55	79.1	25.2	7.6	0.3	1.5	0.4	2.6
Above 55	75.8	30.8	7.4	0.6	1.5	0.6	2.5
Residence							
Rural	75.7	27.8	6.7	0.5	1.3	9.1	2.5
Urban	76.9	15.5	8.8	0.3	2.2	7.3	3.3
Education Level							
None	68.2%	54.2%	5.0%	0.9%	0.9%	2.1%	0.7%
Primary	79.2%	23.9%	6.2%	0.4%	1.2%	7.1%	2.6%
Secondary	75.8%	15.7%	7.8%	0.4%	2.3%	13.4%	3.2%
Tertiary	76.0%	9.8%	14.3%	0.2%	1.9%	3.0%	4.5%
Livelihood							
Dependent	79.1%	21.2%	5.6%	0.4%	1.0%	15.6%	1.9%
Casual Worker	82.3%	19.2%	5.3%	0.3%	1.2%	7.8%	2.3%
Own Business	69.0%	23.5%	12.3%	0.7%	3.7%	3.2%	4.1%
Agriculture	72.7%	30.3%	8.0%	0.5%	1.7%	2.6%	3.9%
Employed	66.2%	21.4%	12.4%	0.4%	2.7%	4.7%	3.8%
Wealth Quintile							
Lowest	74.8%	41.5%	4.8%	0.3%	0.5%	7.4%	1.2%
Second	79.2%	23.5%	6.6%	0.7%	1.4%	11.4%	1.9%
Middle	77.8%	18.1%	6.3%	0.4%	1.9%	8.0%	3.6%
Fourth	75.1%	14.1%	9.6%	0.8%	3.1%	7.4%	3.5%
Highest	72.7%	10.1%	12.1%	0.0%	1.9%	7.5%	4.9%
Overall	**76.2**	**23.4**	**7.4**	**0.5**	**1.6**	**8.4**	**2.8**

Source: 2024 FinAccess Household survey data

Annexure 3: County-level uptake and exclusion statistics

County	Analysis specifications	Uptake	Excluded	Total
Mombasa	Weighted Population Count	34,247	802,149	836,396

County	Analysis specifications	Uptake	Excluded	Total
	% of County's Adult Population	4.1%	95.9%	100.0%
	% of National Uptake/Exclusion Pool	1.9%	3.0%	3.0%
	% of National Adult Population (18+)	0.1%	2.9%	3.0%
Kwale	Weighted Population Count	26,311	437,681	463,992
	% of County's Adult Population	5.7%	94.3%	100.0%
	% of National Uptake/Exclusion Pool	1.5%	1.7%	1.6%
	% of National Adult Population (18+)	0.1%	1.6%	1.6%
Kilifi	Weighted Population Count	11,552	795,161	806,713
	% of County's Adult Population	1.4%	98.6%	100.0%
	% of National Uptake/Exclusion Pool	0.7%	3.0%	2.9%
	% of National Adult Population (18+)	0.0%	2.8%	2.9%
Tana River	Weighted Population Count	5,399	156,732	162,131
	% of County's Adult Population	3.3%	96.7%	100.0%
	% of National Uptake/Exclusion Pool	0.3%	0.6%	0.6%
	% of National Adult Population (18+)	0.0%	0.6%	0.6%
Lamu	Weighted Population Count	1,842	91,250	93,092
	% of County's Adult Population	2.0%	98.0%	100.0%
	% of National Uptake/Exclusion Pool	0.1%	0.3%	0.3%
	% of National Adult Population (18+)	0.0%	0.3%	0.3%
Taita-Taveta	Weighted Population Count	5,264	212,312	217,576
	% of County's Adult Population	2.4%	97.6%	100.0%
	% of National Uptake/Exclusion Pool	0.3%	0.8%	0.8%
	% of National Adult Population (18+)	0.0%	0.8%	0.8%
Garissa	Weighted Population Count	30,941	396,994	427,935
	% of County's Adult Population	7.2%	92.8%	100.0%
	% of National Uptake/Exclusion Pool	1.7%	1.5%	1.5%
	% of National Adult Population (18+)	0.1%	1.4%	1.5%
Wajir	Weighted Population Count	13,639	351,001	364,640
	% of County's Adult Population	3.7%	96.3%	100.0%
	% of National Uptake/Exclusion Pool	0.8%	1.3%	1.3%

County	Analysis specifications	Uptake	Excluded	Total
	% of National Adult Population (18+)	0.0%	1.2%	1.3%
Mandera	Weighted Population Count	29,165	331,494	360,659
	% of County's Adult Population	8.1%	91.9%	100.0%
	% of National Uptake/Exclusion Pool	1.6%	1.3%	1.3%
	% of National Adult Population (18+)	0.1%	1.2%	1.3%
Marsabit	Weighted Population Count	5,105	224,798	229,903
	% of County's Adult Population	2.2%	97.8%	100.0%
	% of National Uptake/Exclusion Pool	0.3%	0.9%	0.8%
	% of National Adult Population (18+)	0.0%	0.8%	0.8%
Isiolo	Weighted Population Count	11,936	140,272	152,208
	% of County's Adult Population	7.8%	92.2%	100.0%
	% of National Uptake/Exclusion Pool	0.7%	0.5%	0.5%
	% of National Adult Population (18+)	0.0%	0.5%	0.5%
Meru	Weighted Population Count	12,770	944,504	957,274
	% of County's Adult Population	1.3%	98.7%	100.0%
	% of National Uptake/Exclusion Pool	0.7%	3.6%	3.4%
	% of National Adult Population (18+)	0.0%	3.4%	3.4%
Tharaka-Nithi	Weighted Population Count	13,535	236,609	250,144
	% of County's Adult Population	5.4%	94.6%	100.0%
	% of National Uptake/Exclusion Pool	0.8%	0.9%	0.9%
	% of National Adult Population (18+)	0.0%	0.8%	0.9%
Embu	Weighted Population Count	35,708	369,856	405,564
	% of County's Adult Population	8.8%	91.2%	100.0%
	% of National Uptake/Exclusion Pool	2.0%	1.4%	1.4%
	% of National Adult Population (18+)	0.1%	1.3%	1.4%
Kitui	Weighted Population Count	17,173	628,289	645,462
	% of County's Adult Population	2.7%	97.3%	100.0%
	% of National Uptake/Exclusion Pool	1.0%	2.4%	2.3%
	% of National Adult Population (18+)	0.1%	2.2%	2.3%

County	Analysis specifications	Uptake	Excluded	Total
Machakos	Weighted Population Count	52,175	859,354	911,529
	% of County's Adult Population	5.7%	94.3%	100.0%
	% of National Uptake/Exclusion Pool	2.9%	3.3%	3.2%
	% of National Adult Population (18+)	0.2%	3.1%	3.2%
Makueni	Weighted Population Count	24,493	572,233	596,726
	% of County's Adult Population	4.1%	95.9%	100.0%
	% of National Uptake/Exclusion Pool	1.4%	2.2%	2.1%
	% of National Adult Population (18+)	0.1%	2.0%	2.1%
Nyandarua	Weighted Population Count	35,469	364,419	399,888
	% of County's Adult Population	8.9%	91.1%	100.0%
	% of National Uptake/Exclusion Pool	2.0%	1.4%	1.4%
	% of National Adult Population (18+)	0.1%	1.3%	1.4%
Nyeri	Weighted Population Count	54,353	487,392	541,745
	% of County's Adult Population	10.0%	90.0%	100.0%
	% of National Uptake/Exclusion Pool	3.1%	1.8%	1.9%
	% of National Adult Population (18+)	0.2%	1.7%	1.9%
Kirinyaga	Weighted Population Count	40,833	386,884	427,717
	% of County's Adult Population	9.5%	90.5%	100.0%
	% of National Uptake/Exclusion Pool	2.3%	1.5%	1.5%
	% of National Adult Population (18+)	0.1%	1.4%	1.5%
Murang'a	Weighted Population Count	77,207	608,946	686,153
	% of County's Adult Population	11.3%	88.7%	100.0%
	% of National Uptake/Exclusion Pool	4.4%	2.3%	2.4%
	% of National Adult Population (18+)	0.3%	2.2%	2.4%
Kiambu	Weighted Population (18 years +) Count	206,989	1,516,754	1,723,743
	% of County's Adult Population	12.0%	88.0%	100.0%
	% of National Uptake/Exclusion Pool	11.7%	5.8%	6.1%
	% of National Adult Population (18+)	0.7%	5.4%	6.1%
Turkana	Weighted Population Count	15,688	471,047	486,735
	% of County's Adult Population	3.2%	96.8%	100.0%

County	Analysis specifications	Uptake	Excluded	Total
	% of National Uptake/Exclusion Pool	0.9%	1.8%	1.7%
	% of National Adult Population (18+)	0.1%	1.7%	1.7%
West Pokot	Weighted Population Count	6,145	281,687	287,832
	% of County's Adult Population	2.1%	97.9%	100.0%
	% of National Uptake/Exclusion Pool	0.3%	1.1%	1.0%
	% of National Adult Population (18+)	0.0%	1.0%	1.0%
Samburu	Weighted Population Count	9,165	145,938	155,103
	% of County's Adult Population	5.9%	94.1%	100.0%
	% of National Uptake/Exclusion Pool	0.5%	0.6%	0.6%
	% of National Adult Population (18+)	0.0%	0.5%	0.6%
Trans Nzoia	Weighted Population Count	32,127	502,359	534,486
	% of County's Adult Population	6.0%	94.0%	100.0%
	% of National Uptake/Exclusion Pool	1.8%	1.9%	1.9%
	% of National Adult Population (18+)	0.1%	1.8%	1.9%
Uasin Gishu	Weighted Population Count	55,617	661,338	716,955
	% of County's Adult Population	7.8%	92.2%	100.0%
	% of National Uptake/Exclusion Pool	3.1%	2.5%	2.5%
	% of National Adult Population (18+)	0.2%	2.3%	2.5%
Elgeyo-Markwet	Weighted Population Count	18,217	232,833	251,050
	% of County's Adult Population	7.3%	92.7%	100.0%
	% of National Uptake/Exclusion Pool	1.0%	0.9%	0.9%
	% of National Adult Population (18+)	0.1%	0.8%	0.9%
Nandi	Weighted Population Count	23,095	486,726	509,821
	% of County's Adult Population	4.5%	95.5%	100.0%
	% of National Uptake/Exclusion Pool	1.3%	1.8%	1.8%
	% of National Adult Population (18+)	0.1%	1.7%	1.8%
Baringo	Weighted Population Count	13,633	342,056	355,689
	% of County's Adult Population	3.8%	96.2%	100.0%
	% of National Uptake/Exclusion Pool	0.8%	1.3%	1.3%

County	Analysis specifications	Uptake	Excluded	Total
	% of National Adult Population (18+)	0.0%	1.2%	1.3%
Laikipia	Weighted Population Count	17,445	297,852	315,297
	% of County's Adult Population	5.5%	94.5%	100.0%
	% of National Uptake/Exclusion Pool	1.0%	1.1%	1.1%
	% of National Adult Population (18+)	0.1%	1.1%	1.1%
Nakuru	Weighted Population Count	53,094	1,269,515	1,322,609
	% of County's Adult Population	4.0%	96.0%	100.0%
	% of National Uptake/Exclusion Pool	3.0%	4.8%	4.7%
	% of National Adult Population (18+)	0.2%	4.5%	4.7%
Narok	Weighted Population Count	35,723	541,466	577,189
	% of County's Adult Population	6.2%	93.8%	100.0%
	% of National Uptake/Exclusion Pool	2.0%	2.1%	2.1%
	% of National Adult Population (18+)	0.1%	1.9%	2.1%
Kajiado	Weighted Population Count	64,743	657,820	722,563
	% of County's Adult Population	9.0%	91.0%	100.0%
	% of National Uptake/Exclusion Pool	3.7%	2.5%	2.6%
	% of National Adult Population (18+)	0.2%	2.3%	2.6%
Kericho	Weighted Population Count	37,254	474,252	511,506
	% of County's Adult Population	7.3%	92.7%	100.0%
	% of National Uptake/Exclusion Pool	2.1%	1.8%	1.8%
	% of National Adult Population (18+)	0.1%	1.7%	1.8%
Bomet	Weighted Population Count	33,817	443,248	477,065
	% of County's Adult Population	7.1%	92.9%	100.0%
	% of National Uptake/Exclusion Pool	1.9%	1.7%	1.7%
	% of National Adult Population (18+)	0.1%	1.6%	1.7%
Kakamega	Weighted Population Count	39,766	967,141	1,006,907
	% of County's Adult Population	3.9%	96.1%	100.0%
	% of National Uptake/Exclusion Pool	2.2%	3.7%	3.6%
	% of National Adult Population (18+)	0.1%	3.4%	3.6%

County	Analysis specifications	Uptake	Excluded	Total
Vihiga	Weighted Population Count	14,712	317,369	332,081
	% of County's Adult Population	4.4%	95.6%	100.0%
	% of National Uptake/Exclusion Pool	0.8%	1.2%	1.2%
	% of National Adult Population (18+)	0.1%	1.1%	1.2%
Bungoma	Weighted Population Count	42,928	811,704	854,632
	% of County's Adult Population	5.0%	95.0%	100.0%
	% of National Uptake/Exclusion Pool	2.4%	3.1%	3.0%
	% of National Adult Population (18+)	0.2%	2.9%	3.0%
Busia	Weighted Population Count	22,012	459,037	481,049
	% of County's Adult Population	4.6%	95.4%	100.0%
	% of National Uptake/Exclusion Pool	1.2%	1.7%	1.7%
	% of National Adult Population (18+)	0.1%	1.6%	1.7%
Siaya	Weighted Population Count	6,608	541,520	548,128
	% of County's Adult Population	1.2%	98.8%	100.0%
	% of National Uptake/Exclusion Pool	0.4%	2.1%	1.9%
	% of National Adult Population (18+)	0.0%	1.9%	1.9%
Kisumu	Weighted Population Count	7,360	667,003	674,363
	% of County's Adult Population	1.1%	98.9%	100.0%
	% of National Uptake/Exclusion Pool	0.4%	2.5%	2.4%
	% of National Adult Population (18+)	0.0%	2.4%	2.4%
Homabay	Weighted Population Count	9,681	584,556	594,237
	% of County's Adult Population	1.6%	98.4%	100.0%
	% of National Uptake/Exclusion Pool	0.5%	2.2%	2.1%
	% of National Adult Population (18+)	0.0%	2.1%	2.1%
Migori	Weighted Population Count	19,379	563,702	583,081
	% of County's Adult Population	3.3%	96.7%	100.0%
	% of National Uptake/Exclusion Pool	1.1%	2.1%	2.1%
	% of National Adult Population (18+)	0.1%	2.0%	2.1%
Kisii	Weighted Population Count	50,347	653,431	703,778
	% of County's Adult Population	7.2%	92.8%	100.0%

County	Analysis specifications	Uptake	Excluded	Total
	% of National Uptake/Exclusion Pool	2.8%	2.5%	2.5%
	% of National Adult Population (18+)	0.2%	2.3%	2.5%
Nyamira	Weighted Population Count	20,980	329,988	350,968
	% of County's Adult Population	6.0%	94.0%	100.0%
	% of National Uptake/Exclusion Pool	1.2%	1.3%	1.2%
	% of National Adult Population (18+)	0.1%	1.2%	1.2%
Nairobi	Weighted Population Count	376,396	2,751,363	3,127,759
	% of County's Adult Population	12.0%	88.0%	100.0%
	% of National Uptake/Exclusion Pool	21.2%	10.4%	11.1%
	% of National Adult Population (18+)	1.3%	9.8%	11.1%
Total	Weighted Population Count	1,772,038	26,370,035	28,142,073
	% of County's Adult Population	6.3%	93.7%	100.0%
	% of National Uptake/Exclusion Pool	100.0%	100.0%	100.0%
	% of National Adult Population (18+)	6.3%	93.7%	100.0%

Source: 2024 FinAccess Household survey data

Annexure 4: County-level insurance uptake by gender

County	Analysis specifications	Female	Male	Total
Mombasa	Weighted adult population in the County	412,962.0	423,434.0	836,396.0
	% adult population within County	49.40%	50.60%	100.00%
	% adult population with insurance within Gender	2.80%	3.10%	3.00%
	% Total of adult population with insurance in the County	1.50%	1.50%	3.00%
Kwale	Weighted adult population in the County	244,676.0	219,315.0	463,991.0
	% adult population within County	52.70%	47.30%	100.00%
	% adult population with insurance within Gender	1.70%	1.60%	1.60%
	% Total of adult population with insurance in the County	0.90%	0.80%	1.60%
Kilifi	Weighted adult population in the County	432,435.0	374,278.0	806,713.0

County	Analysis specifications	Female	Male	Total
	% adult population within County	53.60%	46.40%	100.00%
	% adult population with insurance within Gender	3.00%	2.70%	2.90%
	% Total of adult population with insurance in the County	1.50%	1.30%	2.90%
Tana River	Weighted adult population in the County	83,002.0	79,129.0	162,131.0
	% adult population within County	51.20%	48.80%	100.00%
	% adult population with insurance within Gender	0.60%	0.60%	0.60%
	% Total of adult population with insurance in the County	0.30%	0.30%	0.60%
Lamu	Weighted adult population in the County	42,945.0	50,147.0	93,092.0
	% adult population within County	46.10%	53.90%	100.00%
	% adult population with insurance within Gender	0.30%	0.40%	0.30%
	% Total of adult population with insurance in the County	0.20%	0.20%	0.30%
Taita-Taveta	Weighted adult population in the County	107,356.0	110,220.0	217,576.0
	% adult population within County	49.30%	50.70%	100.00%
	% adult population with insurance within Gender	0.70%	0.80%	0.80%
	% Total of adult population with insurance in the County	0.40%	0.40%	0.80%
Garissa	Weighted adult population in the County	198,538.0	229,397.0	427,935.0
	% adult population within County	46.40%	53.60%	100.00%
	% adult population with insurance within Gender	1.40%	1.70%	1.50%
	% Total of adult population with insurance in the County	0.70%	0.80%	1.50%
Wajir	Weighted adult population in the County	171,833.0	192,808.0	364,641.0
	% adult population within County	47.10%	52.90%	100.00%
	% adult population with insurance within Gender	1.20%	1.40%	1.30%
	% Total of adult population with insurance in the County	0.60%	0.70%	1.30%

County	Analysis specifications	Female	Male	Total
Mandera	Weighted adult population in the County	176,941.0	183,717.0	360,658.0
	% adult population within County	49.10%	50.90%	100.00%
	% adult population with insurance within Gender	1.20%	1.30%	1.30%
	% Total of adult population with insurance in the County	0.60%	0.70%	1.30%
Marsabit	Weighted adult population in the County	109,282.0	120,621.0	229,903.0
	% adult population within County	47.50%	52.50%	100.00%
	% adult population with insurance within Gender	0.80%	0.90%	0.80%
	% Total of adult population with insurance in the County	0.40%	0.40%	0.80%
Isiolo	Weighted adult population in the County	72,850.0	79,358.0	152,208.0
	% adult population within County	47.90%	52.10%	100.00%
	% adult population with insurance within Gender	0.50%	0.60%	0.50%
	% Total of adult population with insurance in the County	0.30%	0.30%	0.50%
Meru	Weighted adult population in the County	486,848.0	470,426.0	957,274.0
	% adult population within County	50.90%	49.10%	100.00%
	% adult population with insurance within Gender	3.40%	3.40%	3.40%
	% Total of adult population with insurance in the County	1.70%	1.70%	3.40%
Tharaka-Nithi	Weighted adult population in the County	128,747.0	121,397.0	250,144.0
	% adult population within County	51.50%	48.50%	100.00%
	% adult population with insurance within Gender	0.90%	0.90%	0.90%
	% Total of adult population with insurance in the County	0.50%	0.40%	0.90%
Embu	Weighted adult population in the County	205,186.0	200,378.0	405,564.0
	% adult population within County	50.60%	49.40%	100.00%
	% adult population with insurance within Gender	1.40%	1.50%	1.40%

County	Analysis specifications	Female	Male	Total
	% Total of adult population with insurance in the County	0.70%	0.70%	1.40%
Kitui	Weighted adult population in the County	348,212.0	297,250.0	645,462.0
	% adult population within County	53.90%	46.10%	100.00%
	% adult population with insurance within Gender	2.40%	2.20%	2.30%
	% Total of adult population with insurance in the County	1.20%	1.10%	2.30%
Machakos	Weighted adult population in the County	460,986.0	450,543.0	911,529.0
	% adult population within County	50.60%	49.40%	100.00%
	% adult population with insurance within Gender	3.20%	3.30%	3.20%
	% Total of adult population with insurance in the County	1.60%	1.60%	3.20%
Makueni	Weighted adult population in the County	308,753.0	287,972.0	596,725.0
	% adult population within County	51.70%	48.30%	100.00%
	% adult population with insurance within Gender	2.10%	2.10%	2.10%
	% Total of adult population with insurance in the County	1.10%	1.00%	2.10%
Nyandarua	Weighted adult population in the County	207,963.0	191,924.0	399,887.0
	% adult population within County	52.00%	48.00%	100.00%
	% adult population with insurance within Gender	1.40%	1.40%	1.40%
	% Total of adult population with insurance in the County	0.70%	0.70%	1.40%
Nyeri	Weighted adult population in the County	280,195.0	261,550.0	541,745.0
	% adult population within County	51.70%	48.30%	100.00%
	% adult population with insurance within Gender	1.90%	1.90%	1.90%
	% Total of adult population with insurance in the County	1.00%	0.90%	1.90%
Kirinyaga	Weighted adult population in the County	218,692.0	209,025.0	427,717.0
	% adult population within County	51.10%	48.90%	100.00%

County	Analysis specifications	Female	Male	Total
	% adult population with insurance within Gender	1.50%	1.50%	1.50%
	% Total of adult population with insurance in the County	0.80%	0.70%	1.50%
Murang'a	Weighted adult population in the County	351,851.0	334,302.0	686,153.0
	% adult population within County	51.30%	48.70%	100.00%
	% adult population with insurance within Gender	2.40%	2.40%	2.40%
	% Total of adult population with insurance in the County	1.30%	1.20%	2.40%
Kiambu	Weighted adult population in the County	886,698.0	837,045.0	1,723,743.0
	% adult population within County	51.40%	48.60%	100.00%
	% adult population with insurance within Gender	6.10%	6.10%	6.10%
	% Total of adult population with insurance in the County	3.20%	3.00%	6.10%
Turkana	Weighted adult population in the County	239,932.0	246,802.0	486,734.0
	% adult population within County	49.30%	50.70%	100.00%
	% adult population with insurance within Gender	1.70%	1.80%	1.70%
	% Total of adult population with insurance in the County	0.90%	0.90%	1.70%
West Pokot	Weighted adult population in the County	149,667.0	138,164.0	287,831.0
	% adult population within County	52.00%	48.00%	100.00%
	% adult population with insurance within Gender	1.00%	1.00%	1.00%
	% Total of adult population with insurance in the County	0.50%	0.50%	1.00%
Samburu	Weighted adult population in the County	79,128.0	75,976.0	155,104.0
	% adult population within County	51.00%	49.00%	100.00%
	% adult population with insurance within Gender	0.50%	0.60%	0.60%
	% Total of adult population with insurance in the County	0.30%	0.30%	0.60%
Trans Nzoia	Weighted adult population in the County	276,860.0	257,626.0	534,486.0

County	Analysis specifications	Female	Male	Total
	% adult population within County	51.80%	48.20%	100.00%
	% adult population with insurance within Gender	1.90%	1.90%	1.90%
	% Total of adult population with insurance in the County	1.00%	0.90%	1.90%
Uasin Gishu	Weighted adult population in the County	362,693.0	354,262.0	716,955.0
	% adult population within County	50.60%	49.40%	100.00%
	% adult population with insurance within Gender	2.50%	2.60%	2.50%
	% Total of adult population with insurance in the County	1.30%	1.30%	2.50%
Elgeyo-Markwet	Weighted adult population in the County	126,688.0	124,362.0	251,050.0
	% adult population within County	50.50%	49.50%	100.00%
	% adult population with insurance within Gender	0.90%	0.90%	0.90%
	% Total of adult population with insurance in the County	0.50%	0.40%	0.90%
Nandi	Weighted adult population in the County	259,071.0	250,749.0	509,820.0
	% adult population within County	50.80%	49.20%	100.00%
	% adult population with insurance within Gender	1.80%	1.80%	1.80%
	% Total of adult population with insurance in the County	0.90%	0.90%	1.80%
Baringo	Weighted adult population in the County	180,705.0	174,984.0	355,689.0
	% adult population within County	50.80%	49.20%	100.00%
	% adult population with insurance within Gender	1.20%	1.30%	1.30%
	% Total of adult population with insurance in the County	0.60%	0.60%	1.30%
Laikipia	Weighted adult population in the County	161,048.0	154,249.0	315,297.0
	% adult population within County	51.10%	48.90%	100.00%
	% adult population with insurance within Gender	1.10%	1.10%	1.10%
	% Total of adult population with insurance in the County	0.60%	0.50%	1.10%

County	Analysis specifications	Female	Male	Total
Nakuru	Weighted adult population in the County	674,664.0	647,945.0	1,322,609.0
	% adult population within County	51.00%	49.00%	100.00%
	% adult population with insurance within Gender	4.70%	4.70%	4.70%
	% Total of adult population with insurance in the County	2.40%	2.30%	4.70%
Narok	Weighted adult population in the County	295,912.0	281,277.0	577,189.0
	% adult population within County	51.30%	48.70%	100.00%
	% adult population with insurance within Gender	2.00%	2.10%	2.10%
	% Total of adult population with insurance in the County	1.10%	1.00%	2.10%
Kajiado	Weighted adult population in the County	365,814.0	356,749.0	722,563.0
	% adult population within County	50.60%	49.40%	100.00%
	% adult population with insurance within Gender	2.50%	2.60%	2.60%
	% Total of adult population with insurance in the County	1.30%	1.30%	2.60%
Kericho	Weighted adult population in the County	258,670.0	252,835.0	511,505.0
	% adult population within County	50.60%	49.40%	100.00%
	% adult population with insurance within Gender	1.80%	1.90%	1.80%
	% Total of adult population with insurance in the County	0.90%	0.90%	1.80%
Bomet	Weighted adult population in the County	245,948.0	231,117.0	477,065.0
	% adult population within County	51.60%	48.40%	100.00%
	% adult population with insurance within Gender	1.70%	1.70%	1.70%
	% Total of adult population with insurance in the County	0.90%	0.80%	1.70%
Kakamega	Weighted adult population in the County	542,367.0	464,540.0	1,006,907.0
	% adult population within County	53.90%	46.10%	100.00%
	% adult population with insurance within Gender	3.70%	3.40%	3.60%

County	Analysis specifications	Female	Male	Total
	% Total of adult population with insurance in the County	1.90%	1.70%	3.60%
Vihiga	Weighted adult population in the County	177,813.0	154,268.0	332,081.0
	% adult population within County	53.50%	46.50%	100.00%
	% adult population with insurance within Gender	1.20%	1.10%	1.20%
	% Total of adult population with insurance in the County	0.60%	0.50%	1.20%
Bungoma	Weighted adult population in the County	452,842.0	401,791.0	854,633.0
	% adult population within County	53.00%	47.00%	100.00%
	% adult population with insurance within Gender	3.10%	2.90%	3.00%
	% Total of adult population with insurance in the County	1.60%	1.40%	3.00%
Busia	Weighted adult population in the County	262,461.0	218,588.0	481,049.0
	% adult population within County	54.60%	45.40%	100.00%
	% adult population with insurance within Gender	1.80%	1.60%	1.70%
	% Total of adult population with insurance in the County	0.90%	0.80%	1.70%
Siaya	Weighted adult population in the County	302,516.0	245,613.0	548,129.0
	% adult population within County	55.20%	44.80%	100.00%
	% adult population with insurance within Gender	2.10%	1.80%	1.90%
	% Total of adult population with insurance in the County	1.10%	0.90%	1.90%
Kisumu	Weighted adult population in the County	356,517.0	317,847.0	674,364.0
	% adult population within County	52.90%	47.10%	100.00%
	% adult population with insurance within Gender	2.50%	2.30%	2.40%
	% Total of adult population with insurance in the County	1.30%	1.10%	2.40%
Homabay	Weighted adult population in the County	327,683.0	266,554.0	594,237.0
	% adult population within County	55.10%	44.90%	100.00%

County	Analysis specifications	Female	Male	Total
	% adult population with insurance within Gender	2.30%	2.00%	2.10%
	% Total of adult population with insurance in the County	1.20%	0.90%	2.10%
Migori	Weighted adult population in the County	315,522.0	267,559.0	583,081.0
	% adult population within County	54.10%	45.90%	100.00%
	% adult population with insurance within Gender	2.20%	2.00%	2.10%
	% Total of adult population with insurance in the County	1.10%	1.00%	2.10%
Kisii	Weighted adult population in the County	382,946.0	320,832.0	703,778.0
	% adult population within County	54.40%	45.60%	100.00%
	% adult population with insurance within Gender	2.60%	2.40%	2.50%
	% Total of adult population with insurance in the County	1.40%	1.10%	2.50%
Nyamira	Weighted adult population in the County	189,572.0	161,397.0	350,969.0
	% adult population within County	54.00%	46.00%	100.00%
	% adult population with insurance within Gender	1.30%	1.20%	1.20%
	% Total of adult population with insurance in the County	0.70%	0.60%	1.20%
Nairobi	Weighted adult population in the County	1,569,621.0	1,558,137.0	3,127,758.0
	% adult population within County	50.20%	49.80%	100.00%
	% adult population with insurance within Gender	10.80%	11.40%	11.10%
	% Total of adult population with insurance in the County	5.60%	5.50%	11.10%
Total	Total weighted adult population	14,493,611.0	13,648,459.0	28,142,070.0
	% of total weighted adult population	51.5%	48.5%	100.0%

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