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Identifying Factors Shaping Urban Poverty in Malaysia: A Household Perspective

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Abstract

Urban household poverty refers to the inability of households in urban areas to meet basic needs due to limited income and resources, exacerbated by rapid urbanization and rising living costs. This study investigates the factors contributing to urban household poverty in Malaysia, focusing on demographic, socioeconomic, and regional determinants. Using data from the 2019 Household Expenditure Survey (HES) and logistic regression analysis, the study examines variables such as age, gender, education, occupation, household size, and regional disparities. The findings reveal that lower educational attainment, unstable employment, larger household sizes, and underdeveloped regions are significant contributors to poverty, with female-headed households being particularly vulnerable. These insights provide a foundation for designing targeted, region-specific interventions to reduce poverty, improve socioeconomic resilience, and support sustainable urban development in Malaysia.

Keywords: Determinants, Logistic Regression, Urban household poverty

Introduction

Urban poverty remains one of the most pressing socio-economic issues in Malaysia. Despite the nation's remarkable economic growth and significant strides in reducing poverty, urban households continue to face challenges in meeting basic needs. Urbanization, while a driver of economic progress, has contributed to increasing living costs, income inequality, and disparities in access to essential resources. These issues are compounded by structural and systemic factors such as educational attainment, employment stability, and demographic characteristics, creating a complex web of poverty determinants.

Malaysia's commitment to eradicating poverty is reflected in its alignment with the United Nations Sustainable Development Goals (SDGs), particularly Goal 1, which aims to end poverty in all its forms [2]. However, achieving this goal in urban settings requires a nuanced understanding of the factors contributing to poverty. Urban poverty often manifests differently than rural poverty, encompassing not only income deficits but also challenges such as inadequate housing, limited access to quality education, and unstable employment. This study seeks to fill the knowledge gap by analyzing the demographic, socioeconomic, and regional determinants of urban poverty in Malaysia, providing insights for policymakers and stakeholders to design targeted interventions.



Background of Study

Urban poverty in Malaysia has evolved alongside the country's rapid urbanization. According to the [1], over 75% of the population resides in urban areas, a significant increase from previous decades. This shift has led to improved access to infrastructure and economic opportunities for many, yet it has also highlighted the vulnerabilities of urban households. The urban poor often face high living costs, substandard housing, and limited access to healthcare and education, contributing to a multidimensional experience of poverty. The revised poverty line income (PLI) of RM2,208 per month underscores the financial pressures faced by urban households, with approximately 400,000 households falling below this threshold [1].

Previous studies, such as those by [3] and [4], have identified key factors influencing urban poverty, including household size, education level, gender, and regional disparities. For instance, households with lower educational attainment are more likely to experience poverty due to limited access to stable and well-paying jobs. Similarly, female-headed households often face additional financial burdens due to wage disparities and caregiving responsibilities. Regional disparities further exacerbate poverty, with underdeveloped areas such as Kelantan, Terengganu, Sabah, and Sarawak experiencing higher poverty rates. This study builds on existing literature by using the 2019 Household Expenditure Survey (HES) to examine these factors in detail and provide evidence-based recommendations.

Methodology

To achieve the objectives of this study, a quantitative approach was employed, leveraging data from the 2019 Household Expenditure Survey (HES) provided by the Department of Statistics Malaysia. The dataset comprised information from 12,345 households residing in urban areas in 2019. The analysis focused on identifying significant predictors of urban poverty through logistic regression, a statistical method suitable for modeling binary outcomes. In this context, the dependent variable (Y) represents the poverty status of households, where $Y = 1$ indicates a household below the poverty line and $Y = 0$ otherwise.

The logistic regression model is specified as follows:

$$\text{logit}(P) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_k X_k \quad (1)$$

where:

- P is the probability of a household being below the poverty line.
- β_0 is the intercept.
- $\beta_1, \beta_2, \dots, \beta_k$ are the coefficients for each of the independent variables.

The independent variables X_k are defined as follows:

- $X_1 = \text{Age}$: Age of the household head.
- $X_2 = \text{Gender}$: Gender of the household head (1=Male, 0 = Female)
- $X_3 = \text{Ethnicity}$: Ethnicity of the household (Malay as benchmark).
 - $X_{3,1}$: 1 if household is Chinese, 0 otherwise;
 - $X_{3,2}$: 1 if household is Indian, 0 otherwise;



- $X_{3,3}$: 1 if household is others, 0 otherwise.
- X_4 = Marital Status: Marital status of the household head (Married as benchmark).
 - $X_{4,1}$: Never Married, 1 if true, 0 otherwise;
 - $X_{4,2}$: Widow/Widower, 1 if true, 0 otherwise;
 - $X_{4,3}$: Divorced, 1 if true, 0 otherwise;
 - $X_{4,4}$: Separated, 1 if true, 0 otherwise.
- X_5 = Education Level: Highest level of education attained by the household head (Degree/Advance Diploma as benchmark).
 - $X_{5,1}$: 1 if Diploma/Certificate, 0 otherwise;
 - $X_{5,2}$: 1 if STPM, 0 otherwise;
 - $X_{5,3}$: 1 if SPM/SPMV, 0 otherwise;
 - $X_{5,4}$: 1 if PMR/SRP, 0 otherwise;
 - $X_{5,5}$: 1 if No Certificate, 0 otherwise.
- X_6 = Occupation: Occupation type of the household head (Services and Sales Workers as benchmark).
 - $X_{6,1}$: 1 if Manager, 0 otherwise;
 - $X_{6,2}$: 1 if Professional, 0 otherwise;
 - $X_{6,3}$: 1 if Technician and Associate Professionals, 0 otherwise;
 - $X_{6,4}$: 1 if Clerical Support Workers, 0 otherwise;
 - $X_{6,5}$: 1 if Skilled Agricultural, Forestry, and Fishery Workers, 0 otherwise;
 - $X_{6,6}$: 1 if Craft and Related Trades Workers, 0 otherwise;
 - $X_{6,7}$: 1 if Plants and Machine Operators and Assemblers, 0 otherwise;
 - $X_{6,8}$: 1 if Elementary Occupations, 0 otherwise;
 - $X_{6,9}$: 1 if Occupations Not Elsewhere Classified, 0 otherwise.
- X_7 = Region: Region of residence (Different regions as benchmark).
 - $X_{7,1}$: 1 if Western Region (includes Kelantan, Terengganu, Pahang), 0 otherwise;
 - $X_{7,2}$: 1 if Northern Region (includes Kedah, Penang, Perak, Perlis), 0 otherwise;
 - $X_{7,3}$: 1 if Eastern Region (includes Sabah, Sarawak, Labuan), 0 otherwise.
- X_8 = Number of Children: Number of children below 15 years old in the household (Number of child 0 as benchmark).
 - $X_{8,1}$: 1 if there is 1 child, 0 otherwise;
 - $X_{8,2}$: 1 if there are 2 children, 0 otherwise;
 - $X_{8,3}$: 1 if there are 3 children, 0 otherwise;
 - ...
 - $X_{8,8}$: 1 if there are 8 children, 0 otherwise.
- X_9 = Number of Male Adults: Number of male adults in the household. (Number of male adults 1 as benchmark).



- $X_{9,0}$: 1 if there are no male adults, 0 otherwise;
- $X_{9,2}$: 1 if there are 2 male adults, 0 otherwise;
- $X_{9,3}$: 1 if there are 3 male adults, 0 otherwise;
- ...
- $X_{9,9}$: 1 if there are 9 male adults, 0 otherwise.
- X_{10} = Number of Female Adults: Number of female adults in the household. (Number of female adults 1 as benchmark).
 - $X_{10,0}$: 1 if there are no female adults, 0 otherwise;
 - $X_{10,2}$: 1 if there are 2 female adults, 0 otherwise;
 - $X_{10,3}$: 1 if there are 3 female adults, 0 otherwise;
 - ...
 - $X_{10,8}$: 1 if there are 8 female adults, 0 otherwise
- X_{11} = Number of Elderly: Number of elderly persons (aged 55 and above) in the household (Number of elderly person 0 as benchmark).
 - $X_{11,1}$: 1 if there is 1 elderly person, 0 otherwise;
 - $X_{11,2}$: 1 if there are 2 elderly persons, 0 otherwise;
 - $X_{11,3}$: 1 if there are 3 elderly persons, 0 otherwise;
 - $X_{11,4}$: 1 if there are 4 elderly persons, 0 otherwise

There are a number of key assumptions for logistic regression to meet for the result derived to be valid as below:

- Binary Dependent Variable:
 - The dependent variable should be binary, such that containing only two possible values. This is not only a theoretical requirement but also practical. For instance, in a study of poverty, the outcome could be in poverty status, poor or not poor. Satisfaction with this assumption makes sure that the model is applicable to real-world scenarios [14].
- Independence of Observations:
 - The observations must be independent. Hence, the occurrence of an event for one observation should not affect the occurrence of the same event for another observation [15].
- Linearity of Logits;
 - Logistic regression is based on the assumption of a linear relationship between the logit. For example, natural logarithm of the odds-of the dependent and independent variables. This can be checked using the Box-Tid Well test [16].
- No multicollinearity:
 - The independent variables should not be highly inter-correlated. High multicollinearity may distort the estimates and affect the stability of the regression coefficients. Multicollinearity can be detected commonly by using variance inflation factors (VIF) [17]. If the VIF value is greater than 10, it means high multicollinearity.



- Large sample size:
 - Logistic regression requires an adequate sample size. A widely used rule of thumb is that there should be at least 10 samples in the data for every predictor variable in the model. This ensures the stability of the estimate and the possibility to generalize the model [18].
- Absence of Outliers:
 - Outliers can have a huge impact on the estimates in logistic regression. Checking for outliers and cleaning them helps in ensuring that the model results are not biased [19]. The Mahalanobis distance is the distance of a point from a distribution with variables covariance. It can be used on a dataset to identify and possibly remove outliers.
- Model Fit:
 - In general, the goodness-of-fit of logistic regression can be checked with the Hosmer-Lemeshow test. Its null hypothesis of no difference between observed and model-predicted values, with its p -value being good for a fit to a model of value greater than 0.05[14].

The criterion evaluation of logistic regression model, including Omnibus test and Hosmer-Lemeshow test were tested to ensure the validity of the model. The model's goodness-of-fit was evaluated using the Hosmer-Lemeshow test, while the Omnibus Test is used to assess the overall significance of the logistic regression model. The significance of predictors was assessed through Wald statistics and odds ratios while predictive efficiency model measure the overall performance of model. Lastly, both Cox & Snell R-squared and Nagelkerke R-squared offer insights into the proportion of variation explained by the model, allowing researchers to evaluate the predictive power and adequacy of the logistic regression model.

Results and Discussion

Descriptive Analysis

The analysis indicated that 62% of urban households in Malaysia were below the poverty level. In 78% of families, the head of households had only primary or no formal education. Female-headed households made up 32% of those living below the poverty line, highlighting the hardships encountered by single-parent families. Families with more than five members accounted for 45 percent of poor households. The Western Region (Kelantan, Terengganu, Pahang) had the highest proportion of poor households (74%). In comparison, only 13% were in the Northern Region (Kedah, Penang, Perak, Perlis) and 13% in the Eastern Region (Sabah, Sarawak, Labuan). The findings highlight the critical need for targeted initiatives in impoverished regions, as well as educational reforms, to reduce poverty.

Assumptions of Binary Logistic Regression

Firstly, the dependent variable; urban household poverty, is binary in nature, which meets the requirement of logistic regression. Households were classified as either below or above the poverty line, ensuring a clear distinction for analysis.

Secondly, the independence of observations was maintained, as the dataset comprised unique



households without repeated measurements, preventing any potential biases. Additionally, the linearity of the logit was tested using the Box-Tidwell test, which confirmed that the continuous predictor, age of the household head, exhibited a statistically linear relationship with the log odds of poverty after appropriate data transformation and cleaning.

To address potential multicollinearity issues, Variance Inflation Factors (VIFs) were computed for all predictor variables. The results indicated that all VIF values were below the critical threshold of 10, demonstrating that no strong correlation existed among independent variables. Furthermore, the dataset's large sample size of 12,345 observations ensured that the model estimates remained stable and generalizable.

Outliers were identified and removed using Mahalanobis Distance, a statistical measure that detects extreme data points that could influence model accuracy. After eliminating these outliers, the dataset exhibited a more normal distribution, thereby enhancing model reliability. Finally, the model's overall fit was assessed using the Hosmer-Lemeshow test, which resulted in a p -value greater than 0.05, confirming that the model adequately fit the data.

Additionally, the Omnibus Test of Model Coefficients validated that at least one predictor significantly contributed to the explanation of urban poverty. The model's predictive efficiency was further reinforced with an overall classification accuracy of 78.65%, which surpassed the acceptable threshold of 60%. This comprehensive validation process ensures that the logistic regression model serves as a robust tool for identifying the determinants of urban poverty in Malaysia.

Binary Logistic Regression Results

The model demonstrated good fit with a Nagelkerke R-squared value of 0.469 as shown in table 1, indicating that approximately 46.9% of the variance in poverty status was explained by the predictors. These results align with prior studies [2, 3], which emphasize the role of education and regional disparities in shaping poverty dynamics.

Table 1: Model Summary

Model	Cox and Snell R²	Nagelkerke R²
Full Model	0.346	0.469

Urban poverty is a multifaceted problem that impairs households' ability to meet necessities. This study examines demographic, socioeconomic, and regional variables to determine the causes of urban household poverty in Malaysia. Significant predictors of poverty were established using the Wald statistic and odds ratios from Table 2. Variables with p -values < 0.05 were considered statistically significant, and odds ratios provided information on the degree and direction of their influence.

The age of the household head is a significant factor influencing urban household poverty, with a coefficient of -0.024 and a p -value of 0.000. This indicates that as the age of the household head increases, the likelihood of falling into poverty decreases slightly. Age influences poverty because older individuals accumulate more experience and resources, helping to reduce the risk of poverty, while younger individuals often lack assets [3]. Younger



household heads frequently bear the burden of starting a family, managing early career instability, and addressing higher living costs, which makes them more vulnerable to urban poverty [4]. Furthermore, a survey [6] found that older household heads often benefit from secure work, family support systems, or pensions, which reduces their susceptibility to poverty.

Gender is another significant determinant of household poverty levels. Male-headed households are far less likely to fall into poverty, as reflected by a coefficient of -0.554 and a p -value of 0.000. This outcome aligns with findings from a study [7], highlighting systemic gender disparities in economic opportunities and wages. Women-headed households in urban centers face a higher likelihood of falling below the poverty line due to income disparities, caregiving responsibilities, and limited access to well-paying occupations. The concept of the “feminization of poverty” underscores the economic instability faced by women, particularly single mothers [8, 9].

Table 2: Parameter Estimates for All Variables

Variables	β	Wald Statistic	p -value	$\text{Exp}(\beta)$
X_1	-0.024	64.753	0.000	0.976
X_2	-0.554	27.258	0.000	0.575
$X_{3.1}$	-0.716	137.191	0.000	0.489
$X_{3.2}$	-0.168	2.900	0.089	0.846
$X_{3.3}$	0.725	21.744	0.000	2.065
$X_{4.1}$	0.340	12.102	0.001	1.406
$X_{4.2}$	0.109	0.702	0.402	1.115
$X_{4.3}$	0.198	1.327	0.249	1.219
$X_{4.4}$	-0.181	0.235	0.628	0.835
$X_{5.1}$	0.854	88.706	0.000	2.348
$X_{5.2}$	1.303	67.763	0.000	3.681
$X_{5.3}$	1.738	378.342	0.000	5.685
$X_{5.4}$	2.192	338.459	0.000	8.953
$X_{5.5}$	2.478	396.117	0.000	11.916
$X_{6.1}$	-1.656	233.249	0.000	0.191
$X_{6.2}$	-1.387	186.082	0.000	0.250
$X_{6.3}$	-0.604	49.817	0.000	0.547
$X_{6.4}$	-0.356	9.921	0.002	0.700
$X_{6.5}$	0.745	15.111	0.000	2.107
$X_{6.6}$	0.209	3.842	0.050	1.232
$X_{6.7}$	0.070	0.493	0.483	1.072
$X_{6.8}$	0.642	23.444	0.000	1.900
$X_{6.9}$	0.936	57.011	0.000	2.551



X _{7.1}	0.869	104.408	0.000	2.385
X _{7.2}	0.810	148.984	0.000	2.247
X _{7.3}	0.564	73.933	0.000	1.757
X _{8.1}	1.123	220.416	0.000	3.073
X _{8.2}	1.623	347.609	0.000	5.069
X _{8.3}	2.328	401.708	0.000	10.259
X _{8.4}	2.089	157.822	0.000	8.076
X _{8.5}	2.260	54.388	0.000	9.587
X _{8.6}	2.555	11.263	0.001	12.876
X _{8.7}	2.951	6.582	0.010	19.130
X _{8.8}	18.186	0.000	1.000	79093289.440
X _{9.0}	-0.907	59.532	0.000	0.404
X _{9.2}	0.475	47.160	0.000	1.608
X _{9.3}	0.403	14.759	0.000	1.496
X _{9.4}	0.094	0.256	0.613	1.099
X _{9.5}	0.139	0.106	0.744	1.150
X _{9.6}	0.644	0.657	0.418	1.904
X _{9.7}	-1.792	1.492	0.222	0.167
X _{9.8}	-22.687	0.000	0.999	0.000
X _{9.9}	-22.789	0.000	0.999	0.000
X _{10.0}	-0.994	92.464	0.000	0.370
X _{10.2}	0.502	55.040	0.000	1.652
X _{10.3}	0.351	10.515	0.001	1.420
X _{10.4}	0.487	5.192	0.023	1.627
X _{10.5}	-1.031	6.426	0.011	0.357
X _{10.6}	1.191	0.690	0.406	3.291
X _{10.7}	-21.679	0.000	1.000	0.000
X _{10.8}	18.076	0.000	1.000	70862674.876
X _{11.1}	0.724	89.993	0.000	2.062
X _{11.2}	1.225	88.468	0.000	3.405
X _{11.3}	1.459	2.553	0.110	4.302
X _{11.4}	21.545	0.000	1.000	2273406269.53

Ethnicity significantly impacts poverty levels. Chinese households are less likely to experience poverty (coefficient of -0.716, p -value of 0.000), while households categorized as “Others” are more vulnerable (coefficient of 0.725, p -value of 0.000). Certain ethnic groups, such as the Chinese, benefit from better access to education, entrepreneurial networks, and urban economic prospects [10]. Conversely, marginalized groups face systemic disadvantages,



including geographic isolation and limited access to education and healthcare [5].

Education is a critical variable, with lower attainment strongly associated with poverty. For example, heads with no formal education have an odds ratio of 11.916, which means these heads of households are nearly 12 times more likely to experience poverty. Similarly, lower educational levels such as PMR/SRP (coefficient: 2.192, p -value: 0.000) and SPM/SPMV (coefficient: 1.738, p -value: 0.000) significantly increase the chances of poverty. Education equips individuals with skills and qualifications needed to secure better-paying jobs [11].

Occupation also profoundly influences poverty outcomes. Managerial roles (coefficient: -1.656, p -value: 0.000) and professional roles (coefficient: -1.387, p -value: 0.000) are associated with a reduced likelihood of poverty, as these jobs provide consistent earnings and additional benefits [3]. On the other hand, low-status occupations such as elementary jobs are linked to higher poverty risks.

Regional disparities are highly significant, with households in the Western Region being 2.385 times more likely to fall into poverty compared to others. Similarly, households in the Northern Region (odds ratio: 2.247) and the Eastern Region (odds ratio: 1.757) face significant poverty risks. These disparities stem from underdeveloped infrastructure, limited industrialization, and geographic isolation [5, 10].

Household composition also impacts poverty. Households with one to seven children show significant effects, with odds ratios ranging from 3.073 to 19.130, meaning the likelihood of poverty increases as the number of children rises. Larger families face additional financial burdens, including childcare and education expenses, which exacerbate poverty risks [12]. Similarly, households with one or two elderly members (odds ratios: 2.062 and 3.405) are more vulnerable due to increased healthcare and caregiving costs [13].

Model Efficiency Summary

The logistic regression model's performance in identifying urban poverty outcomes is evaluated using key metrics of sensitivity, specificity, and overall accuracy. Table 3 presents a summary of these efficiency metrics.

The full model demonstrates strong predictive performance, achieving a sensitivity of 86.44%, indicating its effectiveness in correctly identifying many poverty cases. The specificity, at 66.47%, reflects the model's ability to accurately classify non-poverty households, though there is a higher rate of false positives compared to true negatives.

Table 3: Model Efficiency Metrics

Model	Sensitivity (%)	Specificity (%)	Overall Percentage (%)
Full Model	86.44	66.47	78.65

Overall, the model achieves an accuracy of 78.65%, surpassing the acceptable threshold of 60%. This balance between sensitivity and specificity indicates the model's robustness in predicting urban poverty outcomes effectively. The high sensitivity ensures minimal missed poverty cases (false negatives), while the specificity suggests reasonable accuracy in identifying non-poor households. Collectively, these metrics highlight the model's reliability for addressing



urban poverty-related challenges and informing targeted interventions.

Conclusion

This study focuses on the various elements that contribute to urban household poverty in Malaysia, such as demographics, education, occupation, and regional differences. Older household heads are less likely to be poor, whereas female-headed families remain especially vulnerable. Ethnicity has an important effect, with Chinese households less likely to be poor, while excluded populations such as “Others” are more vulnerable.

Lower educational attainment promotes vulnerability; hence education has a big impact on poverty. Similarly, higher-status occupations, such as management and professional positions, have lower poverty risk, whereas low-wage jobs increase it. There are clear regional disparities, with households in less developed regions, such as the Western and Northern regions, suffering greater poverty issues due to inadequate infrastructure and restricted economic opportunity.

Lower education levels make people more vulnerable to poverty. Education plays an important role in reducing poverty. Similarly, having better jobs, like management or professional positions, lowers the risk of poverty. On the other hand, low-paying jobs increase the risk of poverty.

There are also differences between regions. Less developed areas, like the Western and Northern regions, face more poverty because they lack good infrastructure and economic opportunities. Larger families, especially those with many children or elderly members, face more financial struggles. This evidence shows the need for programs to help families.

In short, reducing urban poverty in Malaysia requires specific actions like improving access to education, creating stable jobs, and reducing differences between regions. By focusing on these areas, policymakers can better support families and help reduce poverty in cities.

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