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# EFFECT OF DEMOGRAPHIC AND SOCIOECONOMIC FACTORS ON HEALTH UTILIZATION IN UASIN GISHU COUNTY, KENYA

**Tanui Kiprotich Leonard[1], Dr. Simeon K. Nganai[2], Dr. Issacs K. Kemboi[3]**
*Department of Economics, School of Business and Economics, Moi University, Kenya*

## ABSTRACT
*This paper empirically examines the influence of demographic and socioeconomic factors specifically gender, age, education, marital status, and employment on health care utilization in Uasin Gishu County, Kenya. The study adopted an explanatory research design and employed a quantitative cross-sectional household survey. Data were collected using structured questionnaires from residents sampled proportionally across the county's six constituencies (n = 385). Hypotheses were tested using binary logistic regression. The results revealed that gender and age had positive and statistically significant effects on utilization while employment had a negative and statistically significant effect. Education showed a positive but borderline effect and marital status was positive but not significant. Taken together, the findings highlight the importance of predisposing (gender, age) and enabling (employment-related time and access constraints) factors in shaping service use. County health managers should prioritize gender-responsive and age-attuned delivery models) and deploy work-compatible access strategies. Complementary health-literacy and navigation supports can help translate the positive albeit marginal education signal into effective use across population groups.*

**KEYWORDS:** *Health care utilization; Gender; Age; Employment; Education; Marital status; Logistic regression; Uasin Gishu County.*

## 1. INTRODUCTION

Health service utilization remains stubbornly unequal worldwide, with need and use misaligned across the social gradient. The most recent global tracking of universal health coverage (UHC) concludes that progress toward SDG 3.8 has stalled: over 4.5 billion people still lack full coverage of essential services and financial hardship from out-of-pocket (OOP) spending is worsening in many settings (WHO & World Bank, 2023; World Bank, 2023). In other words, even where services exist on paper, many people either do not seek care or do so at the cost of catastrophic expenditures—an imbalance that keeps health need from translating into actual use. Classic behavioral theory helps explain this pattern: Andersen's model posits that predisposing factors (e.g., gender, age, education, marital status), enabling factors (e.g., income, insurance, transport), and need (perceived and evaluated) jointly shape care-seeking and service use (Andersen, 1995; Lederle et al., 2021). This framework is widely applied because it connects who people are and what resources they command to the concrete decision to utilize services, making it a useful lens for studying demographic and socioeconomic effects on utilization.

Across sub-Saharan Africa (SSA), multi-country analyses using Demographic and Health Survey (DHS) data consistently show that education, employment, and household wealth are associated with higher use of services, while lack of insurance, lower schooling, and younger age are linked to barriers to access (Tessema et al., 2022; BMC Women's Health, 2022). In these studies, women with secondary or higher schooling, those living in urban areas, and those with autonomy in health decisions are substantially less likely to report big problems accessing care. Conversely, distance to facilities, costs, and permission-seeking norms remain binding constraints. Such results echo Andersen's emphasis on both predisposing and enabling conditions: the same clinical need can yield very different utilization behaviors depending on education, marital status, and employment (Andersen, 1995; Chen & Gu, 2021). The upshot for the region is that improving supply alone does not guarantee equitable use; social position still sorts who gets timely and adequate care.

Kenya reflects these broad SSA patterns while offering unusually rich data to probe them. The Kenya Demographic and Health Survey (KDHS) 2022 reports strong gains in several coverage indicators, including near-universal use of a skilled provider at delivery at the national level, alongside improvements in other maternal and child health metrics (KNBS, 2023). Yet household expenditure and utilization surveys show important counter-currents. Using nationally representative data, the KHHEUS 2018 documented a decline in annual per-capita outpatient visits from 3.1 (2013) to 2.5 (2018) and showed that the poorest quintile averaged 2.2 visits compared with 2.8 in the richest quintile (KNBS, 2018). This suggests that demand-side obstacles like financial, time and informational continue to depress use, especially for poorer and informally employed households. At the same time, OOP payments still expose a meaningful share of households to catastrophic or impoverishing spending, even if Kenya's incidence improved relative to earlier years (Ministry of Health & KIPPRA, 2020–2030; Barasa et al., 2019). These patterns confirm that utilization gaps persist within a system that has otherwise expanded coverage.

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The policy context is shifting quickly. In 2024, Kenya operationalized the Social Health Insurance Fund (SHIF) under the Social Health Insurance Act, 2023, with detailed Social Health Insurance (General) Regulations, 2024 that, among other provisions, require registration with the Social Health Authority and set contribution rules (Republic of Kenya, 2024a, 2024b). The reforms aim to expand primary-care access and reduce OOP barriers through restructured benefit arrangements and financing. However, because SHIF implementation is new, there is limited empirical evidence on whether these financing changes are translating into greater and more equitable utilization across demographic and socioeconomic groups, including informal workers, precisely the sort of enabling-factor shift that Andersen's model predicts should matter for care-seeking. Thus, Kenya offers both a live policy experiment and a need for county-level evidence that can inform enrollment drives, provider empanelment, and demand-generation strategies.

Within Kenya, Uasin Gishu County stands out for relatively strong headline indicators yet likely hidden inequities in who uses what services. KDHS 2022 dissemination materials indicate that Uasin Gishu exceeds national averages on several maternal and child health metrics; for example, county-level fact sheets and media summaries report skilled birth attendance around the mid-90s percent, higher than the national figure, along with higher access to at least basic drinking water services (KNBS, 2023; Kenya News Agency, 2023). Strong supply-side infrastructure anchored by Eldoret and an urbanizing economy help explain these levels. But headline averages can obscure intra-county differences: urban informal settlements, peri-urban belts, and rural peripheries present different cost-time trade-offs for seeking care; youth, unmarried adults, and casually employed workers face specific constraints; and women's autonomy and education vary widely across neighborhoods. County planning documents emphasize ongoing investments in primary care networks and facility quality, yet they leave open questions about who is actually using which services, how often, and with what enabling resources.

Disaggregated national evidence implies that Uasin Gishu's own utilization landscape will be socially patterned. Studies of Kenyan DHS and KHHEUS microdata repeatedly show that education improves health literacy and navigation, marital status shapes decision-making power and social support, and employment, especially in the formal sector, predicts insurance enrollment, which in turn reduces financial barriers and raises use, including preventive care (Barasa et al., 2019; Ngalaka, 2023; PLOS Global Public Health, 2024). For men, norms around help-seeking can suppress primary-care use, especially for noncommunicable conditions; for adolescents and young women, stigma and cost can delay sexual and reproductive health visits. Because Uasin Gishu combines a sizable youthful population with a diverse labor market (formal manufacturing, services, and sizeable informal activity), the gender–age–education–marital status–employment nexus is likely to be a strong predictor of whether residents convert health needs into actual, timely contact with the system. From an Andersen-model perspective, these characteristics operate through both predisposition (e.g., beliefs, norms, knowledge) and enabling resources (e.g., insurance, income, time flexibility, transport).

The national retreat in outpatient visits per capita between 2013 and 2018 illustrates how macro shocks and system frictions can depress use even as service capacity expands. KHHEUS 2018 attributed the decline in part to sectoral disruptions and self-medication, with the steepest shortfalls among poorer households (KNBS, 2018). If the same dynamics operate within Uasin Gishu's low-income settlements or among informal workers, then aggregate county performance could mask micro-pockets of under-utilization, especially for chronic disease management, men's primary care, adolescent services, and completion of antenatal/postnatal contacts. The financial-protection side of UHC remains salient: empirical work using KHHEUS 2018 finds non-trivial levels of catastrophic and impoverishing OOP spending (Barasa et al., 2019), and Kenya's UHC policy documents still flag OOP at roughly one-third of current health expenditure in 2018 (Ministry of Health & KIPPRA, 2020–2030). In turn, these financial pressures interact with employment type: informal and casual workers face unstable incomes and rigid time costs, which depress utilization unless benefits and scheduling are tailored to their constraints.

Several features make a Uasin Gishu–focused analysis both timely and actionable. First, the post-pandemic period has left uneven patterns of care-seeking in Kenya, with evidence of deferred care and a continued need to re-equilibrate utilization toward appropriate levels. Second, the SHIF rollout offers a natural opportunity to measure whether employment status (formal vs. informal) and insurance enrollment are mediating increased use, especially among youth and uninsured groups. Third, while maternal health indicators are strong, other domains (e.g., adult primary care, continuity for hypertension/diabetes, postnatal care completion, preventive screenings, men's health) may still exhibit social gradients that are invisible in headline statistics. Put differently, the county must answer not only "Are services available?" but also "Who is using them, for what, and under what enabling conditions?" and it must do so with disaggregation by gender, age, education, marital status, and employment.

The problem this study addresses, therefore, is the persistent misalignment between health need and health service use among specific social groups in Uasin Gishu County, despite generally strong county averages. The knowledge gaps are concrete. First, there is little county-specific, multi-domain profiling of utilization that jointly examines gender, age, education, marital status, and employment for services beyond maternal and child health. KDHS provides national and some county snapshots, but decision makers need granular, service-type evidence on who uses what, how often, and how quickly (KNBS, 2023). Second, there is limited empirical analysis of the employment – insurance – utilization nexus under SHIF whether the 2024 financing

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reforms are narrowing gaps for informal workers and youth in Uasin Gishu. Third, while national and SSA studies link education to better quality-adjusted contact (e.g., content of ANC), few county analyses distinguish mere contact from effective use (adequate content and continuity), especially for chronic disease management. Fourth, the independent effects of marital status and gender norms on timeliness of care early ANC initiation, prompt care for acute illness remain under-studied at county level once other socioeconomic factors are controlled. Finally, intra-county heterogeneity such as urban informal settlements versus rural peripheries has not been systematically mapped with an equity lens, making it hard to target outreach (e.g., flexible hours for shift workers, workplace clinics for markets or transport hubs). Guided by Andersen's behavioral model, the study quantified how demographic (gender, age) and socioeconomic (education, marital status, employment) factors shape utilization in Uasin Gishu by operating through predisposition and enabling resources (education, health literacy; employment, insurance, marital status, decision space and social support).

## 2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Sikka et al. (2021) analyze baseline data from 1,447 adults with elevated blood pressure enrolled in the LARK Hypertension study in western Kenya (Kosirai and Turbo divisions, the latter in Uasin Gishu County), using latent class regression to classify utilization and costs; they find women report more outpatient visits and prescriptions than men (39% vs 28% and 42% vs 30%, respectively) but also worse self-reported health and higher odds of belonging to a high-cost utilizer class, pointing to a persistent sex gap in both service use and financial burden. In a complementary service-delivery experiment, Patel et al. (2019) evaluate "male clinics" in rural Kenya, comparing utilization before and after introducing male-friendly hours and male providers within existing facilities; they report marked increases in men's primary care attendance and preventive service uptake showing that demand-side barriers tied to gender norms (e.g., stigma, waiting areas perceived as maternal/child spaces) can be structurally reduced when the service environment is reframed for men. Wambiya et al. (2021) conduct a cross-sectional study in a Nairobi informal settlement, employing multivariable models to parse predictors of private versus public utilization; they observe that female sex is positively associated with primary care use while financial and insurance constraints steer both sexes toward public facilities, underscoring how gender intersects with affordability and insurance coverage to shape pathways into care. Kiptim et al. (2022) examine policy linkages between women's economic agency and service use in Kenya using nationally representative data and a utility-maximization framework; they show that a higher share of female income in the household correlates strongly with facility delivery, making the case that gendered financial empowerment translates into concrete utilization of modern obstetric services. In surgical care, Shearer et al. (2021) analyze registry data from a tertiary hospital in Eldoret and show gender differences in NHIF enrollment and health-seeking behaviors surrounding surgical admissions, with implications for timely access to high-cost inpatient services that require prepayment or insurance. Zooming out across the region, Seidu (2020) runs multilevel logistic regressions on DHS data from 24 sub-Saharan African countries and finds that gendered disadvantages (e.g., lack of insurance, manual occupations) heighten barriers to care among women, but also that marital status and wealth can mitigate some of these barriers highlighting the complex, bidirectional ways gender interacts with other socioeconomic attributes to affect access and use. Finally, Ilinca et al. (2019) decompose Kenya's KHHEUS 2018 data and show pro-rich inequity in outpatient, inpatient, and preventive care; their decomposition indicates that education and living standards are the strongest drivers of inequality, while gender and age also contribute positively to pro-rich distributions, evidence that gender gaps in utilization are nested within broader socioeconomic gradients.

Seidu (2020) reports that women aged 35–39 have lower odds of encountering access barriers than those 45–49, after adjusting for education, employment, insurance, parity, and residence; the study suggests an age-related U-shape where very young and older women are more constrained, an effect consistent with life-course variations in economic autonomy, fertility, and mobility. Nishan et al. (2025) test the relationship between age and care use among 51,298 female youths across eight low- and lower-middle-income countries using DHS-based regressions and show that those aged 20–24 are significantly more likely to access care than those 15–19, with Kenyan estimates indicating a positive gradient across primary, secondary, and higher education strata that interacts with age to raise odds of facility visits; they argue that greater autonomy and health awareness in early adulthood partly explain the pattern. Bain et al. (2022) examine maternal healthcare among 43,786 young women (15–24) in 28 SSA countries and, using multilevel logistic models, find that women in their early 20s are more likely than late-teen peers to achieve recommended ANC, skilled birth attendance, and postnatal care, net of wealth, education and age gradient with specific implications for adolescent-friendly services. At the other end of the spectrum, Age and Ageing contributors (2022) synthesize regional evidence to conclude that older Africans (60+) face inadequate, geriatric-responsive services; they forecast a steep rise in the 60+ population to 235 million by 2050 and warn that informal employment histories leave many older adults without pensions, exacerbating cost barriers and under-utilization of needed care. Kenya-specific demographic reviews point to a growing older-adult population and system readiness gaps (long-term care, chronic disease management), implying that age is both a biological and structural determinant of utilization patterns as cohorts age into noncommunicable disease and functional-limitation care needs. In LARK, Sikka et al. (2021) explicitly include age in latent-class membership for utilization and show that age interacts with insurance and employment to sort individuals into "high-cost utilizer," "low-cost utilizer," and "non-utilizer" categories, evidence that age is not merely a proxy for need but part of a multi-factor utilization phenotype. Together, these results indicate that in Uasin Gishu and similar Kenyan

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settings, adolescents and older adults remain two ends of the age range where utilization constraints concentrate adolescents due to limited autonomy and older adults due to financing, transport, and service design gaps.

Nishan et al. (2025) observe that education is a robust predictor of healthcare use among female youths: in Kenya and Tanzania, even primary education increases the likelihood of visiting a facility relative to no education, and in Kenya the effect strengthens at secondary and higher levels; by contrast, Burkina Faso shows an anomalous negative association at some levels, attesting to important context heterogeneity. Bain et al. (2022) similarly find, across 28 SSA countries, that both maternal and partner schooling raise the odds of ANC, skilled attendance, and PNC among young women, suggesting that education amplifies health literacy, navigational skills, and bargaining power in care decisions. Using Kenya's KHHEUS 2018, Ilinca et al. (2019) quantify how educational achievement both of individuals and household heads is a main driver of pro-rich inequity, especially for preventive services; their decomposition shows that education's contribution to inequality is larger for prevention than for inpatient care, indicating that schooling particularly conditions uptake of discretionary, forward-looking services. Mohamed et al. (2021) evaluate utilization in an urban informal settlement and find education gradients in the choice between private and public providers higher schooling correlates with private sector use, while lower schooling and financial barriers steer people toward public and faith-based facilities, these is evidence that education shapes both whether and where people seek care. Regionally, Seidu (2020) documents that women with no schooling have substantially higher odds of reporting barriers to care than those with higher education (AOR≈1.80), and that the absence of health insurance compounds the schooling penalty, an interaction relevant to Kenyan reforms that tie benefit navigation to literacy. At the maternal-child interface, a 2025 Nature Communications analysis of 36 countries links low education to membership in low-utilization clusters for maternal and child services, reinforcing the case that education is a primary lever for equitable uptake of essential services. Together these studies indicate that, in Uasin Gishu County, education likely operates through health literacy, income potential, and insurance literacy to raise utilization, with the steepest education gradients appearing in preventive and maternal services.

Bain et al. (2022) report, via multilevel models, that unmarried young women in SSA have lower odds of ANC, skilled delivery, and PNC than married peers, net of covariates such as education and wealth suggesting that partner support, pooled resources, and social approval embedded in marriage facilitate service use among young mothers. Ayalew et al. (2019) focus on married adolescents in 13 SSA countries and find that, despite marriage, adolescent wives face low utilization of maternal services due to intersecting vulnerabilities (youth, parity, education deficits), implying that the protective effect of marriage is not uniform across age cohorts. Delprato and Akyeampong (2021) analyze early marriage across SSA and Southwest Asia and show that delaying marriage is associated with higher use of prenatal, postnatal, and skilled attendance services, consistent with the idea that early union formation compresses schooling and income accumulation, thereby constraining utilization. Seidu (2020) finds that married women, compared with widowed women, have lower odds of reporting access barriers across 24 SSA countries, after adjusting for wealth, residence, and insurance an indication that widowhood and single status carry distinctive economic and mobility constraints that suppress use. A multi country neonatal survival study in East Africa shows that marital status interacts with pregnancy intention to shape neonatal outcomes, indirectly capturing differential care utilization during pregnancy and after birth; the authors argue that unmarried status and mistimed pregnancies correlate with lower engagement with antenatal/postnatal services. In marginalized Kenyan populations such as pastoralist communities, recent fieldwork finds that polygynous marriage patterns and low female schooling are associated with lower uptake of ANC and facility delivery, highlighting marriage-system heterogeneity within the country and its implications for utilization. Collectively, the literature implies that marital status is a proxy for resource pooling and social support that can either facilitate or impede health-seeking, with adolescent marriage and widowhood emerging as high-risk statuses for under-utilization and poorer outcomes in settings like Uasin Gishu.

A PLOS ONE machine-learning study by Mutuku et al. (2023) uses KHIBS - style household datasets and shows that employment-related income, social security use, and education rank among the strongest predictors of health insurance uptake in Kenya; because insurance lowers direct prices at the point of service, the authors infer a downstream effect on utilization especially for outpatient episodes via affordability channels. Muthiani (2025) examines socioeconomic determinants of NHIF uptake using KHHEUS 2018 and concludes that employment status, marital status, age, gender, and education all significantly shape enrollment, recommending subsidies and curriculum-level insurance literacy as policy levers, evidence that formal and stable employment improves financial access to care. In a cohort-analytic design leveraging Kenya's Integrated Household Budget Survey, Mugo (2023) assesses the impact of health insurance enrollment on health outcomes and finds that insurance is associated with lower mortality, a pathway plausibly mediated by increased utilization and better continuity of care. At the micro-labor market level, Kipchirchir et al. (2025) analyze boda-boda riders and find that higher earnings and formal education increase the probability of insurance enrollment, while perceived unaffordability depresses it; since informal workers dominate Kenya's labor force, these findings connect employment informality to under-insurance and, by extension, under-utilization of needed care. Kenyan evidence from informal settlements likewise shows that insurance status and the ability to pay are chief determinants of where and whether care is sought, with employment patterns shaping both; Wambiya et al. (2021) find that people without insurance gravitate to public providers and that out-of-pocket constraints reduce private care use,

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indicating that labor-market position indirectly structures utilization through financing channels. Ilinca et al. (2019) further report that formal employment and higher living standards are concentrated among richer households and contribute to pro-rich inequality in service use, particularly in preventive and private-sector care; their decomposition underscores employment's role in generating the financial and informational capacities that enable utilization. At the system level, WHO's 2023 health-financing assessment of Kenya flags fragmentation and coverage gaps that disproportionately affect informal workers, while Kenya's 2024–2025 shift from NHIF to a Social Health Authority is framed as an attempt to expand risk pooling and reduce point-of-service costs reforms expected to increase utilization among lower-income and informally employed households in counties like Uasin Gishu if implementation closes affordability and provider-payment gaps.

## 3. TARGET POPULATION AND DATA

The target population for this study comprised all residents of Uasin Gishu County, Kenya across the six constituencies—Soy, Kapseret, Kesses, Turbo, Moiben, and Ainabkoi—totaling 1,163,186 persons as per the 2019 Kenya Population and Housing Census. In line with the study objectives, the population is stratified by constituency to reflect both urban and rural settlement patterns. Primary data was collected from household respondents (urban and rural) using a structured, self-administered questionnaire, while the KNBS (2019) census figures provide the sampling frame for proportional allocation across strata. Unlike a census, the study employs sampling to obtain a representative cross-section of households from each constituency.

**Table 1: Target Population**

| Strata (Constituency) | Target population (y) | Level % Target Population (t) |
|---|---|---|
| Soy | 229,094 | 19.70 |
| Kapseret | 198,499 | 17.07 |
| Kesses | 148,798 | 12.79 |
| Turbo | 267,273 | 22.98 |
| Moiben | 181,338 | 15.59 |
| Ainabkoi | 138,184 | 11.88 |
| **Total (x)** | **1,163,186** | **100.00** |

***Source: KNBS (2019); computations by Researcher (2025).***

### 3.1 Sample Size

The study utilized Cochran's formula to determine the sample size, the formula is widely accepted in Survey research when the population size is large and the proportion of interest like the health utilizing proportion is unknown or assumed to be 50%. (Cochran in 1977). The formula was given by;

$$n_0 = \frac{z^2.\ p.\ (1-p)}{e^2} = \frac{(1.96)^2.\ 0.5.\ (1-0.5)}{(0.05)^2} = 384.16 \sim$$

385 Households

Where: $n_0$ = required sample size, z= z-value (1.96 for 95% confidence), p = estimated proportion of an attribute present in the population (use 0.5 for maximum variability) and e = desired margin of error (e.g., 5% = 0.05).

Data was analyzed using Stata version 14 using the Binary Logistic Regression, in this model the probability that an individual accessed healthcare services in the past 12 months. is determined, 1 = Accessed healthcare while 0 = Did not access healthcare. A binary logistic regression was conducted to identify the influence of age, gender, income, education and marital status on the likelihood of utilizing healthcare.

### 3.2 Model Specification

Count data faces the problems of overdispersion and excess zeros, to handle this problem, the study used of the hurdle model.

$$Pr\left(Yi = 0 \,|Xi\right) = f_1(0) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The positive counts form the second-density function $f_2(.)$

$$Pr\left(Y = K \,|X\right) = \begin{cases} f_1(0) & K = 0, \\ \frac{1-f_1(0)}{1-f_2(0)}\ \mathrm{X}\ f_2(.) & K > 0 \end{cases} \quad \ldots\ldots\ldots\ldots(2)$$

The model collapses to the standard count model only if $f_1(0) = f_2(0)$

The first density function $f_1[.]$ is normally estimated using logistic regression while the second-density function $f_2[.]$ is estimated using count data models like Poisson or negative binomial model. The mean of the hurdle model is determined by the probability of

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crossing the threshold and by the moments of the zero-truncated density as follows:

$$E\left[Y_i \middle| X\right] = \frac{1-f_1(0|X)}{1-f_2(0|X)}\, x\, \mu_2(X) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Where $\mu_2(X)$ is the untruncated mean in density $f_2(y|X)$ . The variance of hurdle model is given by ;

$$var\left[Y_i \middle| X\right] = \frac{1-f_1(0|X)}{1-f_2(0|X)}\, x\, \sigma_2^2 + \frac{(1-f_1(0|X))\left(f_1(0|X)-f_2(0|X)\right)}{(1-f_2(0|X))^2}\, x\, \left(\mu_2(X)\right)^2 \ldots\ldots\ldots(4)$$

Generally, $\pi_i$ is modeled with a logistic regression and $\mu_i$ is modeled as a log-linear regression. The ZI model can be written as,

$$Log\ \mu_1 = (x_1^T \alpha, Logit\ (\pi_1) = Z_1^T \beta$$

Where: $\alpha$ and $\beta$ are regression coefficients for$x_1^T$ the covariates and $Z_1^T \beta$

We assume that the decision to utilize healthcare services is determined by some identified factors (independent variables) as shown below.

$U= (\beta_0 + \beta_1X_1 + \beta_2X_2 \ldots\ldots + \beta_nX_n)VST= \beta_0+ \beta_1Gen_1 + \beta_2Ag_2 + \beta_3Edu_3+ \beta_4MS_4$ ……..(5)

Where: VST is the number of Visits to the hospital. Gen is the Gender, Ag is the Age, Edu is Education and MS is the Marital Status, $\beta_1, \beta_2, \beta_3, \beta_4$ are regression Coefficients.

## 4. DATA ANALYSIS AND INTERPRETATION

### 4.1 Diagnostic Test

The Variance Inflation Factor (VIF) is a diagnostic tool used to detect multicollinearity among explanatory variables in a regression model. A VIF value greater than 10 generally indicates high multicollinearity that may distort the regression estimates (Kutner et al., 2005). In the presented results, the VIF values for all five variables—Gender (1.02), Age (1.40), Education (1.28), Marital status (1.28), and Employment (1.16)—are well below the commonly used threshold of 10 and even the more conservative threshold of 5 suggested by some researchers (O'Brien, 2007). The mean VIF of 1.28 further reinforces that multicollinearity is not a concern in this dataset. A mean VIF close to 1 implies very low intercorrelation among the predictors, indicating that they are not linear combinations of one another to any problematic degree (Hair et al., 2010).

This suggests that each independent variable contributes unique information to the model, and the parameter estimates are likely to be reliable and interpretable. These low VIF values justify the inclusion of all listed variables in the regression model without the need for corrective actions like variable exclusion, transformation, or combining predictors. Centering or regularization for the sole purpose of addressing collinearity is unnecessary here; analysts can proceed with inference and prediction confident that multicollinearity is unlikely to bias standard errors or obscure substantive relationships.

**Table 2: Multicollinearity Test Results**

| Variable | VIF | 1/VIF |
|---|---|---|
| Gender | 1.02 | 0.975795 |
| Age | 1.40 | 0.713223 |
| Education | 1.28 | 0.779818 |
| Marital status | 1.28 | 0.783155 |
| Employment | 1.16 | 0.859734 |
| Mean VIF | 1.28 | |

**Source: Field data (2025)**

### 4.2 Goodness of Fit Test

The non-significant Pearson goodness-of-fit test (p = 0.4462) indicates no evidence of lack of fit, so the logistic model appears to describe the grouped data adequately given 229 covariate patterns and 223 degrees of freedom.

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**Table 3: Goodness-of-Fit Test (Pearson Chi-Square)**

| Metric | Value |
|---|---|
| Observations | 299 |
| Covariate patterns | 229 |
| Pearson $\chi^2$ (df=223) | 225.19 |
| p-value | 0.4462 |

**Source: Field data (2025)**

### 4.3 Model Information Criteria

AIC and BIC assess out-of-sample fit while penalizing model complexity; lower values are better when comparing candidate models estimated on the same data. Here the fitted model improves the log-likelihood over the null (from −191.8943 to −188.1360, a modest gain), yielding AIC = 388.27 and BIC = 410.47. These numbers are not absolute "fit" scores; they become informative only in relative comparisons—use them to choose among alternative specifications (e.g., adding/removing predictors, interactions), favoring the model with the smallest AIC/BIC, noting that BIC penalizes complexity more strongly than AIC.

**Table 4: Model Information Criteria**

| Metric | Value |
|---|---|
| Observations | 299 |
| Log-likelihood (null) | −191.8943 |
| Log-likelihood (model) | −188.1360 |
| Degrees of freedom (parameters) | 6 |
| AIC | 388.2720 |
| BIC | 410.4746 |

**Source: Field data (2025)**

### 4.3 Regression Results

The purpose of this study was to analyze the effects of five demographic and socioeconomic predictors Gender (gen), Age, Education, Marital Status, and Employment on health care utilization in Uasin Gishu County using a binary logistic regression framework. Consistent with the Behavioral Model of Health Services Use, we treat gender and age as predisposing factors, education and employment as key enabling (or constraining) resources, and interpret coefficients as log-odds that can be exponentiated to odds ratios for substantive meaning (Andersen, 1995; Hosmer, Lemeshow, & Sturdivant, 2013). Five hypotheses corresponding to the predictors were tested. Below, we report statistical decisions ($\alpha = .05$), convert estimates to odds ratios (OR = e^β), and place the findings in the context of prior evidence on utilization patterns in Kenya and sub-Saharan Africa.

Gender has a positive and statistically significant association with utilization (β = 1.2856, SE = 0.4662, z = 2.76, p = .006; 95% CI for β: 0.3718, 2.1994). Converting to odds, OR = e^1.2856 = 3.62 (95% CI: 1.45, 9.02). Interpreted substantively, individuals in the coded gender category (gen = 1) have about 3.6 times the odds of using health services relative to the reference gender, holding age, education, marital status, and employment constant. This sizeable effect echoes Kenyan and regional evidence that health-seeking is gendered: women often accumulate more primary-care and preventive contacts, while men may delay care for acute and chronic conditions; at the same time, women can also face higher financial and psychosocial burdens once they present to care (Sikka et al., 2021; Wambiya, Otieno, Mutua, Donfouet, & Mohamed, 2021; Seidu, 2020). The persistence of a gender effect after adjustment indicates gender-responsive service design (e.g., male-friendly hours and spaces; women-centered financial protection) remains warranted.

Age shows a positive, statistically significant association with utilization (β = 0.0436, SE = 0.0160, z = 2.73, p = .006; 95% CI for β: 0.0123, 0.0750). On the odds scale, OR = e^0.0436 = 1.045 (95% CI: 1.012, 1.078). Thus, each additional year is associated

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with about a 4.5% increase in the odds of using care, ceteris paribus. Though modest annually, the effect accumulates over the life course, consistent with higher perceived and evaluated need at older ages and with evidence that older adults draw more frequently on outpatient and chronic-care services (Andersen, 1995; Bain et al., 2022). The CI excludes 1.0, suggesting a robust monotonic gradient. In practice, this supports age-attuned delivery models (e.g., chronic-care clubs, medication synchronization, transport support) that reduce barriers that grow with age.

Education's coefficient is positive but borderline (β = 0.4330, SE = 0.2328, z = 1.86, p = .063; 95% CI for β: −0.0234, 0.8893). The point estimate implies OR = e^0.4330 = 1.54 (95% CI: 0.98, 2.43): the coded education category is associated with ~54% higher odds of utilization, but the 95% CI narrowly includes 1.0. The direction and magnitude align with extensive evidence that schooling improves health literacy, system navigation, and insurance literacy, raising use—especially of preventive and maternal services (Seidu, 2020; Bain et al., 2022). Kenyan decomposition work shows education is a major driver of pro-rich inequity in service use, particularly for prevention (Ilinca, Ondera, Maraga, & Chuma, 2019). The borderline significance here may reflect sample size, broad education categories, or collinearity with employment and marital status. From a policy perspective, the weight of prior evidence and the near-threshold p-value suggest that education-sensitive interventions (plain-language counseling, navigation assistance) could still yield meaningful gains.

Marital status is positive but not significant (β = 0.2928, SE = 0.2727, z = 1.07, p = .283; 95% CI for β: −0.2418, 0.8274). The implied OR = e^0.2928 = 1.34 (95% CI: 0.79, 2.29). The point estimate suggests that the coded marital group has ~34% higher odds of use than the reference, but the wide CI indicates uncertainty. Literature often finds that marriage can boost utilization via pooled resources and decision support, whereas widowhood or single status can dampen use; however, these effects are heterogeneous by age and intersect with education and income (Bain et al., 2022; Seidu, 2020). In Andersen's terms, marital status may influence utilization indirectly by shaping enabling resources, some of which are absorbed by Education and Employment in this model (Andersen, 1995). Stratified analyses (e.g., adolescents vs. older adults, women vs. men) may uncover masked subgroup effects.

Employment is negative and significant (β = −1.2972, SE = 0.4989, z = −2.60, p = .009; 95% CI for β: −2.2750, −0.3194). The implied OR = e^−1.2972 = 0.27 (95% CI: 0.10, 0.73), indicating that being in the coded employment category is associated with ~73% lower odds of using care compared with the reference group, net of other variables. This "employment penalty" likely reflects opportunity costs (clinic hours coinciding with work), time rigidity (especially in informal jobs), and differences in benefit coverage patterns widely noted in Kenya and similar settings (Wambiya et al., 2021; WHO & World Bank, 2023). Kenyan equity analyses show that formal employment and higher living standards cluster in higher-use groups, whereas informal workers face financing and scheduling frictions that depress utilization (Ilinca et al., 2019). The magnitude and precision of our estimate support work-compatible service models (after-hours/weekend clinics, worksite outreach, appointment systems that minimize queuing) to close employment-related gaps.

Three signals are clear. First, gender and age are robust positive predictors of utilization—consistent with a large literature showing gendered patterns of health-seeking and a life-course gradient in need and contact (Sikka et al., 2021; Bain et al., 2022). Second, employment exerts a strong negative effect, matching Kenyan evidence that time/affordability constraints among workers—especially those in informal and casual employment—suppress use (Ilinca et al., 2019; Wambiya et al., 2021; WHO & World Bank, 2023). Third, education trends positive but is borderline at α = .05; given prior findings that schooling underpins preventive and maternal care uptake and reduces reported access barriers, education-sensitive communication and navigation supports remain advisable (Seidu, 2020; Bain et al., 2022). While marital status was not significant in the pooled model, subgroup analyses may reveal context-specific effects (e.g., adolescents, widowed older adults). Methodologically, interpreting coefficients on the odds scale and attending to confidence intervals rather than p-values alone accords with best practice in applied logistic regression (Hosmer et al., 2013). Substantively, the pattern maps cleanly onto Andersen's framework: predisposition (gender, age) and enabling resources and constraints (education, employment) jointly shape whether perceived need becomes actual utilization (Andersen, 1995). For Uasin Gishu, the results motivate a package of gender-responsive, age-attuned, and work-compatible delivery strategies, coupled with health-literacy and navigation supports, to raise effective use across population groups.

**Table 5: Logistic Regression Results**

| Variable | Coefficient | Std. Error | z-value | p-value | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|
| Gender (gen) | 1.285622 | 0.466224 | 2.76 | 0.006 | 0.37184 | 2.199404 |
| Age | 0.043618 | 0.016004 | 2.73 | 0.006 | 0.012251 | 0.074985 |
| Education | 0.43296 | 0.232836 | 1.86 | 0.063 | -0.02339 | 0.88931 |
| Marital Status | 0.292801 | 0.27274 | 1.07 | 0.283 | -0.24176 | 0.827361 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| Employment | -1.29716 | 0.498883 | -2.6 | 0.009 | -2.27496 | -0.31937 |
| Constant (_cons) | -4.29364 | 1.236544 | -3.47 | 0.001 | -6.71722 | -1.87006 |

**Source, Researcher (2025)**

## 5. CONCLUSION AND RECOMMENDATION

This study examined the relationship between demographic and socioeconomic determinants specifically Gender, Age, Education, Marital Status, and Employment and Health Care Utilization in Uasin Gishu County. Household respondents drawn from the county's six constituencies provided primary data, and a binary logistic regression model was employed to assess both the independent and joint effects of the predictors on the odds of utilizing care. The findings indicate that Gender and Age have positive and statistically significant effects on utilization, while Employment exhibits a statistically significant negative effect. Education shows a positive but borderline effect (marginal at the 10% level), and Marital Status is positive but not statistically significant at the 5% level. Interpreted on the odds scale, the coded gender group had higher odds of using services (OR ≈ 3.62), each additional year of age raised odds modestly (OR ≈ 1.05 per year), and being in the coded employment category reduced odds substantially (OR ≈ 0.27). These results suggest that predisposing factors (gender, age) and enabling constraints (time/benefits linked to employment) meaningfully shape whether perceived health needs translate into actual service use, even when accounting for education and marital status.

In light of these findings, several recommendations are offered. First, county health managers should implement gender-responsive service models. This includes male-friendly clinic hours and spaces (e.g., evening/weekend "men's health" sessions, fast-track queues for quick screenings) alongside strengthened support for women's access (e.g., continuity of ANC/PNC, respectful care, targeted financial protection for maternal and reproductive services). These measures address the strong gender effect by reducing stigma and time barriers for men while sustaining women-centered pathways that already drive higher contact.

Secondly, service delivery should be age-attuned. For older adults—whose odds of utilization increase with age but who face mobility and multimorbidity challenges—facilities should expand chronic-care clubs, medication synchronization, differentiated refill models, and community outreach with transport support. For adolescents and young adults, youth-friendly corners, confidential counseling, and flexible appointment systems can convert need into timely use, particularly for sexual and reproductive health and mental health.

Third, to counter the sizable employment-related penalty, the County Department of Health should roll out work-compatible access options: extended clinic hours (early mornings, evenings, weekends), workplace/mobile outreaches in markets, industrial areas, and transport hubs, and appointment systems that minimize queuing. Where feasible, integrate on-site diagnostics (basic labs, BP/BS checks) and e-referrals so employed clients complete more steps per visit. For public facilities, piloting "express lanes" for follow-up and medicine refills can further reduce opportunity costs that deter workers—especially those in informal or shift-based jobs.

Fourth, although Education was only marginally significant, the positive direction warrants health-literacy and navigation supports that make care easier to use for people with lower schooling. Plain-language counseling, multilingual/visual job aids, digital reminders, and peer navigators can raise effective use of preventive and chronic services. These efforts should be paired with benefits literacy (how to enroll, what's covered, where to go) so that information barriers do not blunt demand.

Fifth, while Marital Status was not significant at the 5% level in the pooled model, the county should still monitor subgroups where marital context may matter (e.g., adolescents, single parents, widowed older adults). Targeted community health worker (CHW) follow-up, social support linkages, and group education can help translate need into use for those with weaker household support.

Sixth, financing and coverage mechanisms should be leveraged to reduce time and cash barriers that interact with employment status. County teams should integrate on-site or assisted enrollment into the prevailing national scheme during clinic visits and community outreaches, proactively enrolling informal workers and encouraging facility empanelment that brings services closer to workplaces. Aligning appointment cycles with pay cycles and offering small transport or time-saving incentives for follow-up visits can further improve completion of care.

Seventh, to institutionalize these gains, the county should adopt a micro-planning and performance approach: (a) set constituency-level targets for male attendance, after-hours visits, chronic-care continuity, and adolescent service uptake; (b) track indicators monthly; and (c) iterate operating hours and outreach sites based on utilization patterns. Facility managers should receive simple dashboards that display age-by-sex utilization and revisit rates so they can adjust rosters and clinic flows in real time.

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