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Research article

Analysis of incidence, intensity, and gender perspective of multidimensional urban poverty in Kenya

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ABSTRACT

Poverty continues to be one of the biggest challenges facing many economies worldwide, and its incidences and intensities are very high in developing economies. This paper utilized the Alkire-Foster (AF) method to compute the multidimensional poverty index (MPI) and analyze the incidence and intensity of multidimensional poverty among urban households in Kenya. The findings indicated that 8.7 % of urban households are multidimensionally deprived in 33.3 % of the selected dimensional indicators. Also, the results showed that over 50 % of urban households are deprived of drinking water and sanitation services. In addition, the findings revealed that higher poverty incidence, intensity, and urban multidimensional poverty exist among female-headed households, old household headships, and households residing in peri-urban regions. The Probit regression analysis indicated that large household size, number of children under five years, household head age, gender, marital status, urban food insecurity, health status, and residing in Malaria endemic zone are significant positive predictors of urban multidimensional poverty. On the other hand, an increase in the number of educated women, owners of insurance coverage, agricultural land, and wealthy and home-owning households is linked to a decline in urban multidimensional poverty. The paper professes that policymakers should cautiously consider household socioeconomic differences while designing poverty alleviation policies.

1. Introduction

Poverty is one of the most deleterious challenges plaguing many economies worldwide, and its incidences and intensities are very high in low-and middle-income countries (LMICS) [1]. Although several efforts have been implemented to alleviate poverty in all its dimensions, most LMICS still face enormous challenges to poverty eradication due to its dynamic, multidimensional, context-specific complexities [2]. For instance, national patterns of poverty obscure distinctive variations across countries, states, counties, rural and urban areas, and socioeconomic clusters of people [3,4]. Even though poverty is largely a global social issue, it is a more pressing and difficult policy concern in several developing countries, predominantly Sub-Saharan African countries where urbanization is stirring, pushing a significant share of citizens living in abject poverty, with over 36 % of the entire population regarded as multidimensionally poor [5–7]. Moreover, although trendemous efforts have been put forth to contain the poverty situation in SSA region, the intensity and incidence vary significantly, with poverty headcount averaging above 35 % in the last three decades as described in Appendix Figure A. Multidimensional poverty index also points a fairly decreasing trend in SSA, though with dynamic trends in the

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recent decade. As described in Fig. 1, the MPI is still high in the SSA region, with an average value above 0.20 between 2010 and 2022 [8]. This can be attributed to the distinct MPI values of each country in the region. For example, about 39.8 % of the population in South Africa is multidimensionally poor [9]. Using a poverty line of $2.15 per day in 2019, 35.03 % of Kenyan population, 44.95 % of Tanzanian population, 50.91 % of Niger's population, 30.86 % of Nigerian population, 31.12 % of the Angolan population, 60.79 % of Zambian population, 74.38 % of Mozambique's population, 26.98 % of Ethiopian population and 15.22 % of Mali's population were considered extremely and multidimensionally poor [8,10].

Therefore, disaggregating the analysis of multidimensional poverty into its context-specific incidences, intensities, gendered perspective, and specific household characteristics is of great essence in formulating evidence-based poverty alleviation policy strategies. The first goal of Sustainable Development Goals (SDS) focuses on ending poverty in all dimensions, and the eleventh goal of SDGs focuses on making cities and human settlements inclusive, safe, resilient, and sustainable [11]. Realizing these two critical SDGs have to bear direct patterns of urbanization and the severity of multidimensional poverty [12]. Current stirring urbanization and increasing socioeconomic inequalities remain a great challenge for developing regions like SSA [13,14]. By 2050, more than two-thirds of the world's population will be urban, with many living in informal and unplanned settlements and growing cities in SSA [15]. This is identifiable in the recent urban population growth trends; it rose from 13.09 million in 2000 to 14.35 million people in 2010 to over 17.97 million in 2022 [15,16]. Such an upsurge in urban population compounded with rural-urban migration has resulted in an increased share of the urban population living in slums and dilapidated settlements with inadequate access to social services such as water, energy, sanitation, housing, and widening income inequality [17,18].

Kenya, one of the SSA countries, is facing myriad urbanization-related socioeconomic challenges. For instance, the country has witnessed a rapid urbanization rate with an average annual increase of 4 % between 1999 and 2019 [19]. This has resulted in a constantly rising urban share of the population in slums, with an average value above 51 % between 2010 and 2020 [20]. The largest share of the socioeconomic challenges is in its major five cities such as Nairobi, Mombasa, Kisumu, Nakuru, and Eldoret, which hold over 30 % of the total urban population, out of which 56 % of the people living in slums occupy an eighth of land in Nairobi City [19]. Other cities like Kisumu have about 47 % of its population living in informal settlements [19]. Notably, the rising urban population in most of these cities is engrossed in informal settlements with poor housing conditions, poor standard of living, poor access to social amenities, and a generally high prevalence of poverty [19]. Rapid urbanization in these cities is attributable to poor urban planning and limited institutional frameworks, leading to overcrowded informal settlements without access to electricity, sanitation services, and poor quality housing conditions [21]. Besides regional differences, an enormous gender gap in the four dimensions of multidimensional poverty averaged 67.1 % in 2020, with health and education scoring as high as 98 % and 93.8 %, respectively [22]. More challenging, female-headed households in Kenyan urban areas continue to face severe poverty challenges as access to socioeconomic productive resources is still gender-segregated [23,24]. The latest national poverty reports using 2014 DHS data indicate Kenya's MPI standing at 0.171, incidence at 37.5 %, and intensity at 45.6 %, with 35.8 % of the country's population classified as vulnerable to multidimensional poverty [8]. Urban analysis points out the latest MPI value of 0.079, incidence value of 18.8 %, and intensity value of 42.0 %, with 25.6 % of Kenya's urban population classified as vulnerable to multidimensional poverty [8]. Scaling the analysis down to the subnational level, Nairobi, which is fully urban, ranks with the lowest MPI value of 0.028, compared to Nakuru and Eldoret cities in the Rift Valley region, whose MPI value is 0.206; coastal cities like Mombasa, whose MPI value is 0.212, and Kisumu city in Nyanza region with an MPI value of 0.165 [8].

Although a handful of empirical literature measuring and analyzing poverty from different approaches and units of analysis exists, it is essential to acknowledge that findings vary significantly depending on specific contexts. Still, despite the significant variation of dimension and indicator application, a considerable section of studies estimating monetary and non-monetary (multidimensional poverty) poverty further the road towards attaining SDGs 1 and 11. Hence, variation in household demographic attributes becomes vital for analyzing multidimensional poverty. In connection with this, this study contributes to the literature above in three distinct

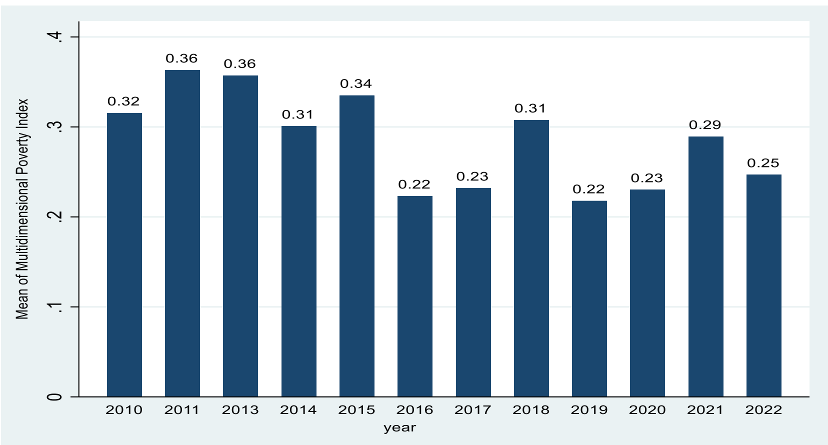

Fig. 1. Multidimensional poverty trends in SSA; 2010–2022.
Source: Own Construction [2024].

ways. First, the study contextually selects dimensions and indicators, out of which incidences, the intensity of poverty, and the multidimensional poverty index (MPI) in an urban setting using the Alkire and Foster (AF) framework are computed. Secondly, the study analyzes multidimensional poverty from a gender perspective. Thirdly, the study utilizes Probit regression to analyze the incidence, intensity, and gender perspective of multidimensional poverty in Kenya's selected five major urbanized counties. Lastly, the study utilizes the instrumental variable (IV-Probit) model to correct the endogeneity problem and carry out robustness checks using the Lewbel 2SLS technique.

The remainder of this paper is structured as follows: Section two theorizes poverty and empirical literature, out of which research gaps are uncovered. Section three explains the material and methods, including data description and sources, sampling, MPI computation, selected household regressor description, and logistic regression model. Section four shows the statistical analysis and discussion of findings per the study objective. Lastly, conclusions, policy recommendations, and study limitations are presented in section five.

2. Literature review

Concerning conceptualization and measuring urban poverty, two dominant views have been widely explored in literature: monetary and non-monetary [25]. The monetary approach defines poverty as an inability to get minimum income or resources to satisfy at least basic consumption needs of life [26]. The monetary approach measures poverty using one indicator, utilizing consumption and income to classify households as poor or non-poor [27]. On the other hand, the non-monetary approach defines poverty using multiple dimensions and indicators [28]. Therefore, the non-monetary approach views poverty as the failure of an individual or household to realize basic capabilities to sufficiently meet critical functions at a minimal level [29]. Although the monetary approach is simple to apply and interpret, it has been discounted because it doesn't view poverty from the welfare dimension, making it insufficient [30,31]. Due to this shortcoming, the non-monetary or multidimensional approach has been widely accepted in recent literature, focusing on several dimensions of household welfare indicators such as education, living conditions, and healthcare access [29,32,33].

Understanding poverty dynamics from the urbanization perspective remains complex, and empirical literature on its different aspects is limited [34]. Arguably, inadequate access to water, sanitation, and energy, low wage income, environmental hazards, and gendered inequalities are the main challenges of the urban poor population [12]. A quick review of the worldwide poverty rate shows that alleviating monetary poverty is slower in urban than rural regions [35]. Additionally, poverty is high in small and medium cities, augmented by insufficient supply and access to improved drinking water, sanitation, waste management, and clean energy [36]. Moreover, understanding poverty and its determinants from a gender perspective is a critical step toward effective poverty alleviation [37]. Mainly, women are constrained by socioculturally imposed limitations, denying them equal access to social services and affecting their well-being and urban livability [37,38].

Due to its measurement complexity, urban poverty has attracted a long-standing dynamic debate. Thanks to the innovative contribution of Sen, recent studies have shifted from a single monetary perspective of urban poverty to a multidimensional poverty approach [37,39,40]. The multidimensional poverty approach has been widely accepted as a robust measure of poverty, including various dimensions, such as education, living conditions, and health, with multiple indicators [33,41]. Based on a multidimensional poverty approach, the Oxford Poverty and Human Development Imitative (OPHI) and UNDP collaboratively established the global MPI in 2010, and since then, it has been regarded as a robust measure of poverty in developing economies and regional contexts [28,39]. Following this approach, various empirical studies in developing economies have provided contextual estimates of the multidimensional poverty index (MPI) using distinctive dimensions and indicators [33,42,43]. Following the 2018 revision, the World Bank officially adopted MPI to monitor global poverty patterns, enhancing a scholarly consensus on the use of MPI as a holistic measure of poverty [44–46]. MPI covers three key indicators (education, living standards, and health) with different indicators, and in recent decades, there has been empirical consensus that it addresses poverty holistically [45,47]. In addition, the revised version of MPI by Alkire et al. [48] evaluates poverty by presenting two thresholds. The first threshold is deprivation, which regards different dimensions reserved in poverty computation and categorizes individuals or households in deprivation in every retained dimension. Secondly, the threshold defines the minimum number of dimensions in which households are deprived of being summed as poor. Robustly, MPI allows analysis of poverty incidence, magnitude, and severity and helps decompose across household characteristics such as household head gender, age, and place of residence [47–49].

Most empirical studies have applied varying dimensions and indicators in deriving and estimating multidimensional poverty and observed different outcomes in rural and urban regions. For instance, poor housing quality, household health, and adult illiteracy are significant predictors of urban poverty, whereas deprived education and public infrastructure feature rural poverty [50]. This indicates that the household is a significant unit for analyzing multidimensional poverty incidences and intensity [51]. In line with this latest strand of literature, Melese et al. [52], using a logit regression model, concluded that household size and head gender are significant determinants of urban poverty in Ethiopian Nekente Town. Similarly, Mberu et al. [53] observed that household head gender, age, and education attainment significantly predict urban household poverty transitions in Kenya. Similarly, Ichawara et al. [54] applied Blinder-Oaxaca decomposition alongside a nonlinear regression technique in a recent study. The findings indicated that female-headed households are more likely to fall into multidimensional poverty than male-headed households.

Applying different dimensions and indicators in computing MPI, several empirical studies have analyzed the household sociodemographic and socioeconomic determinants of poverty in urban households. For instance, Akerele et al. [55] investigated the poverty of urban households in Nigeria, clearly observing that household head education, gender, and assets are significant predictors of multidimensional poverty. The study professed wage schemes and poverty safety net programs as key poverty alleviation strategies. Similarly, Beriso et al. [56] evaluated determinants of urban household poverty in Arsi Zone, Ethiopia. They observed that household size and head education status significantly influence monetary income poverty. In a recent study, Tadesse et al. [57], applying descriptive and logistic regression methods, observed that household gender, family size, head age, head education status, and access to healthcare services are significant determinants of urban poverty in North Shewa Zone, Ethiopia. Incorporating the gender perspective, Jayamohan and Kitesa [38] applied a Probit regression model and observed that urban poverty is higher among female-headed households than male-headed households in Ethiopia.

Similarly, Ezkezia [58] concluded a high incidence of urban poverty among female-headed households (73 %), with a gendered poverty gap of 20 % in Ethiopia. In agreement, the findings of Mthethwa and Wale [59] pointed out the significant influence of food insecurity on multidimensional poverty in municipalities in Eastern Cape Province, South Africa. Still, in South African municipalities, Ngumbela et al. [60] concluded that a high household unemployment rate significantly predicts poverty in Eastern Cape Province, South Africa. Investigating the multidimensional poverty situation in South Africa, Adetoro et al. [10] observed that a unit increase in household size and extension contract results in a 5 % and 49 % rise in household's vulnerability to multidimensional poverty, respectively. Ichwara et al. [54] applied the Blinder-Oaxaca decomposition technique alongside non-linear regression on the gendered perspective of poverty. They observed that poverty incidences and severity were higher for female-headed households (8.33 %) than for male-headed households (6.69 %) in Kenya. The study recommended the government's role in cash transfers, gender policy affirmative action, and enhancing literacy levels through increased secondary and tertiary enrolments as poverty alleviation strategies.

In summary, the reviewed literature highlights the critical role of different household characteristics in analyzing multidimensional poverty. Also, it shows the varying incidence and severity of poverty depending on gender perspective. Thus, it must be acknowledged that there exist gaps in the literature, and the incidence and severity of poverty are context-specific. Therefore, this study seeks to fill these gaps in three different ways. First, as applied in previous studies, the study aims to evaluate poverty's incidence, intensity, and determinants in an urban household rather than a national setting. Secondly, the study further disaggregates multidimensional poverty by gender perspective, as the literature indicates that poverty varies significantly by household head gender. Lastly, to the best of my knowledge, little empirical evidence exists for Kenyan urban poverty studies, and this study will form part of the pioneering studies to create a new knowledge base for future studies.

3. Material and methods

3.1. Data and variable description

This study utilized the 7th wave of nationally representative Kenya Demographic and Health Survey (KDHS) data collected by KNBS in collaboration with the Ministry of Health (MoH) and other stakeholders across Kenyan counties from 17th February to July 13, 2022. The 2022 KDHS recruited a nationally representative sample of 42 300 households with an inclusion and eligibility criterion of men aged 15–54 and women aged 15–49 years who are usual residents of the identified households or those who had spent a night before the survey. This sample was drawn from the Kenya Household Master Sample Frame (K-HMSF), where all 47 counties were stratified into rural and urban strata, except Nairobi City County, which was treated as purely urban in the survey. A questionnaire probing a wide range of sociodemographic profiles of households, education, health, housing characteristics, water access, sanitation, asset ownership, and government poverty programs such as urban food programs, food for persons living with disabilities, and health insurance coverage was the primary data collection instrument aided by Computer-Assisted Personal Interviews (CAPI), an android-based computer tablets programmed with CSPro data tool.

This study considered 2022 KDHS data for its empirical analysis of multidimensional poverty for two reasons. First, the data is very current, and the questionnaire added more robust innovative modules to monitor several social and economic indicators of the SDGS [61]. Second, the data provides in-depth information on non-monetary indicators such as household education, health, sanitation, water access, housing qualities, and general living standards, which aid in measuring urban poverty in Kenya from a multidimensional approach. In addition, the data covers household gender characteristics, necessary for evaluating the incidence and severity of multidimensional poverty from a gender and institutional perspective in an urban setting. This satisfies the AF methodological threshold of data requirement for each critical multidimensional poverty indicator from the survey linked to urban household poverty [28,32].

The study adopted a cross-sectional survey research design to analyze urban poverty and its household determinants in Nairobi, Mombasa, Kisumu, Nakuru, and Uasin Gishu counties, which are located in the heart of major cities in Kenya, following Kaminska and Lynn's [62] approach. Therefore, different sampling techniques were used to select household respondents, using a single stratum identifier reflecting the exact sampling in the national sample. In this effect, a multi-stage stratified random sampling technique was applied to select the urban households from the five major urbanized counties. First, a purposive sampling technique was utilized in selecting Nairobi, Mombasa, Kisumu, Nakuru, and Uasin Gishu counties, which were adequately represented as urban in the national sample. In the second step, a random sampling of 4662 households from the counties was selected after cleaning and deleting missing and incomplete data entries. Concerning variable inclusion, the study included multidimensional urban poverty as the dependent variable, which varies significantly by household sociodemographic and socioeconomic factors, which were included as the explanatory variables as applied in previous studies [63].

3.2. Computation of multidimensional poverty index (MPI)

The study employs the Alkire and Foster (AF) method following Sen's capability approach to compute the multidimensional poverty index (MPI) (Alkire & Foster, 2011). The AF method considers the deprivation threshold used in determining whether a household is deprived in a particular dimension [64]. Also, it entails a poverty line threshold, which defines a set of the required minimum number of dimensions in which a household is considered poor [64]. Also, the AF method is sufficiently flexible to allow an in-depth evaluation of multidimensional poverty by including more monetary or non-monetary dimensions and indicators [63,65]. Assume a population of N households represented by an $N * D$ dimensional matrix $X[x_{ij}]$, where x_{ij} represents the achievement of household i in dimension j. In this case, the D-dimensional row vector $Z = (z_1, \ldots, z_D)$ is used in producing the deprivation threshold z_j. Thus, household i is non-deprived in dimension j if the household's attainment. $x_{ij} > z_j$ and $g^0_{ij} = 0$ and is deprived if $x_{ij} < z_j$ and $g^0_{ij} = 1$, whereby $g^0[g^0_{ij}]$ is the obtained deprivation matrix from dimensional matrix X and vector Z. Additionally, the D-dimensional weight vector $W = (w_1, \ldots, w_D)$ depicts the comparative significance of every dimension $(\sum_{j=1}^{D} w_j = 1)$. Therefore, the weighted deprivation score for every household i is represented as $S_{i=}(\sum_{j=1}^{D} w_j g^0_{ij})$. If a household is deprived of all selected dimensions, then $S_{i=}1$ and if not $S_{i=}0$.

The second threshold by AF is the poverty cutoff or line $C(0 < C < 1)$ and its associated indicator function $pC(x_i, z)$ is utilized in identifying the multidimensional poor households. In particular, a household is regarded as poor if $S_i > C$ and $pC(x_i,z) = 1$; otherwise, not poor if $S_i < C$ and $pC(x_i,z) = 0$. Thus, the multidimensional poverty headcount (H) is denoted as $H = \left(q/_{N}\right)$, where $q = \sum_{i=1}^{N} pC(x_i, z)$, which describes the share of the poor population. Specifically, H measures the incidence of multidimensional poverty. However, it does not illustrate the contribution of each selected dimension to poverty, which captures the severity or intensity of multidimensional poverty. As one of the objectives of this study is to determine the severity of urban poverty, the study follows the Alkire and Foster [2011] proposed index, which is obtained by censoring the headcount ratio (H). The authors defined dimension j's censored headcount ratio as $h_i(C) = \frac{1}{N}\sum_{i=1}^{N} g^0_{ij}(C)$, where $g^0_{ij}(C) = g^0_{ij}(C) \times pC(x_i, z)$ represents the deprivation matrix. Thus, the poverty intensity or severity among the poor household population is denoted as $A = \sum_{i=1}^{q} S_i(C)/_{q} = \sum_{i=1}^{q} \sum_{j=1}^{D} w_j g^0_{ij}(C)$, where $S_i(C) = \sum_{j=1}^{D} w_j g^0_{ij}(C)$ is the censored deprivation score of the household i. The AF method aggregation stage utilizes an adjusted headcount ratio H^0 otherwise known as the MPI, which combines multidimensional headcount ratio (H) and the severity or intensity of poverty shown in equation (1) as follows:

$$MPI = H^0 = H \times A = \frac{1}{N}\sum_{i=1}^{N} S_i(C) = \frac{1}{N}\sum_{i=1}^{N} w_j h_i(C) \tag{1}$$

For this research, analyzing urban poverty from a gender perspective, equation (1) is built by two mutually exclusive sub-groups, $FHH_{i(nf)}$ and $MHH_{i(nm)}$ where $nf + nm = N$, which denotes the total number of households. Subdividing the $N * D$ dimensional matrix Y into two exclusive Y_f and Y_m, thus the gendered perspective of multidimensional poverty index (MPI) is denoted by equation (2) as:

$$MPI = \frac{\mathrm{nf}\, MPI(Y_f)}{N} + \frac{\mathrm{nm}\, MPI(Y_m)}{N} \tag{2}$$

and the contribution of female-headed households (FHH) and male-headed households (MHH) to the overall poverty is presented in equation (3) as:

$$MPI = \frac{\mathrm{nf}\, MPI(Y_f)}{\mathrm{N}MPI(Y)} \quad \text{or} \quad \frac{\mathrm{nm}\, MPI(Y_f)}{NMPI(Y)} \tag{3}$$

Where H denotes the share of multidimensionally poor households in the total sample population, and A represents the average percentage of indicators in which poor households are deprived [48]. Therefore, MPI can be referred to as a share of deprivation experienced by the multidimensionally poor household as a percentage of the deprivation experienced if the entire sample population was multidimensionally poor and deprived of all selected indicators. Regarding the dimensions and indicators for computing MPI, the study selected the dimensions of education, health, and living standards per Alkire and Foster's [28] AF method. The dimensions were applied with small adjustments to allow for more indicators due to data availability and to make the MPI robust [65,66]. Although

Table 1
Dimensions, indicators, weights, and descriptive statistics of MPI elements.

Dimension	Indicator	Deprivation cutoff (deprived if … …)	SDG	Weight	Mean	SD
Education	Attainment	Member attained no or primary levels	SDG4	1/6	0.222	0.415
	School attendance	Member currently not attending school	SDG4	1/6	0.029	0.168
Health	Nutrition	Any person under 70 years did not eat in the last 7 days preceding the survey	SDG2	1/6	0.270	0.444
	Child mortality	No child <5 years slept in a mosquito net	SDG3	1/6	0.093	0.291
Living Standards	Drinking water	Drinking water not sufficient last month	SDG 6	1/18	0.341	0.474
	Housing quality	The house floor is made of earth/sand.	SDG11	1/18	0.042	0.201
	Electricity	The household has no electricity access	SDG7	1/18	0.092	0.289
	Cooking fuel	Household cooks using firewood	SDG7	1/18	0.052	0.221
	Asset Ownership	Household does not own at least one asset	SDG1	1/18	0.010	0.301
	Sanitation facility	Shared toilet with other households	SDG 6	1/18	0.400	0.490

Note: Drinking water includes public piped water, wells, protected springs, and hand and motor pumps. Asset ownership of at least one asset for accessing information (TV, radio, computer, mobile phone), mobility (car/truck, motorcycle/scooter, bicycle, animal-drawn cart), and livelihood (bank account and mobile phone for financial transactions). *Source*: Alkire et al. [32], and UNDP and OPHI [68].

there is no consensus in the literature regarding the standard weighting method, this study applied equal weights (0.33) to each selected dimension and within each dimension's indicators, giving equal significance to each dimension in computing MPI as depicted in literature [48,67]. Table 1 presents each indicator's definitions, descriptive statistics, and associated weights.

3.3. Econometric modelling of multidimensional urban poverty

Multidimensional poverty is measured following the Alkire and Foster [28] method, whereby the poor and non-poor households are determined through sequential deprivation scores in several indicators; the index depends on the joint distribution of several deprivation indicators, out of which a dichotomous variable is determined. Therefore, the study utilized a Probit regression in modeling urban household sociodemographic and economic factors influencing multidimensional poverty status. The Probit model was selected because the poverty status variable is a profile variable consisting of probability; thus, the effect of the selected independent variable increases or decreases as the predicted probability nears 0 or 1 [64,69]. Poverty status variable (Pov_i) of household i is dichotomous, depicting a household as poor if the multidimensional deprivation cutoff score $S_i > C$ (selected cutoff threshold = 0.33), described by equation (4) as follows:

$$Pov_i = \begin{cases} = 1 \text{ if } \mathrm{S_i} \geq 0.33 & \text{Household is dimensionally poor} \\ = 0 \text{ if } \mathrm{S_i} < 0.33 & \text{Household is dimensionally non} - \text{poor} \end{cases} \tag{4}$$

The Probit regression model depicting the relationship between urban household sociodemographic and economic characteristics and multidimensional poverty of the selected city counties in Kenya is presented in equation (5) as follows:

$$Pr\left(\frac{Pov_{ij}}{X_{ij}}\right) = \alpha + \beta HSE_{ij} + \gamma Z_{ij} + \vartheta_j + \varepsilon_{ij} \tag{5}$$

where Pov_{ij} is the binary variable for the poverty status of urban households i in urban county j. HSE_{ij} denotes the urban household sociodemographic and economic covariates measured in binary and continuous in urban household i in the urban county. Z_{ij} denotes the dummy variable for urbanization level, where one indicates fully-urban and 0 indicates per-urban county. The city-county-specific fixed effects are captured by ϑ_j. The error term assumed to be well-behaved is denoted by ε_{ij}. The slope coefficient, coefficient estimates of household characteristics, and dummy variable of urbanization level are denoted by $\alpha, \beta,$ and γ. Besides determining the coefficient estimates of each urban household covariates used to determine multidimensional poverty, the marginal effects are also determined to enhance the discussion and deductions concerning the variation in effects of each independent variable.

Table A in the Appendix section shows the descriptive and summary statistics of multidimensional poverty and urban household covariates used as the determinants of household poverty. The computed multidimensional poverty was included as the dependent variable measured in binary form. Among the many sociodemographic covariates, household size, number of children under five years, household head gender, age, marital status, and number of house rooms were included in line with the previous literature [70–73]. For instance, Munoz-Boudet et al. [74] observed that the poverty status of households changed along with changes in their demographic composition and that demographic characteristics such as household head age, education, gender, and household type were important determinants of poverty among urban poor households. The descriptive statistics show that 16.2 % of the sampled urban households are multidimensionally poor, deprived of education, health, and living standard indicators. In terms of sociodemographics, the majority of households have an average of 1 child under five years, a family size of 3, 71.7 % are male-headed, 63.8 % of household heads are currently married, live in an average of 2-roomed houses, the average age of the household head is 37.925 years, and the average education of the household women members is secondary.

The study also considered several socioeconomic covariates such as ownership of agricultural land, insurance cover, home ownership status, reception of social assistance, food insecurity, health status of the members in the last 12 months, difference in regional urbanization level and endemicity zone of the residence place in line with the previous studies such as Militao et al. [75] and Verger et al. [76] who observed that food insecurity is the main channel of urban poverty. The descriptive statistics of the socioeconomic characteristics of the urban households show that 31.3 % own agricultural land, 49.2 % stay in low-risk malaria endemic zones, 78.6 % pay rent, 45.2 % have insurance cover, 5.5 % have been admitted to health facilities in the last 12 months, 47.5 % are categorized as richest households, 9.6 % are food insecure, 39.5 % own livestock. 1.4 % receive social assistance from NGOs, and 24.5 % of the households stay in fully-urban counties. Table C shows the absence of multicollinearity among household covariates.

Table 2
Multidimensional poverty index (MPI) estimates in selected city counties.

MPI/Category	Incidence (H)	Intensity (A)	M0(H*A)
City County MPI Value	0.196	0.443	0.087
Male-Headed Households (MHH)	0.166	0.434	0.072
Female-Headed Households (FHH)	0.268	0.459	0.123
Young Household Heads (Age≤35 years)	0.143	0.434	0.062
Old Household Heads (Age>35 years)	0.257	0.447	0.115
Peri-Urban Counties	0.217	0.447	0.097
Fully-Urban Counties	0.154	0.429	0.066

Source: Author's Computation from KDHS 2022 data [2024].

4. Empirical analysis and discussion

The computed MPI satisfies the weak monotonicity, dimensional monotonicity, ordinality, and population subgroup decomposability axioms [28]. This implies that the computed MPI can be decomposed or disaggregated by household head gender, age categories, and city-county regions. The MPI was calculated to estimate the multidimensional poverty in the selected five major city counties and further segregate it by gender, age of the household head, and city counties to depict the variation of the poverty by household headship categories and regional heterogeneities. Table 2 presents the multidimensional poverty index (MPI) of 0.087, implying that 8.7 % of the urban households in Kenya's selected five major city counties are multidimensionally deprived in 33.3 % of the selected dimensional indicators. The urban household headcount ratio (H) is 19.6 %, and the intensity of poverty (A) is 44.3 %. Disaggregating the MPI further by household head gender and age categories, the findings reveal high incidence (H), intensity (A), and MPI of poverty among female-headed households (0.268; 0.459; 0.123) compared to male-headed households (0.166; 0.434; 0.072). These findings are in line with the findings observed by previous studies focusing on multidimensional poverty by gender perspective in Kenya, which observed that higher multidimensional poverty incidences and intensity exist among female-headed households compared to male-household headships [53,54].

Looking at the MPI variation by age categories of household head, there is also a wide variation, as indicated by a higher MPI value of 0.115 for the urban older-headed households and 0.062 for younger-household headships. This is supported by previous studies such as Mberu et al. [53] and Odhiambo [77], who revealed that households headed by older heads are more likely to become poorer compared to younger household heads and the rest of the age groups. Lastly, disaggregating MPI by the urbanization level showed that high incidence (0.217), intensity (0.447), and MPI (0.097) exist in peri-urban counties compared to fully urban counties (0.154, 0.429, and 0.066, respectively). This signifies that urban multidimensional poverty differs significantly by the level of urbanization, as pointed out by social differences such as income inequality [14]. Aligning with this observation, Odhiambo [77] observed that households living in fully-urban regions are less poor in Kenya.

Fig. 2 presents the cross-county analysis of multidimensionally deprived urban households' incidence, intensity, MPI, and distribution. The results reveal great regional heterogeneity in MPI, incidence, intensity, and distribution of households. For instance, the intensity (A) for Mombasa City County is ranked high at 0.461, followed by Nakuru City County ranked at 0.452, Kisumu City County at 0.437, Uasin Gishu County at 0.431, and Nairobi City County ranks slightly the lowest at 0.429. Nakuru City County ranks the highest incidence (H) and MPI at 0.272 and 0.123, respectively. Although the multidimensional poverty index (MPI) is low at 0.066 in Nairobi City County, the majority (33.8 %) of the household population are multidimensionally poor, followed by Mombasa City County, with 25.2 % of households ranked as multidimensionally poor. Kisumu City County has the lowest share (12.2 %) of the urban households categorized as multidimensionally poor. These findings are supported by observations made by earlier studies, such as Simiyu et al. [78] and Smith [79], that most Kenyan cities are characterized by limited sanitation facilities, water supply, and deplorable informal settlement conditions, causing the intensity of poverty to go high across all city counties.

Fig. 3 presents the percentage share contribution of each poverty indicator in the computation of multidimensional poverty index (MPI). The findings indicate that the health (child mortality and nutrition) dimension contributes 42.5 % to the urban MPI, followed closely by the education dimension (education attainment and school attendance), which contributes 33.7 %, and the living standards dimension (cooking fuel, main floor material, sanitation, drinking water, electricity access, and asset ownership) contributes to 23.8 % of the overall urban MPI in the selected five major city counties in Kenya. The findings can be supported by the fact that most of the urban households in Kenya live in informal settlements with a limited supply of water, sanitation, and constrained health facilities; thus, most of them are deprived of health indicators [78].

Fig. 4 presents the percentage share of households in the selected city counties deprived of each of the ten indicators used in computing the multidimensional poverty index (MPI). The findings show that most (39.5 %) of urban households in the selected Kenyan city counties are deprived of basic sanitation facilities (household members sharing a toilet with other households), (30.7 %) are deprived of sufficient drinking water, (30.5 %) are deprived of education (household member have no or primary level of education attainment), (26.9 %) are deprived of basic healthcare (household members aged 70 years and below did not eat in the last seven days

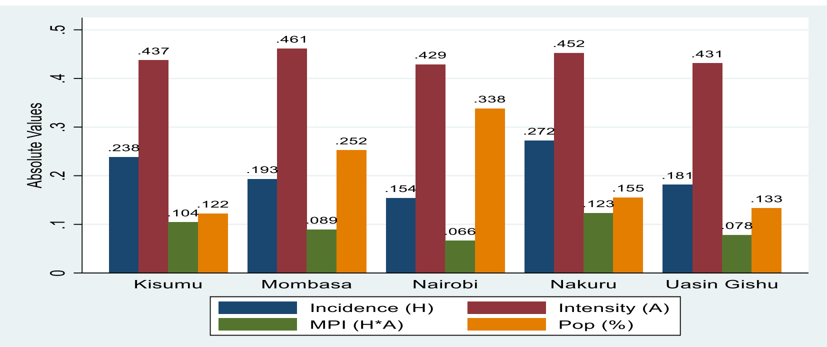

Fig. 2. Spatial patterns of cross-county MPI and percentage of multidimensionally poor households.
Source: Own Construction [2024].

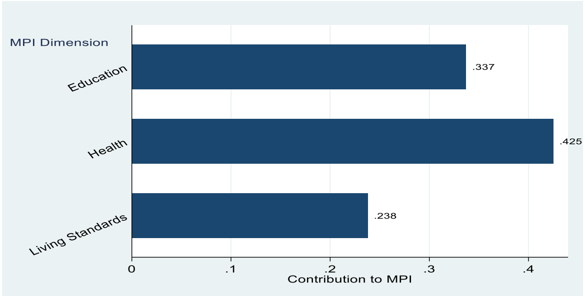

Fig. 3. Dimensional Contribution to Overall urban MPI.
Source: Author's Construction [2024].

prior to the commencement of the survey), (13.3 %) are deprived of child mortality (No child <5 years slept under mosquito net), (13.1 %) are deprived of asset ownership (household does not own at least radio, TV, car, motor cart, bicycle, computer, telephone, refrigerator, motorbike, and mobile for financial transactions), (8.8 %) are deprived of electricity (household has no access to electricity), (7.1 %) are deprived of cooking fuel (household cooks using firewood), (6.3 %) are deprived of housing quality (house main floor is made of earth/sand), and (3.6 %) of the urban households are deprived of school attendance (household member currently not attending school). Lack of sanitation facilities and insufficient drinking water ranks the highest in major Kenyan cities due to weak governance and regulation of public water, natural sources, and distribution of services ([14,80,81]). Part of the challenges is the increasing urban population and limited urban infrastructural development in key Kenyan cities [23,82].

4.1. Probit analysis of household determinants and gender perspective of multidimensional urban poverty

Table 3 shows the Probit regression results for the urban household multidimensional poverty and the associated sociodemographic and socioeconomic covariates following estimation of the model in equation [5]. Also, the gendered perspective of multidimensional poverty is analyzed by decomposing the Probit model analysis by household head gender. Column 1 shows the coefficient estimates for the urban household multidimensional poverty. Column 2 shows the marginal effect of the selected urban household covariates on MPI. Columns 3 and 4 show the coefficient estimates of the Probit model of female-headed households (FHHs) and male-headed households (MHHs), correspondingly. Looking at the log-likelihood ratios (LR), they are significant at a 1-percentage significance level ($P<0.01$), revealing the overall statistical significance of the pooled FHHs and MHHs models. In addition, the Probit model fits well, with a negative log-likelihood value and normal distribution of the disturbance term. Lastly, the inverse Mills ratio coefficient is negative and insignificant, indicating the absence of sample selectivity bias. Starting with the pooled Probit regression model in columns 1 and 2, the household sociodemographic covariates such as household size, number of household children under five years, household head gender, household head age, and head marital status are significant positive predictors of urban household multidimensional poverty at 1 %, 5 %, and 10 % confidence levels.

For instance, an increase in household size and the number of children under five years raises multidimensional poverty by 10.8 % and 4.7 %, respectively (see column 2). These findings can be attributed to the increased household food and healthcare consumption liabilities that expand as the household size by vulnerable population category rises. These findings align with the observations made by recent studies [63,71,83,84], which deduced that an increased household child dependency ratio increases the likelihood of the household being multidimensionally poor. In addition, large family size in terms of a large number of children under five years diverts

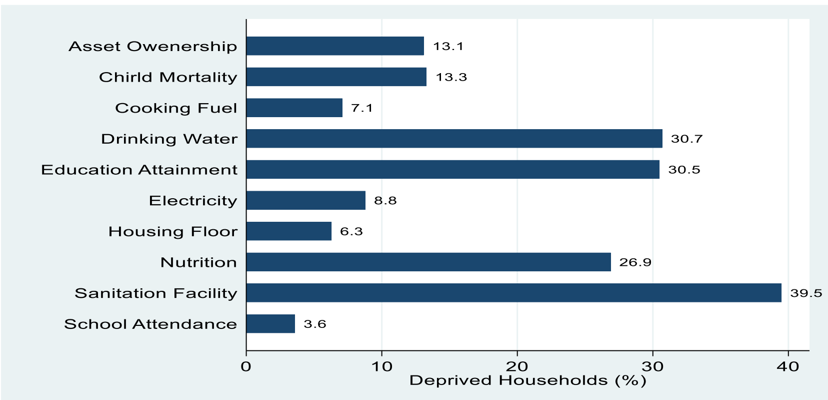

Fig. 4. Percentage of deprived households by dimensional indicators.
Source: Author's Construction [2024].

Table 3
Baseline probit regression coefficients and marginal effects and gender perspective.

Variable	Pooled Coefficient [1]	Marginal Effects [2]	Gendered Coefficients	
			FMHs [3]	MHHs [4]
Constant	1.285** (0.458)	–	2.769** (0.853)	1.335** (0.552)
Household Head Gender	0.420*** (0.129)	0.213** (0.451)	–	–
Urban Food Insecurity	1.554** (0.106)	0.309** (0.016)	2.188** (0.212)	1.389** (0.131)
Household size	0.181** (0.046)	0.108** (0.036)	0.192** (0.085)	0.175** (0.059)
No. of children <5 years	0.361** (0.097)	0.047** (0.013)	0.355 (0.197)	0.353** (0.123)
No. of House Rooms	−0.105 (0.129)	0.093** (0.027)	−0.189 (0.117)	0.013 (0.096)
Household Head Age	0.030* (0.008)	−0.014 (0.019)	0.032** (0.012)	0.027* (0.010)
Agricultural Land Ownership	−0.292** (0.121)	−0.008** (0.002)	−0.147 (0.239)	−0.373** (0.149)
Residing in Malaria Prone	0.171** (0.044)	0.075** (0.032)	0.099 (0.083)	0.209** (0.059)
Home Ownership Status	−0.328 (0.213)	−0.044** (0.013)	−0.265 (0.207)	−0.199 (0.144)
Household Head Marital Status	0.139** (0.045)	0.044 (0.041)	0.097 (0.063)	0.158 (0.130)
Insurance Cover	−0.292** (0.096)	−0.036** (0.012)	−0.323** (0.167)	−0.308** (0.127)
Woman Education Status	−0.404** (0.101)	−0.041* (0.044)	−0.586** (0.190)	−0.296** (0.137)
Health Status	0.717** (0.220)	0.104** (0.029)	0.804** (0.313)	0.925** (0.321)
Household Wealth Index	−1.117** (0.210)	−0.185** (0.054)	−1.038** (0.398)	−1.107** (0.282)
Livestock Ownership	0.007 (0.105)	−0.288** (0.063)	0.013 (0.192)	0.010 (0.117)
NGO Social Assistance	−0.065 (0.334)	0.002 (0.026)	0.396 (0.439)	−0.091 (0.457)
Inverse Mills Ratio (IMR)	−0.581 (0.449)	0.017 (0.083)	−0.493 (0.493)	−0.587 (0.337)
Urban County fixed effects	YES	YES	YES	YES
Pseudo R^2	0.257		0.5929	0.179
Log-likelihood	−535.60		−119.99	−345.16
LR Chi^2	225.32		206.05	118.84
Prob > Chi^2	0.000		0.000	0.000
AIC	1109.519		279.97	726.32
BIC	1205.45		362.11	808.82
No. of Observations	4662		1786	2876

Note: Standard errors are enclosed in parenthesis; $*p < 0.01$; $**p < 0.05$ &$***p < 0.001$; FHHs; Female-Headed Households; MHHs; Male-Headed Households.
Source: Own Construction [2024].

the work, especially women's productive time in economic activities, resulting in lower income and high household poverty [64, 85–88]. Collaboratively, Gebreidan et al. [89] observe that household size correlates positively with the vulnerability of the urban household to multidimensional poverty.

The marginal effect results also show that an increase in the age of the household head by one year increases the urban household multidimensional poverty by 0.8 %, holding all other factors constant. This observation can be argued that as household heads get older, they get exhausted and become ineffective in their production, increasing their likelihood of becoming multidimensionally poor. These findings align with the deduction made by Oyebamiji and Khan [90], who posited that older household heads are more likely to fall into multidimensional poverty. Moreover, this can be alluded to by the fact that older household heads cannot withstand risks caused by loss of labor productivity [32,87]. Also, the results showed that an increase in female-headed households by 1 unit leads to an increase in urban household multidimensional poverty by 10.8 %. As indicated earlier, multidimensional poverty, in terms of incidence and intensity among female-headed households, confirms the observations made by Cheteni et al. [91] that an increase in female-headed households increases the level of urban household multidimensional poverty. Further, the findings reveal that an increase in married household heads increases urban multidimensional poverty by 3.6 %. This can be alluded to because most marriages in Kenya bring extended families together, increasing household consumption expenditure on social amenities such as sanitation facilities, water, and education costs. These findings contradict the observations of Olarinde et al. [87], who observed that married household heads tend to bear the brunt of financial pressure to finance household expenditure, so they have a greater risk of experiencing multidimensional poverty than unmarried household heads.

The study also investigated the effect of the household socioeconomic determinants of urban multidimensional poverty. The findings revealed a mix of effects on multidimensional poverty. On one hand, the marginal effect results indicated that an increase in the number of households owning agricultural land results in a decline in multidimensional poverty by 7.5 %, holding all other factors constant. This can be attributed to urban households engaging in small-scale farming, reducing their likelihood of falling into multidimensional poverty. Also, the findings indicated that an increase in the number of educated household women is associated with a decline in multidimensional poverty by 4.4 %, holding all other factors constant. This points out the importance of breaking gender inequality through women's empowerment through education, as Zenebe et al. [37] argue that educating women reduces multidimensional poverty in both direct and indirect ways.

Furthermore, the findings revealed that an increase in households that own insurance cover and are categorized as wealthy is associated with a decline in multidimensional poverty by 7.5 % and 28.8 %, respectively. Indeed, empowered households with insurance coverage are less likely to be deprived of health and can focus on income-generating activities, reducing their chances of becoming multidimensionally poor [63]. Similarly, wealthy households can afford dietary needs and access other social amenities such as clean energy, hence cutting their likelihood of falling into multidimensional poverty, affirming assertions of previous studies [63,64, 92] that a household has a lower likelihood of becoming multidimensionally poor as sanitary conditions such as adequate access to piped drinking water increases.

On the other hand, household covariates such as urban food insecurity, health status regarding whether household members were admitted to a health facility in the last 12 months, and households residing in malaria-endemic zones were significant positive predictors of urban household multidimensional poverty. For instance, the marginal effect results showed that an increase in the number of urban households that are food insecure increases the urban multidimensional poverty by 30.9 %, holding all other factors constant. Additionally, the number of household members admitted to the health facility in the last 12 months predicted an 18.54 % increase in urban household multidimensional poverty, holding all other factors constant. These findings can be explained in the context of increased household health liabilities, which tend to increase along with natural catastrophes such as food insecurity, sickness, accidents, and family dependency ratio [71]. This results in financial strain and reduced living space, which cause unhealthy living resulting from inadequate access to living facilities and continued multidimensional poverty [63,93].

Decomposing the Probit model analysis by household gender, the significant household determinants of urban MPI are sustained, although with varied effect sizes by the gender of the household head. For instance, a rise in the number of urban food insecure FHHs increases multidimensional poverty by 2.188 times higher than MHHs with an effect size of 1.389 units. These observations are affirmed by Maket et al. [14], who alluded urban poverty to an increase in the urban population, resulting in social inequalities such as inadequate access to food and amenities. Also, an increase in the household size results in a higher increase in MPI by 19.2 % in FHHs compared to the 17.5 % effect in MHHs. This aligns with the sentiments of Saddique et al. [63] that an increase in household dependency ratio reduces the female-headed households' chance of engaging in income-generating activities, thereby making them liable to multidimensional poverty. This applies to household head age, which raises MPI among FHHs by a higher effect of 3.2 % compared to the corresponding 2.7 % in MHHs. These findings align with those observed by Zenebe et al. [37], who concluded that FHHs are poorer than MHHs and that household size and head age are significant predictors of multidimensional poverty. Interestingly, an increase in the number of household members admitted to a health facility in the last 12 months increases multidimensional poverty by 92.5 % in MHHs compared to 80.4 % in FHHs. This can be attributed to the fact that most urban households in Kenya are male-headed, living in informal settlements without adequate access to sanitation and water services, increasing multidimensional poverty [78,79].

Additionally, just like in Table 2, an increase in the number of urban MHHs owning agricultural land and are categorized as wealthy is associated with a decline in multidimensional poverty by 37.3 % and 110.7 % compared to FHHs whose effect is 14.7 % and 103.8 % correspondingly. These findings are affirmed by Amao et al. [94], who observed that land ownership is associated with a decline in multidimensional poverty in Nigeria. Interestingly, an increase in the number of educated women and households owning insurance covers reduces multidimensional poverty by higher effects of 58.6 % and 32.3 % among FHHs compared to 29.6 % and 30.8 % among MHHs. This points out the need to empower women through education and increased health insurance coverage as this cuts down multidimensional poverty by a bigger margin, as supported by the findings observed by Zenebe et al. [37]. An increased number of educated household women not only reduces the urban MPI but also breaks the gender inequality that has been associated with household poverty, especially in developing economies where economic decisions and ownership of productive assets are controlled by male headships [37,54].

4.2. Dealing with endogeneity and robustness checks

Socioeconomic factors such as urban household food insecurity status have been found endogenous in predicting multidimensional household poverty, especially in an urban setting [95]. On the one hand, several studies have revealed the effect of household poverty on urban food insecurity in most cities in Global South economies [96]. On the other hand, research has also pointed out that poor urban households may face disrupted food security under natural catastrophes such as diseases and lack of social amenities [79]. In addition, household covariates such as household head age, marital status, education level, gender, and household size are determinants of both urban household food insecurity and multidimensional poverty [79]. With these documented literature observations, it is obvious that an endogenous problem exists that must be solved; otherwise, the observed results will be biased. Thus, Probit regression with instrumental variables to overcome the endogeneity problem must be applied as informed by earlier household multidimensional poverty [97]. Thus, the paper considers a two-step instrumental Probit regression model (IV-Probit) to address the endogeneity issue [98].

In this case, the paper applies the product of household head age and gender as the instrumental variable. The argument is that a handful of literature has documented high multidimensional poverty, intensity, and headcount ratio among female-headed and older-headed households. In addition, the higher the FHHs who are older, the higher the likelihood of them falling into multidimensional poverty as they are exhausted and less productive in income-generating activities [99]. Consistent with studies such as Rono et al. [99] and Koomson et al. [100], this paper resolves the endogeneity problem in the study by applying IV-Probit model regression whereby the product of household head age and gender is applied as the instrumental variable. As indicated in Table B in the Appendix section, the falsification results show that the association between the selected IV and the response variable (household poverty, which is dichotomous) is weak, while the selected IV is significantly associated with the treatment variable (food insecurity) [101,102]. The results support the validity of the selected IV [102]. In addition, the paper utilizes the selected IV in testing for the consistency of results using Lewbel's [2012] 2SLS technique, which has been extensively used in literature to address the endogeneity problem [101,103,104].

Table 4 presents the findings of standard Probit, IV-Probit, and 2SLS model results. As expected, the endogeneity corrected Probit results in column 2 sustain the coefficient signs of the standard Probit, although with a smaller effect size among most of the predictors.

In addition, the Wald test statistical value is above the threshold of 10, implying that the selected instrument is not weakly associated with the reference food insecurity factor. Moreover, the instrumented results are lower than the preliminary Probit results, pointing out that the endogeneity of urban food insecurity overestimated the preliminary Probit results. As observed before, the results of the instrumented Probit model agree with the preliminary results, though with reduced bias. For instance, an increase in the number of urban food insecure households by 100 % results in an increase in the urban household multidimensional poverty by 72.3 %, holding all other covariates constant. Further, consistent with the literature, the Lewbel 2SLS results, which are endogenously corrected, are lower than standard and IV-Probit estimates [103,104]. Thus, this implies that the urban household multidimensional determining effect of the household sociodemographic and socioeconomic factors are consistent across different endogeneity-correcting models [14,100,105,106].

4.3. *Sensitivity of MPI to cutoff threshold (K) adjustments*

Post-estimation analysis–robustness checks and diagnostics were conducted to determine the sensitivity of the multidimensional poverty estimates to changes in poverty computation thresholds (cutoff values). Generally, in computing MPI, the poverty cutoff, the minimum deprivation level above which a household is considered poor, is fixed. The overall cutoff is set just like a poverty line, and an individual or household falling below or at the poverty line is regarded as poor. The multidimensional poverty with its intensity and head count ratio at various cutoff points are provided in Fig. 4 below. In general, as the poverty cutoff (K) threshold value rises, the head count ratio (H) and MPI values decline, and the indicators whereby households are deprived in or intensity (A) increase.

As indicated in Fig. 5, at a cutoff point of 0.15, the head count ratio (H; incidence) is 0.551, intensity (A) equals 0.297, and the MPI is 0.163. As the cutoff point increases to 0.25, incidence (H) and MPI values decrease to 0.275 and 0.109, respectively. On the other hand, the poverty intensity (A) increased to 0.395. Rising the cutoff point to 0.33 prompts the poverty intensity (A) to increase steadily to 0.443, while poverty incidence (H) and MPI declined drastically to 0.196 and 0.087, respectively. Raising the cutoff point to 0.5, beyond 0.4, causes both incidence (H) and MPI to drop very fast to 0.057 and 0.033, while poverty intensity (A) rose drastically to 0.586. Moreover, by increasing the cutoff point toward 1, the poverty incidence (H) and MPI decline, similarly approaching zero. On the other hand, poverty intensity (A) increases very fast, approaching 1. Based on these findings, it can be deduced that multidimensional poverty varies across different poverty cutoff thresholds, signifying that the adjusted headcount ratio (MPI) is highly sensitive to the choice of cutoff value. These findings agree with the assertions by Ma et al. [102] and Tigre [107], who deduced that poverty cutoff and MPI value vary in different and opposite directions (see Fig. 6).

The study utilized the receiver operating accuracy (ROC) diagnostic technique in evaluating the accuracy performance of the estimated Probit and IV-Probit regression models. ROC depicts sensitivity against 1-specificity, which differentiates between sensitivity and specificity. Sensitivity describes the probability of accurately determining multidimensionally positive poor households

Table 4
Endogeneity-corrected probit regression coefficients and lewbel 2SLS robustness checks.

Depended Variable: Multidimensional Poverty	Coefficients		
	Standard Probit [1]	IV-Probit) [2]	Lewbel 2SLS [3]
Constant	0.132 (0.478)	−8.344*** (2.022)	−3.641 (2.925)
Urban Food Insecurity	1.554** (0.106)	0.723** (0.467)	0.397** (0.050)
Household Size	0.179** (0.060)	0.056 (0.065)	0.009 (0.018)
No. of Children <5 years	0.523*** (0.125)	0.557*** (0.117)	0.209*** (0.125)
Household Head Gender	0.554** (0.159)	6.165*** (1.252)	2.943* (2.047)
No. of House Rooms	0.008 (0.085)	−0.110 (0.079)	−0.052 (0.048)
Household Head Age	0.035*** (0.010)	0.260*** (0.048)	0.122** (0.0844)
Agricultural Land Ownership	−0.250 (0.149)	−0.112 (0.122)	−0.030 (0.041)
Residing in Malaria Prone	0.243** (0.076)	0.135** (0.075)	0.037** (0.017)
Home Ownership Status	−0.301** (0.130)	−0.295** (0.112)	−0.109*** (0.063)
Household Head Marital Status	0.139** (0.055)	0.231*** (0.039)	0.096** (0.058)
Insurance Cover	−0.239** (0.111)	−0.172** (0.101)	−0.059* (0.039)
Health Status	0.831*** (0.276)	0.488* (0.262)	0.109*** (0.054)
Household Wealth Index	−1.139* (0.309)	−0.690* (0.319)	−0.211* (0.062)
Livestock Ownership	0.080 (0.117)	0.028 (0.090)	0.008 (0.037)
NGO Social Assistance	0.100 (0.341)	0.064 (0.345)	−0.000 (0.116)
Woman Education Status	−0.546** (0.141)	−0.317* (0.158)	−0.092** (0.033)
Age × Household Head Gender	0.011 (0.009)	−0.162*** (0.038)	−0.078** (0.056)
Inverse Mills Ratio (IMR)	−0.797** (0.370)	−0.516 (0.275)	−0.105 (0.075)
Urban County Fixed Effects	YES	YES	YES
Log Pseudolikelihood	−420.65	−3980.56	–
Wald Chi^2	365.70	865.57	393.06
Prob > Chi^2	0.000	0.000	0.000
AIC	883.30	8053.117	–
BIC	989.70	8286.175	–
No. of Observations	4662	4662	4662

Note: Standard errors are enclosed in parenthesis; $*p < 0.01$; $**p < 0.05$ &$***p < 0.001$.
Source: Own Construction [2024].

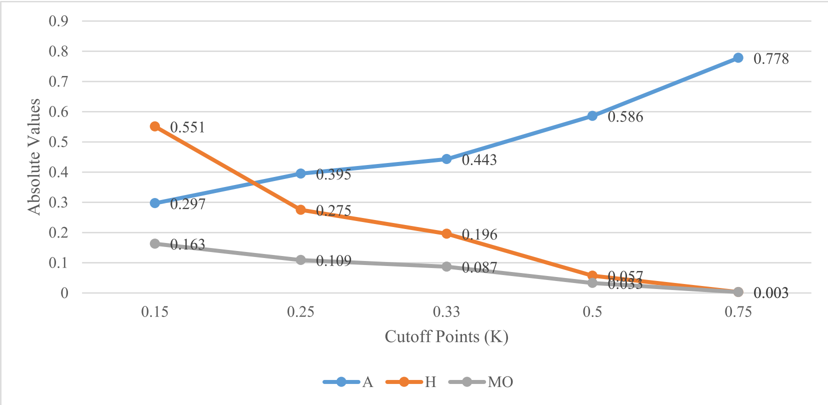

Fig. 5. Incidence (H), intensity (A), and MPI estimates by cutoff variations.
Source: Author's Construction [2024].

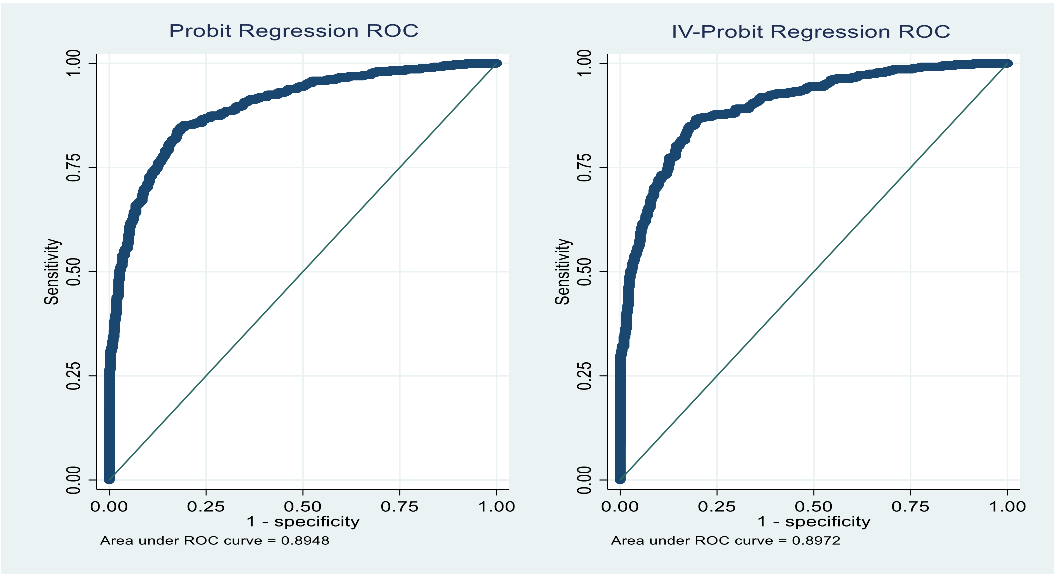

Fig. 6. ROC for estimated standard probit and IV-probit regression models.
Source: Author's Computation [2024].

categorized correctly. Specificity refers to the likelihood of correctly classifying the actual negative multidimensionally non-poor households. Figure 6 shows the areas under the ROC curves for the standard Probit regression as 0.8948, and that of IV-Probit regression as 0.8972, implying that the models adequately classified negative and positive multidimensional poverty outcomes explained by urban household sociodemographic and socioeconomic characteristics.

5. Conclusion and policy recommendations

The main aim of this paper was to analyze urban household multidimensional poverty by evaluating its incidence, intensity, and multidimensional gendered perspective. The study utilized the 7th round of Kenya Demographic and Health Survey (KDHS) data collected between February and July 2022 by the Kenya National Bureau of Statistics (KNBS) in collaboration with the Ministry of Health (MoH). The study selected three dimensions (education, health, and living conditions) together with ten associated indicators in computing poverty incidence (H), intensity (A), and MPI using a non-monetary dimensional approach using the AF technique for five most urbanized counties; Nairobi, Mombasa, Kisumu, Nakuru and Uasin Gishu located in the only five cities in Kenya. The study followed a multidimensional approach in developing MPI as it is flexible in adjusting for more indicators and covers both monetary and non-monetary aspects of household well-being. The findings revealed that 8.7 % of urban households in the five Kenyan counties suffer from multidimensional poverty, as reflected by indicators of deprivation of health, education, and living conditions. In addition, the study revealed that more than 50 % of the households in urban households in the selected city counties are deprived of drinking water and sanitation facilities, depicting inefficient water and sanitation governance systems [77,78].

Following the gender perspective, the study revealed enormous heterogeneity in incidence, intensity, and multidimensional household poverty across household head gender and age categories. In line with the dominant view that female-headed households are more likely to become multidimensionally impoverished than male-headed households, this study reveals that there is the feminization of urban poverty in Kenya, as depicted by earlier studies focusing on urban Kenyan households [54]. Probit regression analysis was conducted to ascertain significant determinants of multidimensional urban poverty. Among them, the findings revealed that large households, in terms of the large family size and number of children under five years, household head age, gender, marital status, and residing in malaria-prone zones, are more likely to become multidimensionally poor. Also, socioeconomic factors such as urban food insecurity and health status regarding the increase in household members admitted to health facilities in the last 12 months before the survey were significant positive predictors of multidimensional poverty. On the other hand, an increase in the number of educated household women, wealthy households, owning insurance cover, and owning agricultural land results in a decline in multidimensional poverty among urban households in Kenya. Moreover, disaggregating the Probit regression model by gender perspective revealed that the observed significant predictors have different effect sizes, with higher effects recorded among female-headed urban households in Kenya's selected most urban counties.

Given the observed varied incidences, intensity, and multidimensional poverty index by household gender, age, and level of urbanization in this study, this empirical evidence provides timely discussions around contextual policy initiatives targeting alleviating multidimensional poverty from urbanization and a gendered perspective. First, the computed MPI estimates depict that policymakers should cautiously consider household differences while designing poverty alleviation policy strategies. For instance, the government could divert resources following program-based allocation strategies as these would enhance access to crucial social services such as improved sanitation, clean water, healthcare facilities, and heightened electricity supplies. Moreover, national and local governments should work harmoniously to undertake policy initiatives to expand education accessibility and provide industrialization frameworks through which urban households could make wage incomes and have easier access to food consumption. Furthermore, social protection programs targeting households' vulnerable groups, such as children under five years, consist of cash transfers and enhanced *Linda Mama* insurance cover, enabling more accessible access to healthcare services, hence cutting down households' liabilities for multidimensional poverty. Lastly, with the feminization of urban household poverty, this study suggests that policy measures for promoting gender equality, such as equal access to education and employment opportunities, would fasten the multidimensional poverty eradication process and ensure a socially equal urban society in Kenya. Despite the exhaustive evidence provided by this study regarding the incidence and intensity of urban household multidimensional poverty, this study is limited in some ways. This study considered a one-time survey data collected in 2022, which may limit the time variation of the multidimensional poverty dynamics. Secondly, the study considered a few urban study areas, which paves the way for future use of panel survey data analyses and modeling to enhance the understanding of urban household multidimensional poverty from a gendered perspective.

Ethical consideration

Respondents' Consent.

Kenya National Bureau of Statistics (KNBS) sought the respondents' consent from the identified household respondents across the 47 Kenyan counties.

Researcher's Data Access.

The researcher applied to access the household data collected by KNBS and compiled and stored by the World Bank. The researcher formally assured the data privacy of the respondents that data was sought for academic and research purposes only and not shared with a third party.

Data availability

The data used in this study will be made available upon reasonable request.

CRediT authorship contribution statement

Isaiah Maket: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: No additional relationships. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e30139.

Appendices.

Table A
Description of Variable and Summary Statistics

Variable	Description	Mean	SD.
Multidimensional Urban Poverty	Urban household is considered poor if the deprivation score is ≥ 0.25 cut-off point (1 = poor; 0 = non-poor)	0.162	0.368
Household size	No. of family numbers living in the household	3.228	2.032
No. of children <5 years	No. of all household children under five years	0.459	0.676
Household Head Gender	Gender of household head; 1 = male; 2 = female	0.717	0.451
No. of House Rooms	No. of rooms in the household's house	1.527	0.865
Household Head Age	Age of household head in years	37.925	12.701
Agricultural Land Ownership	Ownership of agricultural land (0 = no; 1 = yes)	0.313	0.464
Residing in a malaria-prone endemic zone	Malaria-prone endemic zone (1 = Lake endemic; 2 = Highland epidemic; 3 = Coast endemic; 4 = Low risk)	0.492	1.493
Home Ownership Status	Household home ownership (1 = Owns; 2 = pays rent; 3 = no rent with owner; 4 = no rent/squatting)	0.786	0.455
Household Head Marital Status	Current marital status (0 = never married; 1 = married; 2 = widowed; 3 = divorced; 5 = not living together)	0.638	1.331
Insurance Cover	Household has insurance cover (0 = no; 1 = yes)	0.452	0.513
Woman Education Level	Education level of household women (0 = no education; 1 = primary; 2 = secondary; 3 = tertiary)	0.377	0.842
Household health Status	Household member admitted to a health facility in the last 12 months (0 = no; 1 = yes; 2 = don't know)	0.055	0.352
Household Wealth index	Household wealth index score (1 = poorest; 2 = poorer; 3 = middle; 4 = richer; 5 = richest)	0.475	0.843
Household food insecurity	Food insecurity (0 = food-secure; 1 = food-insecure)	0.096	0.295
Livestock Ownership	Household owns livestock (0 = no; 1 = yes)	0.395	0.489
NGO Social Assistance	Receives social assistance from NGO (0 = no; 1 = yes)	0.014	0.116
Dummy for urbanization status	County Urbanization (0 = peri-urban; 1 = fully-urban)	0.245	0.430
No. of Observations	4662	4662	4662

Note: Dimensionally poor household if the weighted deprivation score is ≥ 0.25 cutoff threshold (poor = 1; non-poor = 0).
Source: Author's Construction [2023].

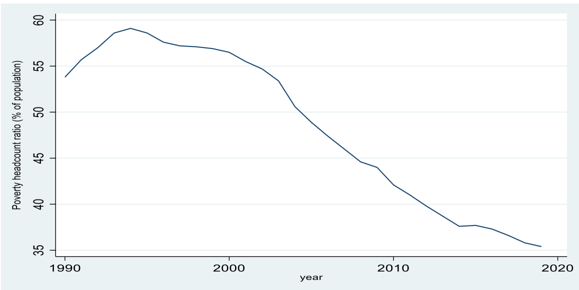

Fig. A. Poverty headcount ratio at $2.15 a day (2017 PPP) (% of the population) - Sub-Saharan Africa
Source: Own Construction [2024].

Table B
Falsification Results

Associations			
Multidimensional Poverty	1.000		
Urban Food Insecurity	0.4246**	1.000	
Head Age × Gender	0.0180**	0.439**	1.000

Note: ***P<0.05.*
Source: Own Construction [2024].

Table C
Correlation Matrix of Independent Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Household size	1.00																
Children <5 years	0.55	1.00															
Head Gender	−0.07	−0.06	1.00														
House Rooms	0.51	0.10	0.01	1.00													
Head Age	0.29	−0.07	0.02	0.46	1.00												
Agricultural Land	0.06	−0.03	−0.15	0.14	0.22	1.00											
Malaria endemic	−0.04	0.02	0.03	0.00	0.02	0.00	1.00										
Home Ownership	−0.28	−0.03	−0.02	−0.49	−0.35	−0.11	0.04	1.00									
Marital Status	0.07	0.02	0.34	0.06	0.28	−0.02	0.00	−0.06	1.00								
Insurance Cover	0.05	0.03	−0.03	0.13	0.06	0.04	0.08	−0.08	−0.06	1.00							
Woman Education	−0.18	−0.06	0.02	0.08	−0.10	0.04	0.01	0.01	−0.18	0.23	1.00						
Health Status	0.01	0.00	0.05	0.03	0.04	0.04	−0.02	−0.02	0.03	0.00	0.00	1.00					
Wealth index	0.07	0.01	−0.01	0.22	−0.02	0.05	0.17	−0.06	−0.13	0.24	0.40	0.01	1.00				
Food insecurity	0.05	0.04	0.05	−0.05	0.01	−0.05	−0.04	0.02	0.08	−0.11	−0.19	0.02	−0.19	1.00			
Livestock Ownership	0.05	−0.05	−0.18	0.13	0.15	0.41	0.02	−0.14	−0.02	0.04	0.05	0.00	0.00	−0.04	1.00		
NGO Assistance	0.05	0.00	0.03	0.03	0.03	−0.02	0.00	−0.06	0.01	−0.02	−0.05	0.02	−0.04	0.03	0.00	1.00	
Urbanization Dummy	−0.03	0.04	−0.03	−0.03	−0.01	0.08	0.60	0.09	−0.04	0.07	0.09	0.00	0.20	−0.05	0.06	−0.03	1.00

Source: Own Construction [2024].

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