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Evaluating Binary Logistic and Multilevel Logistic Regression Model by Analyzing the Factors Associated with Early Childhood Development in Bangladesh

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Abstract

This study aims to evaluate the factors influencing Early Childhood Development (ECD) in Bangladesh, highlighting its long-term economic and social benefits and the need for equitable access to developmental resources for all children. Data was drawn from the Bangladesh Multiple Indicator Cluster Survey (MICS). Binary logistic regression and multilevel logistic regression models were applied to examine the associations between ECD outcomes and key socio-demographic, economic, and caregiving variables. Model comparisons were conducted using Akaike's Information Criterion (AIC). Access to children's books and store-bought toys was found to be significantly associated with positive outcomes. Additionally, the use of internet and mobile phones showed a protective effect. The multilevel logistic model (AIC = 4845.4) demonstrated a better fit than the binary logistic model (AIC = 4928.5). Both individual and community-level interventions are essential to enhance early childhood development in Bangladesh. Quality early childhood programs foster cognitive, emotional, and social growth, contributing to improved educational outcomes, stronger family environments, and more resilient communities.

Keywords: ECDIN, Logistic regression, Multilevel logistic regression, AIC.

I. Introduction

Early Childhood Development (ECD) forms the foundation for future health, learning, and well-being, particularly in low- and middle-income countries (LMICs) like Bangladesh, where limited access to healthcare and educational resources constrains development potential for many children. Despite global advancements, children in LMICs face socioeconomic and environmental factors that hinder optimal development, making ECD research a high-priority field for intervention and policy design et al[1].

In Bangladesh, approximately 40% of children aged below five are at risk of not meeting key developmental milestones, with disparities influenced by household wealth, caregiver education, and access to resources[10]. By employing both binary logistic and multilevel logistic models, this study aims to identify the critical drivers of ECD in Bangladesh and assess the model that best captures both individual and contextual variables, providing policymakers with a reliable statistical framework to inform strategies to reduce disparities in ECD outcomes across regions.

Sk et al. 2019 found that providing children with at least three books and encouraging fathers to engage in four or more activities with their children was strongly associated with positive early ECD outcomes. Children residing in the mountains in Nepal showed a better ECD compared to the children living in the Terai regions. Jeong et al. 2016 conducted a study to determine if varying degrees of paternal stimulation are connected to ECD demonstrating severely limited paternal stimulation in LMICs and how its absence has unfavorable connections with developmental outcomes.

In this study, Akaike's Information Criterion (AIC) will guide model selection, while the intraclass correlation coefficient (ICC) will be calculated to quantify variations attributable to community-level effects, allowing for a nuanced comparison of model performance[9]. This research thus not only advances the application of statistical models in ECD studies but also underscores the importance of multi-level analysis in understanding complex socio-environmental impacts on early childhood outcomes, with implications for scalable interventions in LMICs like Bangladesh.

II. Data and Methods

Data source and study population

The data is extracted from the sixth Bangladesh Multiple Indicator Cluster Survey (MICS) 2019. A two-stage stratified cluster sampling design was used to select the sample. The survey collected detailed data on 23,099 children under five, offering a rich dataset for comprehensive analysis. In this study, about 9194 children were selected from the original sample, where children were 3 to 5 years old, and provided information on many indices about early childhood development.

Outcome variable

To assess Early Childhood Development (ECD), each child aged 36–59 months was evaluated across four domains: literacy-numeracy (3 items), physical (2 items), social-

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emotional (4 items), and learning (2 items). A child was considered "on track" in a domain if they met the minimum item threshold—2 of 3 for literacy-numeracy, 1 of 2 for physical, 2 of 4 for social-emotional, and 1 of 2 for learning.

A composite ECD score (ranging 0–4) was calculated by summing the number of domains in which a child was "on track." The binary outcome variable ECD was defined as follows:
ECD = 1 if a child was on track in ≥3 domains,

ECD = 0 otherwise.

This binary ECD indicator was used as the dependent variable in the analysis.

Explanatory variable

Various family-level and child-related characteristics are analyzed to examine how the factors influence the ECDI in Bangladesh based on the literature review [1], [2], [3], [4], & [6]. We considered area, division, wealth index, internet using status, ownership of mobile phone, mother's and father's engagement with the child, media exposure of mother, mother's education, mother's and father's caregiving, and age category of women as family-level variables. In the case of child-level variables, we considered the age of the child, gender of the child, availability of homemade toys, toys from shops, children's books in the household, and whether the children were left alone in the household or not.

Statistical analysis

For the statistical modelling phase, we employed both logistic regression and multilevel logistic regression analyses. The multilevel logistic regression model was chosen to account for the potential hierarchical structure in the data, incorporating both random and fixed effects.

To evaluate the fit of the logistic and multilevel logistic regression models, we calculated Akaike's Information Criterion (AIC) for both models. The AIC values provided a basis for comparing the relative goodness of fit between the two models, with lower AIC values indicating better model fit. Additionally, we computed the intraclass correlation coefficient (ICC) for the multilevel logistic regression model to assess the variation in the ECD status that is attributable to the group-level effects. The ICC is given by the formula

$$ICC = \frac{\sigma}{\sigma + \pi\frac{2}{3}}$$

The conclusion regarding which model better fits the data was based on the AIC values. The model with the lower AIC value was selected as the more appropriate model for describing the relationships between the covariates and the outcome variable.

III. Results

The descriptive univariate analysis provides an overview of the demographic, socio-economic and caregiving characteristics of the study population. Our outcome variable, the ECDI, showed that 91.9% of children met the developmental milestones.

The percentage of each variable category is arranged in Table-1, which shows the results of the univariate analysis.

Table 1. Univariate and Bivariate Table

Variables	Frequency (Percentage)	ECDI Yes (1)	ECDI No (0)	p-value
ECDI				
Yes	8453 (91.9%)			
No	741 (8.1%)			
Covariates:				
New age category				
36-47 months	4676 (50.9 %)	4262 (89.78)	485 (10.22)	<0.001**
48-60 months	4518 (49.1 %)	4191 (94.24)	256 (5.76)	
Area				0.08
Urban	1754 (18.4%)	1631 (92.98)	123 (7.02)	
Rural	7688 (81.65%)	7052 (91.73)	636 (8.27)	
Gender of child				0.166
Male	4873 (51.6%)	4463 (91.59)	410 (8.41)	
Female	4569 (48.4%)	4220 (92.36)	349 (7.64)	
Age categories of women				0.345
Below 30	5473 (59.5%)	5044 (92.16)	429 (7.84)	
More than or equal 30	3721 (40.5%)	3409 (91.61)	312 (8.39)	
Wealth index				<0.001**
Poorest	2379 (25.3%)	2140 (89.95)	239 (10.05)	
Poorer	1993 (21.2%)	1823 (91.47)	170 (8.53)	
Middle	1766 (18.9%)	119 (44.74)	147 (55.26)	
Richer	1738 (18.7%)	1616 (92.98)	122 (7.02)	
Richest	1518 (15.9%)	1439 (94.80)	79 (5.20)	
Mother's educational level				
No education	1255 (12.4%)	1115 (88.84)	140 (11.16)	
Primary	2340 (25%)	2103 (89.87)	237 (10.13)	

Secondary	4546 (49.2%)	4230 (93.05)	316 (6.95)	
Higher	1301 (13.5%)	1235 (94.93)	66 (5.07)	
Media exposure				<0.001**
No	3908 (42.5%)	1086 (85.17)	189 (14.83)	
Yes	5534 (57.5%)	7597 (93.02)	570 (6.98)	
Division				<0.001**
Barisal	826 (8.7%)	763 (92.37)	63 (7.63)	
Chattogram	1981 (20.9%)	1803 (91.01)	178 (8.99)	
Dhaka	1807 (19.1%)	1667 (92.25)	140 (7.75)	
Khulna	1314 (14%)	1231 (93.68)	83 (6.32)	
Mymensingh	573 (5.9%)	500 (87.26)	73 (12.74)	
Rajshahi	1031 (11%)	953 (92.43)	78 (7.57)	
Rangpur	1116 (11.8%)	1060 (94.98)	56 (5.02)	
Sylhet	794 (8.5%)	706 (88.92)	88 (11.08)	
Mother caregiving				<0.001**
Yes	7712 (44.9%)	7144 (92.63)	568 (7.37)	
No	1730 (55.1%)	1539 (88.96)	191 (11.04)	
Father caregiving				0.407
Yes	4206 (44.9%)	3857 (91.70)	349 (8.30)	
No	5236 (55.1%)	4826 (92.17)	410 (7.83)	
Caregiver of the child				<0.001**
None	1394 (15.2%)	1238 (88.81)	156 (11.19)	
Either father or mother	3854 (41.9%)	3590 (93.15)	264 (6.85)	
Both father and mother	3946 (42.9%)	3625 (91.87)	321 (8.13)	
Ever used internet				<0.001**
Yes	1029 (11.2%)	987 (95.92)	42 (4.08)	
No	8160 (88.8%)	7461 (91.43)	699 (8.57)	
No response	5 (0.1%)	5 (100)	0 (0)	
Own a mobile phone				<0.001**
Yes	7172 (77.4%)	6653 (92.76)	519 (7.24)	
No	2077 (22.6%)	1853 (89.21)	224 (10.79)	
No response	2 (0%)	2 (100)	0 (0)	
Homemade toys				<0.001**
Yes	3907 (41.3%)	3650 (93.42)	257 (6.58)	
No	5530 (58.6%)	5160 (93.24)	374 (6.76)	
Don't know	5 (0.1%)			
Toys from shops				<0.001**
Yes	8167 (86.6%)	7597 (93.02)	570 (6.98)	
No	1275 (13.4%)	1086 (85.17)	189 (14.83)	
Mother engage in four or more activities				0.004**
Yes	4340 (53.5%)	4654 (91.22)	448 (8.78)	
No	5102 (46.5%)	4029 (92.84)	311 (7.16)	
Father engage in four or more activities				0.178
Yes	1047 (11.1%)	974 (93.03)	73 (6.97)	
No	8395 (88.9%)	7709 (91.83)	686 (8.17)	
Mother or father engage in four or more activities				0.019**
None	4829 (52.5%)	425 (8.80)	4404 (91.20)	
Either father or mother	3433 (37.3%)	253 (7.37)	3180 (92.63)	
Both	932 (10.1%)	63 (6.76)	869 (93.24)	
3 or more children's books in the household				<0.001**
Yes	1135 (11.9%)	1099 (96.83)	36 (3.17)	
No	8307 (88.1%)	7584 (91.29)	723 (8.71)	
Did the parents left the child alone				0.497
Yes	1474 (15.5%)	7334 (92.04)	634 (7.96)	
No	7968 (84.5%)	1349 (91.52)	125 (8.48)	
Religion				0.187
Muslim	8361 (89.1%)	7700 (92.10)	661 (7.90)	
Others	1081 (10.9%)	983 (90.93)	98 (9.07)	

$p<0.05$ (Coefficient is significant at the 0.05 level (2-tailed))

Table 1 also represents the bivariate associations between the independent variables and the ECDI outcome.

A significantly higher percentage of children in the 48-60 months age group exhibit the outcome (50.6%) compared to those in the 36-47 months group (34.5%), and the p-value is < 0.001. There is a minor difference between genders, with male children showing the outcome more frequently (48.8%) than female children (45.2%). However, the difference was not statistically significant (p-value=0.166). The age categories of women were found to have an insignificant association with the ECDI.

A strong association exists between maternal education and the outcome. Children of mothers with secondary education or higher exhibit better outcomes (p-value<0.001), with the highest percentage (49.2%) seen among those whose mothers completed secondary education. Socio-economic factors play a significant role in early childhood development. Children from rural areas are more likely to exhibit the ECDI (36.1%) than those in urban areas (7.5%) and this association is statistically significant (p-value<0.001). Similarly, the wealth index is strongly associated with the outcome (p-value<0.001), with children from the poorest households (10.05%) more frequently exhibiting failure in the outcome compared to those from the richest households (5.20%).

Having resources such as internet usage and phone ownership is positively associated with better outcomes. Children from households that use the internet (4.10%) or own a mobile phone (7.24%) exhibit lower rates of failure in early childhood development than those without these accesses. Media exposure of mothers is strongly related to the ECD, as the children of a mother who is exposed show 93.02% of early childhood development, and in the case of the children whose mothers are not exposed to media showed 85.17% positive ECD.

Mother caregiving showed a notable relationship with the development index. Children whose mothers engage in caregiving activities exhibit better outcomes, and the association is significant. But in the case of the children whose fathers are involved in caregiving, the relationship is not significant. The parental caregiving had a significant relationship with the ECD. The children who had homemade toys and toys from shops showed significantly better outcomes (both with p-values < 0.001). Children from households with three or more children's books had a significantly higher percentage of meeting the ECDI milestones than those without (p-value<0.001). The activities of the mother and father affect the ECD significantly. The religion of the household was found to be insignificant for the ECD in our country. These findings underscore the impact of both socio-economic, and demographic factors and parental involvement on early childhood development outcomes.

After the bivariate analysis, we compared the logistic and multilevel logistic regression incorporating all the significant covariates found in the bivariate analysis. The results of the binary and multilevel logistic regression analyses are presented in Table 2. These models aimed to identify significant covariates associated with the ECDI.

Table 2. Comparing logistic and multilevel logistic regression

Covariates	**Categories**	**Binary logistic regression**				**Multilevel logistic regression**			
		estimate	SE	p-value	aOR	estimate	SE	p-value	aOR
Intercept		2.58	0.2651	<0.001	13.20	3.1937	0.3182	<0.001	24.38
Mother's education-al level	No education				1				1
	Primary	0.0264	0.1205	0.820	1.03	-0.0049	0.1379	0.971	0.99
	Secondary	0.2364	0.1243	0.057	1.27	0.2366	0.1423	0.096	1.27
	Higher	0.2987	0.1838	0.104	1.32	0.2988	0.2055	0.146	1.35
Age category	36-47 months				1				1
	48-60 months	0.6404	0.0818	<0.001	1.90	0.7245	0.0911	<0.001	2.06
Wealth Index	Poorest				1				1
	Poorer	-0.0785	0.1145	0.493	0.92	-0.0770	0.1316	0.558	0.93
	Middle	-0.1676	0.1253	0.181	0.84	-0.1749	0.1442	0.225	0.84
	Richer	-0.0802	0.1419	0.571	0.92	-0.0690	0.1621	0.670	0.93
	Richest	0.0491	0.1719	0.775	1.05	0.0370	0.1969	0.851	1.04
Division	Barisal				1				1
	Chattogram	-0.1336	0.1604	0.405	0.87	-0.2300	0.2081	0.269	0.79
	Dhaka	-0.0352	0.1681	0.834	0.96	-0.1111	0.2137	0.602	0.89
	Khulna	0.1200	0.1812	0.507	1.13	0.0634	0.2273	0.780	1.07
	Mymensingh	-0.5197	0.1913	0.006	0.59	-0.706	0.2543	0.005	0.49
	Rajshahi	-0.0205	0.1831	0.910	0.98	-0.0928	0.2327	0.689	0.91
	Rangpur	0.4932	0.1944	0.011	1.64	0.4181	0.2401	0.081	1.52
	Sylhet	-0.1906	0.1839	0.299	0.83	-0.2144	0.2468	0.385	0.81
Mother caregiving	No				1				1
	Yes	0.4191	0.2475	0.090	1.52	0.4686	0.2795	0.093	1.60
Caregiver of the child	None				1				1
	Either father or mother	0.0682	0.2496	0.784	1.07	-0.0266	0.2833	0.925	0.97
	Both father and mother	-0.2984	0.2692	0.267	0.74	-0.2428	0.3053	0.426	0.78
	Yes				1				1

Ever used internet	No	-0.4406	0.1748	0.011	0.64	-0.4823	0.1892	0.010	0.62
Own a mobile phone	Yes				1				1
	No	-0.1826	0.0920	0.047	0.83	-0.2018	0.1048	0.054	0.82
	Yes				1				1
Homemade toys	No	-0.306.	0.0856	<0.001	0.74	-0.3203	0.0972	0.001	0.73
	Don't know	-1.1897	1.1373	0.295	0.30	-1.0509	1.3130	0.423	0.35
Toys from shops	Yes				1				1
	No	-0.5819	0.1002	<0.001	0.56	-0.6243	0.1156	<0.001	0.54
Media exposure	No				1				1
	Yes	0.1716	0.0918	0.061	1.19	0.1633	0.1046	0.118	1.18
	No				1				1
mother engage in four or more activity	Yes	0.0239	0.38733	0.950	1.03	0.2128	0.4301	0.620	1.27
	none				1				1
Activities									
	Either father or mother	-0.1876	0.3867	0.627	0.83	-0.3848	0.4298	0.370	0.68
	Both father and mother	0.0171	0.4235	0.967	1.02	-0.1452	0.4712	0.757	0.86
3 or more child's books in the household	No				1				1
	Yes	0.6898	0.18505	<0.001	2.00	0.7171	0.1956	<0.001	2.05
AIC		4928.5				4845.4			
ICC		0.324							

The intercept for the binary logistic regression and multilevel logistic regression indicates a significant baseline effect in both models. Neither the binary nor the multilevel logistic regression models showed a significantly adjusted association between the mother's educational level and the ECDI. However, there is a trend towards higher education levels being associated with slightly higher odds ratios, though these are not statistically significant. The older age group (48-60 months) showed a significant positive association with the outcome in both models. The adjusted odds ratio (aOR) for the binary logistic regression is 1.90 ($p < 0.001$), and for the multilevel logistic regression, it is 2.06 ($p < 0.001$). So, in both models, the children of higher age had 2 times the odds of developing compared to the children aged between 36-47 months. The wealth index did not show any significant associations with the outcome variable in either model. The odds ratios are all close to 1, indicating no meaningful effect. Most divisions did not show significant associations with the outcome. However, Mymensingh showed a significant negative association in both models (aOR for binary logistic regression = 0.59, $p = 0.006$; aOR for multilevel logistic regression = 0.49, $p = 0.005$). Rangpur showed a significantly positive relationship in the logistic model, but it became insignificant in the multilevel logistic regression. Mother caregiving showed a marginally significant positive association in the multilevel logistic regression (aOR = 1.60, $p = 0.093$) but not in the binary logistic regression (aOR = 1.52, $p = 0.090$). The caregiver of the child, categorized into none, either father or mother, and both father and mother, did not show significant associations with the outcome variable in either model.

Internet use and lack of mobile phone ownership were negatively associated with ECD, though the latter was not significant in the multilevel model. Absence of homemade or store-bought toys showed significant negative associations in both models. Media exposure had a marginally significant positive effect in the binary model only. Parental engagement and activity involvement showed no significant associations. However, having three or more children's books was strongly and significantly associated with better ECD outcomes in both models (aOR ≈ 2, $p < 0.001$).

Age category, internet use, mobile phone ownership, homemade toys, toys from shops, and having three or more children's books in the household were significant predictors of the ECDI in our country. These findings have important implications for understanding the factors that influence the ECD and suggest areas for intervention and further research.

The ICC was calculated to be approximately 0.324, indicating that 32.4% of the variance in the outcome can be attributed to differences between clusters, and the AIC was used to compare the models. The multilevel logistic regression model (AIC = 4845.4) showed a better fit compared to the binary logistic regression model (AIC = 4928.5), indicating that it accounts for some hierarchical structure in the data that the binary logistic regression model does not.

IV. Conclusion

This study explored the influence of various socio-economic and behavioral factors on ECD in Bangladesh, focusing on the role of maternal education, age, wealth, caregiver engagement, internet and mobile phone use, and access to learning materials such as books and toys. As demonstrated in Table 2, the mother's level of education, particularly at secondary and higher levels, was positively associated with early childhood development; however, these associations did not reach statistical significance, indicating that while maternal education might support developmental outcomes, other factors may also play key roles. Furthermore, findings in Table 3 underscore that children aged 48-60 months had significantly greater odds of ECD achievement than those aged 36-47 months, corroborating age as an essential factor in early childhood outcomes[1].

Among socio-economic indicators, the wealth index was not significantly associated with ECD, suggesting that financial resources alone may not determine ECD in this population. Conversely, access to educational resources such as books and toys was notably impactful. Children from households with three or more books or access to store-bought toys were about twice as likely to meet ECD milestones, aligning with research indicating that access to stimulating resources is a crucial determinant of childhood development[4,5]. Moreover, digital access, as indicated by internet and mobile phone use, showed a protective effect, particularly in multilevel logistic regression, underscoring the potential role of digital resources in supporting early learning[10].

The Intraclass Correlation Coefficient (ICC $\approx$ 0.324) suggests a substantial degree of clustering, highlighting that group-level factors significantly influence the observed outcomes. Such a finding aligns with recommendations in multilevel modeling, where an ICC above 0.1 suggests that multilevel analysis is appropriate to account for group dependencies[6].

Model comparison between the binary and multilevel logistic regression analyses revealed that the multilevel model provided a superior fit over the binary logistic model, implying that accounting for hierarchical structures in data yields more reliable insights. This approach also highlighted the intraclass correlation coefficient (ICC), indicating community-level variation in ECD, which binary logistic models may overlook[9]. These findings collectively suggest that individual-level and community-level interventions are necessary to foster optimal ECD in Bangladesh. Future research should examine additional environmental and behavioral factors and leverage hierarchical modelling to capture contextual influences better, aiming to inform targeted interventions for policy and program development.

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Declaration of Conflicting Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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Data Availability Statement

This study utilized data from the Multiple Indicator Cluster Survey (MICS) conducted by the Bangladesh Bureau of Statistics (BBS) with support from UNICEF. The dataset is publicly available through the MICS website and can be accessed upon request at https://mics.unicef.org/.

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Macroeconomic Drivers of Poverty Reduction in Bangladesh: A Time-Series Analysis with ARDL Approach

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Abstract

Poverty reduction remains a core objective of economic development, especially in growing economies like Bangladesh. This research examines the dynamic effects of key macroeconomic factors: inflation, GDP, unemployment, and trade openness, on poverty in Bangladesh. The analysis has been performed utilizing annual time-series data from 1983 to 2023, collected from the World Bank. To assess the short-run and long-run effects of the selected macroeconomic variables on poverty, the Autoregressive Distributed Lag (ARDL) model has been employed which is flexible to accommodate variables with mixed stationary integration order, either I(0) or I(1). The optimal model ARDL(3,3,3,1,3) has been selected using minimum Akaike Information Criterion (AIC), satisfying model diagnostic properties. The Bounds test result confirms the existence of long-term cointegration of variables. Short-run estimates indicate that current trade openness significantly reduces poverty, while GDP has a delayed impact. The study findings reveal that past inflation and unemployment have significant negative effects on poverty. In the long run, the growth of GDP notably reduces poverty, whereas inflation and unemployment worsen it. Policy implications highlight the need for short-term trade and employment reforms, alongside long-term strategies focused on growth, inflation control, and structural unemployment.

Keywords: ARDL, AIC, Cointegration, Bounds test, Error correction term (ECT).

I. Introduction

Poverty is a multidimensional condition encompassing deprivation of economic resources, denial of fundamental rights, and unfulfilled human capabilities[1]. As a sustainable development principle, poverty reduction is still a worldwide concern, especially in emerging nations[2,3]. Despite progress has been made, one in ten people still live in extreme poverty worldwide, which hampers economic growth[4,5]. Developing countries like Bangladesh have focused on meeting Sustainable Development Goal (SDG) 1 of eradicating global poverty in order to strengthen their economy. Although Bangladesh has made progress in poverty reduction, the most recent *State of the Real Economy* report by the Power and Participation Research Centre (PPRC) reveals that 27.9% of the population lives below the upper poverty line[6]. This reflects an almost 10 percentage point increase from the Household Income and Expenditure Survey (HIES) 2022 estimate of 18.7%, indicating a concerning reversal in poverty alleviation[7]. Although the economy grew from 5.78% in 2023 to 5.82% in 2024, rising inequality (Gini index from 0.482 in 2016 to 0.499 in 2022) and inflation (from 9.02% in 2023 to 9.73% in 2024) have offset gains, indicating persistent economic challenges[7,8,9]. These dynamics suggest that growth alone is insufficient for poverty reduction, highlighting the need to address structural challenges. Debates persist regarding the relative influence of macroeconomic variables such as growth, inflation, unemployment, and trade openness on poverty in developing economies[10]. Economic growth can alleviate poverty by creating jobs and revenues, whereas inflation undermines purchasing power and exacerbates inequality[11,12]. Unemployment is a major cause of poverty, as the absence of stable income prevents people from meeting basic needs[8]. In contrast, trade openness may reduce poverty by promoting economic growth and job creation, though its benefits may not be evenly distributed across all segments of society[13]. Understanding these interactions is critical for designing effective policies.

Time series models such as Autoregressive Distributed Lag (ARDL), Vector Autoregressive (VAR), and Autoregressive Integrated Moving Average (ARIMA) are widely used to assess macroeconomic influences on poverty dynamics. VAR and ARIMA models require variables to be stationary at the same order and may not effectively capture long-run relationships. In contrast, the ARDL model is particularly powerful, as it can handle variables with different orders of integration. It also captures both short-run and long-run relationships among variables, making it especially suitable for policy analysis[14]. While some studies have applied ARDL to analyze poverty in other contexts, only a few numbers of research have examined its application in Bangladesh. There is a notable lack of research that investigates the short-run and long-run impacts of macroeconomic factors on poverty. No prior studies have employed the ARDL approach to analyze poverty dynamics in Bangladesh. This study addresses that gap by using ARDL to analyze the effects of inflation, GDP, unemployment, and trade openness on poverty in Bangladesh. This experiment equips policymakers with a deeper understanding of how inflation, GDP, trade openness, and unemployment impact poverty in

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both the short-term and long-term, enabling the formulation of further targeted and effective policy interventions.

II. Literature Review

The relationship between poverty and macroeconomic variables has been widely examined across diverse contexts using time-series and panel data techniques.

Ekpeyong reported that inflation and unemployment significantly affected short-term poverty in Nigeria, though sustained growth reduced long-term poverty[10]. Henneh found that GDP, government expenditure, and lagged poverty rates inversely influenced poverty in Ghana, while Sánchez Dávila highlighted the strong role of economic growth in reducing poverty in Latin America[15,16]. Nurdiana et al. found unemployment raises poverty in South Sulawesi, while growth and inflation have little effect[17]. Tabosa et al. showed that economic growth reduces poverty in Brazil[18].

Similarly, Ebunoluwa and Yusuf found that growth lowers poverty in Nigeria, while unemployment increases it[19]. Studies in Bangladesh, Indonesia, and Pakistan similarly indicate growth lowers poverty, while unemployment, inflation, and trade openness can worsen it[20,21,22].

Overall, empirical evidence consistently indicates that economic growth remains the most consistent driver of poverty reduction, although its effects are mediated by unemployment, inflation, and inequality.

III. Data and Variables

This study utilizes annual time series data for Bangladesh from 1983–2023, primarily sourced from the World Bank. The Ramsey Regression Equation Specification Test (RESET) indicated nonlinearity in inflation and poverty, while unemployment was linear[23]. Missing values for the nonlinear variables were imputed using Kalman smoothing[24], and unemployment gaps were estimated through linear extrapolation[25]. Diagnostic plots and summary statistics confirmed consistency with overall data patterns. The variable names along with their definitions have been presented in Table 1.

IV. Methodology

This study employs the Autoregressive Distributed Lag (ARDL) model to analyze short-run and long-run relationships between selected macroeconomic variables and poverty, based on its theoretical and operational framework detailed below.

Table 1. List of variables.

Variable	Symbol	Definition (Unit of measurement)	Source
Dependent variable			
Poverty	POV	Proportion of the population living below \$3.65/day, 2017 PPP, expressed as a headcount ratio (%)	World Bank
Independent variables			
Inflation Rate	INF	Annual percentage change in the consumer price index (CPI), reflecting the rate at which general price levels in the economy are rising (%)	World Bank
Gross Domestic Product	GDP	Annual growth rate of real GDP, measuring the overall economic performance of a country (%)	World Bank
Trade Openness	TRD	Ratio of the sum of exports and imports of goods and services to GDP, indicating the degree of integration with the global economy (%)	World Bank
Unemployment	UNEMP	Share of the labor force that is without work but actively seeking employment (% of total labor force)	World Bank

Autoregressive Distributed Lag (ARDL) Model

The Autoregressive Distributed Lag (ARDL) model is a widely applied econometric approach for examining both short-run and long-run relationships among time series variables. The ARDL model may evaluate the long-run relationship between variables regardless of whether the regressors exhibit a mix of stationarity properties, being either I(0) or I(1); however, it cannot be used if any of the variables are I(2)[15]. Long-run relationships are established through the ARDL bounds testing approach to cointegration[14].

The general ARDL specification is expressed as:

$$\Delta Y_t = \beta_0 + \sum_{j=1}^{p} \beta_j \Delta Y_{t-j} + \sum_{k=0}^{q} \gamma_k \Delta X_{1t-k} + \sum_{l=0}^{r} \delta_l \Delta X_{2t-l} + \sum_{m=0}^{s} \varphi_m \Delta X_{3t-m} + \sum_{n=0}^{t} \kappa_n \Delta X_{4t-n} + \theta_0 Y_{t-1} + \theta_1 X_{1t-1} + \theta_2 X_{2t-1} + \theta_3 X_{3t-1} + \theta_4 X_{4t-1} + \varepsilon_t$$

Where Y_t is the dependent variable, X_{it} $(i = 1,2,3,4)$are explanatory variables, Δ denotes first difference, $\beta, \gamma, \delta, \varphi, \kappa$ are short-run coefficients, $\theta_i(i = 0,1,2,3,4)$ are long-run coefficients and ε_t is the white noise disturbance term.

In the context of this study, the ARDL model is specified as:

$$\Delta POV_t = \beta_0 + \sum_{j=1}^{p} \beta_j \Delta POV_{t-j} + \sum_{k=0}^{q} \gamma_k \Delta INF_{t-k} + \sum_{l=0}^{r} \delta_l \Delta GDP_{t-l} + \sum_{m=0}^{s} \varphi_m \Delta TRD_{t-m} + \sum_{n=0}^{t} \kappa_n \Delta UNEMP_{t-n} + \theta_0 POV_{t-1} + \theta_1 INF_{t-1} + \theta_2 GDP_{t-1} + \theta_3 TRD_{t-1} + \theta_4 UNEMP_{t-1} + \varepsilon_t$$

Bounds Testing for Cointegration

The ARDL bounds test evaluates the existence of a long-run relationship by testing the joint significance of the lagged level variables:

$$H_0: \theta_0 = \theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$$

against

$$H_1: \theta_0 \neq \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq 0$$

If the computed F-statistic exceeds the upper bound critical value, the null hypothesis of no cointegration is rejected, confirming the presence of a long-run equilibrium[28].

Error Correction Model (ECM)

Once cointegration is confirmed, the short-run dynamics are captured through the reparameterized ARDL Error Correction Model (ECM):

$$\Delta POV_t = \beta_0 + \sum_{j=1}^{p} \beta_j \Delta POV_{t-j} + \sum_{k=0}^{q} \gamma_k \Delta INF_{t-k} + \sum_{l=0}^{r} \delta_l \Delta GDP_{t-l} + \sum_{m=0}^{s} \varphi_m \Delta TRD_{t-m} + \sum_{n=0}^{t} \kappa_n \Delta UNEMP_{t-n} + \varphi ECT_{t-1} + \varepsilon_t$$

where ECT_{t-1} is the lagged error correction term and φ represents the speed of adjustment back to equilibrium after short-term shocks.

To ensure the robustness of the model, a series of diagnostic tests, i.e. Breusch-Godfrey-Bertolo LM test, Breusch-Pagan-Godfrey Lagrange Multiplier Test, Jarque-Bera normality test, and Ramsey RESET tests are conducted. These included examinations of serial correlation, heteroscedasticity, normality, and functional form. In addition, stability is assessed using the CUSUM and CUSUMSQ tests, as recommended by Pesaran[14]. The null hypothesis of parameter stability cannot be rejected if the plots remain within the 5% significance boundaries.

Stationarity Test of the Data

Prior to conducting the analysis, the stationarity properties of the data are examined. This assessment is carried out using both graphical techniques and formal unit root tests, namely the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

V. Results

Descriptive Statistics

Univariate analysis is performed to examine the statistical properties and trends of the variables, with descriptive statistics presented in Table 2. Poverty value varies from 29.646 to 83.100, with a mean of 64.531 and a standard deviation of 15.693. Inflation ranges between 2.007 and 11.395, averaging 6.310, while GDP growth varies from 2.416 to 7.882, with a mean of 5.298. Trade openness fluctuates between 16.688 and 48.111, with a mean of 29.663. Unemployment shows a minimum of 0.920 and a maximum of 5.000, with a mean of 3.301. Skewness coefficients indicate left-skewness in poverty, GDP, and unemployment, while inflation and trade openness are right-skewed. Kurtosis values suggest platykurtic distributions for all variables except inflation, which is nearly normally distributed.

Figure 1 illustrates the dynamics of the study variables. Poverty follows a steady downward path, while inflation fluctuates around a relatively stable mean. GDP growth remains volatile with shifts in average levels but no clear long-term trend. Trade openness shows a gradual upward trajectory with spikes, and unemployment rises persistently after the early 1990s before stabilizing at higher levels.

Stationarity tests

To check whether the variables are stationary, the ADF and PP unit root tests are carried out, and the results are reported in Table 3. Identifying unit roots is crucial for testing stationarity, and rejection of H_0 confirms stationarity, enabling further econometric analysis. Within the ARDL framework, this verification ensures that variables are I(0) or I(1), but not I(2), thereby satisfying the fundamental assumptions of the model. The results indicate that poverty, trade openness, and unemployment are integrated of order one, I(1), as they become stationary after first differencing. Conversely, inflation and GDP are stationary in levels, i.e., integrated of order zero, I(0). The presence of a mixture of I(0) and I(1) variables validates the use of the ARDL bounds testing framework to investigate long-run relationships.

Table 2. Descriptive statistics of variables.

Variables	Mean	Med	Max	Min	SD	Skewness	Kurtosis
POV	64.531	68.463	83.100	29.646	15.693	-0.722	2.451
INF	6.310	6.045	11.395	2.007	2.136	0.134	3.088
GDP	5.298	5.239	7.882	2.416	1.342	-0.142	2.210
TRD	29.663	28.388	48.111	16.688	9.145	0.379	2.231
UNEMP	3.301	3.620	5.000	0.920	1.228	-0.565	2.046

Fig. 1. Trend of variables included in the study.

ARDL Bounds test for Cointegration

To investigate the long-run equilibrium among the variables, the ARDL bounds testing approach[14] is employed following stationarity analysis. This method accommodates variables integrated at different levels, I(0) or I(1), but not I(2). The computed F-statistic (12.388) from the bounds test, presented in Table 4, exceeds the upper bound critical values at all significance levels, indicating statistical significance at 1%. Consequently, the null hypothesis of no cointegration is rejected, confirming a stable long-run relationship between poverty and selected macroeconomic factors in Bangladesh. This result supports the estimation of an Error Correction Model (ECM) to capture short-run dynamics and adjustment toward long-run equilibrium.

Figure 2 shows AIC values for top 20 models. Based on minimum AIC value, the optimal lag structure, ARDL (3,3,3,1,3) is chosen for this study.

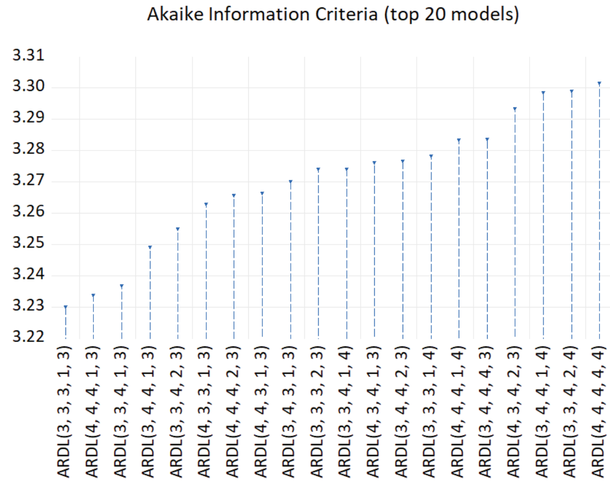

Fig. 2. Akaike information criterion model selection.

Short-run and Long-run estimates

Table 5 presents the short-term effects of key macroeconomic factors on poverty using the ARDL model (3, 3, 3, 1, 3). The first and second lagged differences of poverty have significant negative coefficients (-0.885 and -0.368), showing that past reductions continue to impact current poverty.

While current inflation has a positive but insignificant effect on poverty (coefficient = 0.132), coefficients for the first and second lagged differences are significantly negative (-0.419 and -0.248, respectively). This implies that while immediate inflation doesn't significantly impact poverty, its lagged effects may slow poverty rise, possibly through wage adjustments or policy responses.

Table 3. Unit root tests.

Variables	ADF unit root test		PP unit root test		Integration order
	At Level	Δ	At Level	Δ	
Poverty	5.102	-7.215***	4.713	-7.152***	I(1)
Inflation	-4.353***	-7.856***	-4.3971***	-11.813***	I(0)
GDP	-3.600**	-8.173***	-3.655***	-15.467***	I(0)
Trade	-1.417	-5.775***	-1.454	-5.780***	I(1)
Unemployment	-1.377	-5.489***	-0.781	-7.162***	I(1)

Note: **, *** indicates significance at 5% and1% respectively.

Current GDP growth has a negative but insignificant effect on poverty (coefficient = -0.272), while the first and second lagged terms show significant positive effects (0.642 and 0.373). This suggests that, in the short-run, lagged GDP growth may paradoxically increase poverty, likely due to delayed and unequal distributional effects of economic expansion.

Trade openness has a significant short-run negative effect on poverty (coefficient = -0.285), indicating that a 1% increase in trade openness immediately reduces poverty by 0.29%. Current unemployment has a positive but insignificant effect on poverty (coefficient = 0.659), whereas the first and second lagged differences have significantly negative impact (-1.540 and -1.217). This suggests that past increases in unemployment may slow short-term poverty growth.

Table 4. Bounds Test Results.

Null Hypothesis: No levels relationship		
F-statistic	12.388***	
	Critical Values	
Significance Level	**I(0)**	**I(1)**
10%	2.45	3.52
5%	2.86	4.01
1%	3.74	5.06

Note: *** indicates significance at 1%.

The error correction term is highly significant (coefficient = 0.160), confirming a stable long-run relationship among the variables. This might imply that the contribution of inflation, GDP, and unemployment manifests over a longer period or through indirect channels, which will be explored in the long- run.

Table 6 represents the long-run estimates, showing that inflation has a significant positive effect on poverty (coefficient = 0.731). This suggests that a 1% rise in inflation increases poverty by 0.73% over time, primarily by eroding purchasing power and reducing the real incomes of poorer households.

Table 5. Short-run estimates

Economic Model:
$POV = f(INF, GDP, TRD, UNEMP)$

Variable	Coefficient	t-Statistic
$D(POV(-1))$	-0.885	-5.872***
$D(POV(-2))$	-0.368	-2.439**
$D(INF)$	0.132	1.226
$D(INF(-1))$	-0.419	-2.377**
$D(INF(-2))$	-0.248	-2.041*
$D(GDP)$	-0.272	-1.274
$D(GDP(-1))$	0.642	2.171**
$D(GDP(-2))$	0.373	1.883*
$D(TRD)$	-0.286	-3.919***
$D(UNEMP)$	0.659	1.127
$D(UNEMP(-1))$	-1.539	-2.550**
$D(UNEMP(-2))$	-1.217	-2.146**
$ECMt-1$	0.160	8.622***

Note: ∗, ∗∗, ∗∗∗ indicates significance at 10%, 5% and 1% respectively.

GDP growth has a significant negative long-run relationship with poverty (coefficient = -1.091), implying that a 1% rise in GDP reduces poverty by 1.091%. This confirms that economic growth is crucial for poverty reduction in the long run, as it creates employment opportunities and improves living standards.

Trade openness shows a negative but statistically insignificant effect on poverty (coefficient = -0.088), suggesting its impact may be indirect or require longer time horizons. By contrast, unemployment has a significant positive effect (coefficient = 1.497), indicating that a 1% rise in unemployment increases poverty by nearly 1.5%, underscoring joblessness as a major driver of poverty. The intercept is also highly significant (coefficient = -14.177), reflecting the baseline poverty level when other explanatory variables are held at zero.

Table 6. Long-run estimates

Economic Model:
$POV = f(INF, GDP, TRD, UNEMP)$

Variable	Coefficient	t-Statistic
INF	0.730724	2.736489***
GDP	-1.090699	-2.326691**
TRD	-0.087898	-1.443198
UNEMP	1.497464	2.161457**
Cons	-14.17720	-2.949040***

Note: ∗, ∗∗, ∗∗∗ indicates significance at 10%, 5% and 1% respectively.

Stability test

The diagnostic results, presented in Table 7 indicate that the LM, BPG, Jarque-Bera, and Ramsey RESET tests all produce p-values above conventional significance levels, confirming no evidence of serial correlation, heteroskedasticity, non-normality, or misspecification.

Table 7. Stability tests results

Diagnostic Test Results			
Tests	**Test statistic**		**P-value**
LM test	1.5941		0.2305
BPG test	1.5639		0.1685
JB test	0.6561		0.7203
RESET test	0.0143		0.9062
Robust Statistics			
R-squared	0.9976	Adjusted R-squared	0.9956
AIC	3.2047	SIC	3.9804
HQC	3.4807	Durbin-Watson stat	2.3206

Robustness statistics presented in Table 7 validates the model, with an adjusted R^2 of 0.9956, low AIC, SIC, and HQC values, and a Durbin-Watson statistic (2.3206) within the acceptable range, confirming strong explanatory power and well-behaved residuals.

Stability is confirmed by the CUSUM and CUSUMSQ tests, shown in Figure 3, as both plots remain within the 5% significance bounds. Overall, the model is robust, stable, and well-specified, ensuring reliable empirical estimates.

VI. Discussion

The observed difference between the macroeconomic variables' short-term and long-term effects on poverty alleviation paints an intricate and multidimensional picture. In the short-run, trade openness significantly reduces poverty by improving market access, efficiency, and employment opportunities[13]. GDP influences poverty primarily through its lagged effects, consistent with the "trickle-down" theory[11], while current inflation is largely insignificant. However, lagged inflation and past unemployment exert significant short-term effects, reflecting delayed wage adjustments, policy interventions, and the vulnerability of jobless individuals[23]. These findings suggest that immediate poverty reduction strategies may benefit from targeted employment programs and short-term trade facilitation measures.

(a) CUSUM test (b) CUSUMSQ test

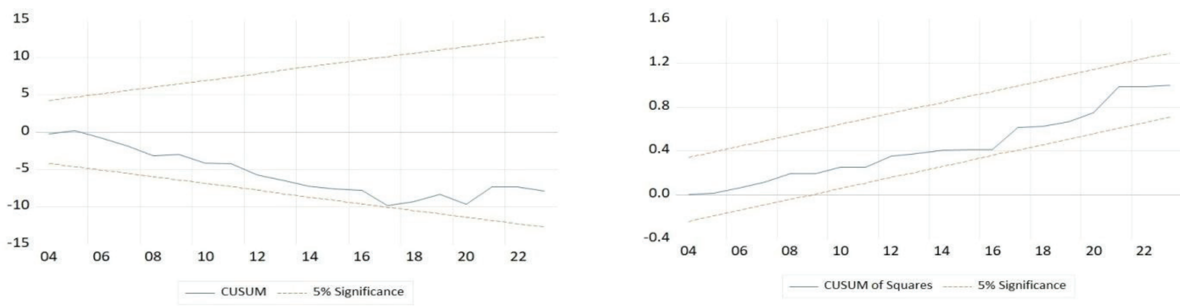

Fig. 3. CUSUM and CUSUMSQ tests.

This study has found that GDP has a negative and significant long-run effect on poverty, suggesting that economic growth contributes to poverty reduction over time. This supports the pro-poor growth hypothesis proposed by Dollar and Kraay [29], which argues that economic growth benefits the poor proportionally. Moreover, this study's finding shows consistency with the findings of Henneh[15] and Sa´nchez Da´vila[16]. In contrast, long-term inflation and unemployment significantly exacerbate poverty, reflecting structural issues such as inflation eroding real income and prolonged unemployment limiting earning capacity[11,12]. Trade openness, while effective in the short-run, appears insufficient for sustained poverty reduction without complementary domestic policies and infrastructure. This nuance encourages future research to explore indirect pathways, such as technology diffusion, labor market reforms, and social safety nets, through which trade openness might affect poverty over extended periods.

VII. Conclusion

According to this study, the ARDL (3,3,3,1,3) model proves to be a reliable tool for examining both the short-run dynamics and long-run equilibrium relationships between poverty and key macroeconomic variables. By capturing these interactions, the model offers deeper structural insights that can guide effective policy formulation. This study results suggest that sustainable poverty reduction in Bangladesh requires policy implementations aimed at maintaining robust GDP growth, ensuring price stability, and lowering unemployment, while also fostering trade openness through strategies that enhance domestic competitiveness. However, the study has certain limitations, including unavailability monthly or quarterly data, the omission of regional differences, and the exclusion of potentially important factors such as income inequality and social expenditure. Future research should therefore consider incorporating broader datasets and additional variables to provide a more comprehensive understanding of the macroeconomic drivers of poverty.

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