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Impact of Household Economic Vulnerability on Child Labour Participation: Mediating Role of School Dropout and Moderating Role of Government Welfare Support

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Abstract:
Child labour remains a persistent socio-economic challenge in developing nations, rooted in household economic fragility and the failure of educational systems to retain children. This study investigates the impact of household economic vulnerability (HEV) on child labour participation (CLP), examining the mediating role of school dropout (SD) and the moderating role of government welfare support (GWS). Grounded in Human Capital Theory and the Social Exclusion Framework, a quantitative cross-sectional survey design was employed with 440 households across rural, semi-urban, and urban areas of Karnataka, India. Confirmatory Factor Analysis (CFA) confirmed reliability and validity of all constructs (CR > 0.83; AVE > 0.55; HTMT < 0.90). Structural Equation Modeling (SEM) in AMOS and Hayes PROCESS macro (Model 1) were employed for hypothesis testing. Results revealed that HEV significantly and positively influenced CLP ($\beta = .763$, $p < .001$) and SD ($\beta = .851$, $p < .001$). School dropout fully mediated the HEV–CLP relationship (indirect effect: $\beta = .723$, 95% CI [.539, .969], $p < .001$). GWS marginally moderated the HEV–CLP relationship ($\beta = -.052$, $p = .082$). These findings contribute to the literature on child labour determinants and provide actionable policy recommendations.

Keywords: Household Economic Vulnerability, Child Labour Participation, School Dropout, Government Welfare Support, Structural Equation Modeling, India

1. INTRODUCTION

Child labour is one of the most severe manifestations of poverty and social inequity in developing nations. Despite significant global progress, an estimated 160 million children worldwide remain engaged in child labour, with South Asia bearing the highest burden (ILO, 2021). In India, approximately 4.35 million children between the ages of 5 and 14 years are engaged in labour activities (UNICEF, 2022), representing both a cause and a consequence of intergenerational poverty.

Household economic vulnerability—characterized by income insufficiency, food insecurity, inability to afford education and healthcare, and dependence on irregular labour—constitutes a primary structural driver of child labour participation. Economically vulnerable households frequently perceive their children's labour as a necessary livelihood strategy, creating a vicious cycle in which poverty perpetuates itself across generations. The relationship between economic vulnerability and child labour, however, is rarely direct; rather, it is mediated through the educational domain, particularly through school dropout. When children discontinue schooling due to economic pressures, they become available for labour market participation.

Government welfare interventions—including conditional cash transfers, mid-day meal schemes, free education initiatives, and livelihood support programs—have been widely implemented as policy tools to

address both economic vulnerability and educational retention. Yet empirical evidence on the moderating role of such welfare support in buffering the vulnerability-to-child-labour pathway remains limited in the Indian context. This study addresses this gap by proposing and testing a moderated mediation model in which school dropout mediates the HEV–CLP relationship and government welfare support moderates the direct HEV–CLP path. Drawing on Human Capital Theory (Becker, 1964) and the Social Exclusion Framework (Sen, 2000), the study provides theoretically grounded insights for policymakers and development practitioners.

2. LITERATURE REVIEW

2.1 Household Economic Vulnerability and Child Labour

Household economic vulnerability (HEV) encompasses persistent income deficits, exposure to economic shocks, food insecurity, and inability to finance human capital investments (Chambers, 1989). Basu and Van (1998) formalized the link through the luxury axiom, positing that child labour arises only when adult income falls below a subsistence threshold. Subsequent studies across South Asian contexts corroborate this relationship (Edmonds, 2008; Ray, 2000). In India, Gupta (2000) demonstrated that households below the poverty line were significantly more likely to send children to work, and national survey analyses confirm that income shocks substantially increase child labour participation probabilities (Deshpande, 2011).

H1: *Household economic vulnerability has a significant positive effect on child labour participation.*

2.2 Household Economic Vulnerability and School Dropout

School dropout—premature discontinuation of formal schooling—is both a direct consequence of household poverty and a proximate cause of child labour. Economic vulnerability reduces household willingness and ability to invest in children's education through inability to pay school fees, prioritization of immediate income over long-term human capital returns, and the need to deploy children's time in household or labour market activities (Filmer & Pritchett, 1999; Tansel, 2002). In India, despite the Right to Education Act (2009) and Sarva Shiksha Abhiyan, dropout rates remain substantially elevated among the economically marginalized (Dreze & Sen, 2013; ASER Centre, 2022).

H2: *Household economic vulnerability has a significant positive effect on school dropout.*

2.3 School Dropout and Child Labour Participation

When children exit formal education, their opportunity cost of time decreases substantially, and households face incentives to redirect children's time toward productive activities. Cross-sectional studies consistently demonstrate that school non-attendance is among the strongest immediate predictors of child labour entry (Edmonds & Pavcnik, 2005; Ravallion & Wodon, 2000). In India, surveys indicate that over 70% of working children have either never attended school or dropped out prior to completing secondary education (NSSO, 2018).

H3: *School dropout has a significant positive effect on child labour participation.*

2.4 Mediating Role of School Dropout

A mediation framework wherein school dropout transmits the effect of household economic vulnerability onto child labour is theoretically supported by human capital investment models (Becker, 1964) and social reproduction theory (Bourdieu, 1986). When economic vulnerability reduces educational investment, dropout removes the institutional protective barrier that schooling provides against child labour entry. Wahba (2006) demonstrated in Egypt that school non-attendance fully explained the income–child labour relationship. In India, Duraisamy (2002) found that the positive poverty–child labour relationship was substantially attenuated when school enrollment was controlled.

H4: *School dropout mediates the relationship between household economic vulnerability and child labour participation.*

2.5 Moderating Role of Government Welfare Support

Government welfare support—encompassing conditional cash transfers, free education programs, mid-day meal schemes, scholarships, and livelihood support—constitutes a critical institutional resource that can buffer vulnerable households against economic imperatives driving child labour. The Social Exclusion

Framework (Sen, 2000) posits that effective welfare systems can interrupt poverty-induced disadvantage by providing households sufficient resources to invest in children's education. Edmonds and Schady (2012) demonstrated that cash transfer programs in developing countries reduced child labour by approximately 15–20 percentage points. India's National Child Labour Project (NCLP) and Integrated Child Development Scheme (ICDS) have shown varying effectiveness in reducing child labour incidence and increasing school retention.

H5: *Government welfare support significantly moderates the HEV–CLP relationship, such that higher welfare support weakens the positive effect of economic vulnerability on child labour.*

3. METHODOLOGY

3.1 Research Design

This study employed a quantitative, cross-sectional survey design consistent with established practices in social science research (Hair et al., 2019). The positivist epistemological stance allows systematic testing of theoretically derived hypotheses through statistical analysis. Cross-sectional data collection was deemed appropriate for examining contemporaneous relationships among the four study constructs.

3.2 Sampling and Data Collection

The target population comprised households with at least one school-age child (aged 5–14 years) in rural, semi-urban, and urban areas of Karnataka, India. A purposive stratified sampling strategy ensured representation across geographic zones and economic strata. The sample size of 440 exceeds the minimum threshold of 200 for SEM applications (Hair et al., 2019). Data were collected via structured questionnaire through trained field enumerators across 22 community clusters over four months, with confidentiality assured. A pilot study (n = 40) confirmed item clarity and internal consistency.

3.3 Sample Profile

The final sample (N = 440) was predominantly male (60.2%), aged 36–45 years (33.9%), and rural-dwelling (59.1%). Agriculture labour (27.0%) and daily wage work (27.3%) were dominant occupations. Most households reported monthly incomes below Rs. 10,000 (35.5%). Nuclear families constituted 62.7% of the sample, and 62.7% received at least one government welfare benefit. Agriculture work was the most common child labour type (35.0%), followed by construction work (25.0%). Full demographic details are presented in Table 1.

Table 1

Demographic Profile of Respondents (N = 440)

Variable	Category	N	%
Gender	Male	265	60.2%
	Female	163	37.0%
	Other	12	2.7%
Age	Below 25 years	30	6.8%
	25–35 years	138	31.4%
	36–45 years	149	33.9%
	46–55 years	79	18.0%
	Above 55 years	44	10.0%
Residence	Rural	260	59.1%
	Semi-Urban	105	23.9%
	Urban	75	17.0%
Education	Illiterate	70	15.9%
	Primary Education	86	19.5%

	Secondary Education	117	26.6%
	PUC/Diploma	108	24.5%
	Graduate and Above	59	13.4%
Parent's Occupation	Agriculture Labour	119	27.0%
	Daily Wage Worker	120	27.3%
	Small Business	65	14.8%
	Private Employee	71	16.1%
	Government Employee	30	6.8%
	Other	35	8.0%
Monthly Income	Below Rs. 10,000	156	35.5%
	Rs. 10,001–Rs. 20,000	140	31.8%
	Rs. 20,001–Rs. 30,000	82	18.6%
	Rs. 30,001–Rs. 50,000	48	10.9%
	Above Rs. 50,000	14	3.2%
Number of Children	One	80	18.2%
	Two	162	36.8%
	Three	127	28.9%
	More than three	71	16.1%
Family Type	Nuclear Family	276	62.7%
	Joint Family	164	37.3%
Welfare Benefit	Yes	276	62.7%
	No	164	37.3%
Child Work Type	Agriculture Work	154	35.0%
	Hotel/Tea Stall Work	55	12.5%
	Construction Work	110	25.0%
	Domestic Work	49	11.1%
	Street Vending	32	7.3%
	Other	40	9.1%

Note. N = 440 households. Percentages may not sum to exactly 100% due to rounding.

3.4 Measurement Instrument

A structured questionnaire with 16 items measured four constructs using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Household Economic Vulnerability (HEV) was measured with four items assessing income insufficiency, food insecurity, inability to afford education/health costs, and dependence on irregular income. School Dropout (SD) was measured with four items assessing economic pressure-induced school exit, affordability barriers, work-school conflict, and accessibility barriers. Child Labour Participation (CLP) was measured with four items adapted from ILO (2004) scales. Government Welfare Support (GWS) was measured with four items assessing receipt of nutrition schemes, scholarships, cash transfers, and livelihood support.

3.5 Common Method Bias Assessment

Common method bias was assessed using Harman's single-factor test (Podsakoff et al., 2003). A single factor extracted from all 16 items explained 46.53% of total variance—below the 50% threshold—indicating CMB is unlikely to substantially distort findings. The KMO was .943 and Bartlett's test was significant ($\chi^2 = 3{,}873.265$, df = 120, $p < .001$), confirming data suitability for factor analysis.

3.6 Data Analysis Strategy

Data analysis proceeded in three stages: (1) CFA in IBM AMOS 26 to assess measurement model fit and construct validity; (2) SEM to test direct structural hypotheses (H1–H3); and (3) Hayes PROCESS macro (Version 4.2, Model 1) with 5,000 bias-corrected bootstrap samples to examine the moderating effect of GWS (H5) and the mediation effect of SD (H4).

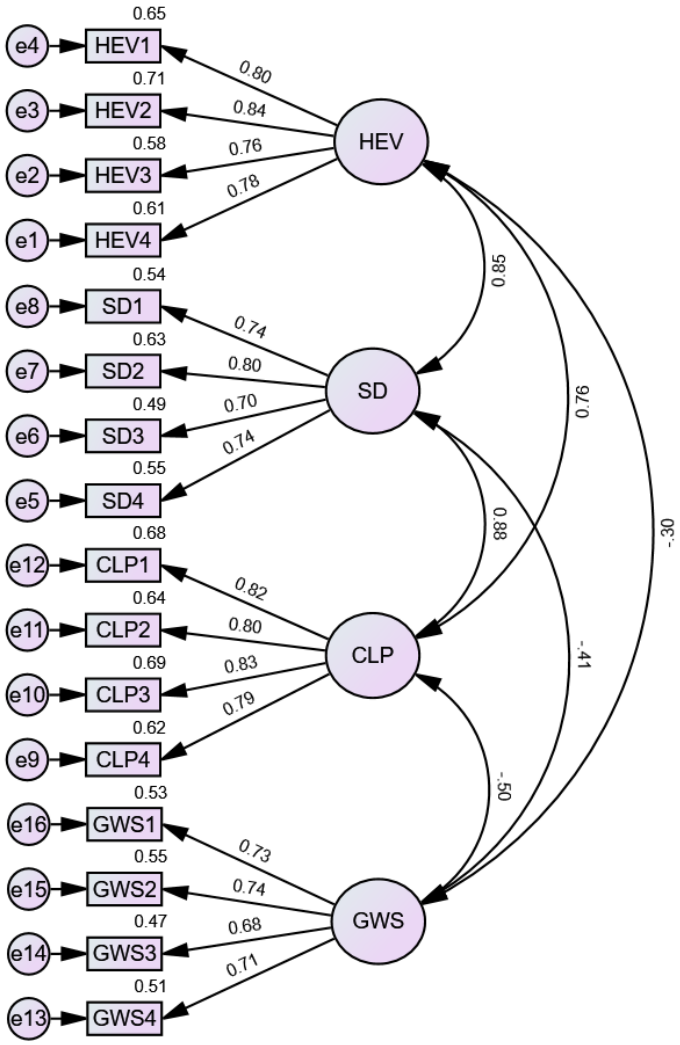
4. RESULTS

4.1 Confirmatory Factor Analysis

The four-factor CFA model with 16 indicators was estimated using maximum likelihood in AMOS and yielded excellent fit: $\chi^2(98) = 111.527$, $p = .165$; $\chi^2/df = 1.138$; CFI = .996; TLI = .996; NFI = .972; GFI = .970; AGFI = .959; RMSEA = .018 (90% CI [.000, .032]; PCLOSE = 1.000). All fit indices met or exceeded established thresholds, confirming excellent model-data fit. Figure 1 presents the CFA path diagram.

Figure 1

Confirmatory Factor Analysis (CFA) Model with Standardized Factor Loadings



Note. CFA model with four latent constructs: Household Economic Vulnerability (HEV), School Dropout (SD), Child Labour Participation (CLP), and Government Welfare Support (GWS). Numbers on indicator arrows are standardized factor loadings (λ); numbers near indicator boxes are squared multiple correlations (R^2). Curved double-headed arrows represent inter-factor correlations. All loadings significant at $p < .001$. Model fit: $\chi^2(98) = 111.527$, $p = .165$; CFI = .996; RMSEA = .018.

Table 2

CFA Factor Loadings, Composite Reliability, and Average Variance Extracted

Construct	Item Description	λ	CR	AVE
Household Economic Vulnerability (HEV)	HEV1 – Income insufficient for basic household needs	.804	.891	.672
	HEV2 – Household faces regular food insecurity	.841		
	HEV3 – Inability to afford education and health costs	.761		
	HEV4 – Household depends on irregular daily wage income	.780		
School Dropout (SD)	SD1 – Child left school due to economic pressure	.737	.845	.576

	SD2 – Household could not afford school fees or materials	.796		
	SD3 – Child's schooling discontinued due to work demands	.699		
	SD4 – Distance and costs prevented regular attendance	.738		
Child Labour Participation (CLP)	CLP1 – Child engaged in paid work outside the home	.827	.884	.657
	CLP2 – Child misses schooling due to work obligations	.802		
	CLP3 – Child contributes to household income through labour	.825		
	CLP4 – Child works in hazardous or demanding conditions	.795		
Government Welfare Support (GWS)	GWS1 – Household benefits from government food/nutrition schemes	.729	.833	.555
	GWS2 – Child enrolled in government scholarship/education programs	.744		
	GWS3 – Household receives cash transfers or livelihood support	.684		
	GWS4 – Welfare support reduces work pressure on children	.715		

Note. λ = standardized factor loading. CR = Composite Reliability. AVE = Average Variance Extracted. All loadings significant at $p < .001$. CR > .80 and AVE > .50 indicate satisfactory convergent validity (Hair et al., 2019).

4.2 Reliability and Validity

Composite Reliability (CR) ranged from .833 (GWS) to .891 (HEV), all exceeding .70. Average Variance Extracted (AVE) ranged from .555 (GWS) to .672 (HEV), all exceeding .50 (Fornell & Larcker, 1981), confirming convergent validity. All HTMT values fell below .90 (highest: CLP–SD = .884), confirming discriminant validity (Henseler et al., 2015). Tables 3, 4, and 5 present model fit indices, inter-construct correlations, and HTMT ratios.

Table 3

Model Fit Indices for CFA and Structural Models

Model	χ^2	df	χ^2/df	CFI	TLI	NFI	GFI	RMSEA
CFA Model	111.527	98	1.138	.996	.996	.972	.970	.018
Structural Model	69.979	51	1.372	.994	.992	.978	.975	.029
Recommended	—	—	< 3	> .95	> .95	> .95	> .95	< .08

Note. CFI = Comparative Fit Index. TLI = Tucker-Lewis Index. NFI = Normed Fit Index. GFI = Goodness of Fit Index. RMSEA = Root Mean Square Error of Approximation. All values meet recommended thresholds.

Table 4

Inter-Construct Correlations and HTMT Discriminant Validity Ratios

Construct	HEV	SD	CLP
Household Econ. Vulnerability (HEV)	—		
School Dropout (SD)	.851	—	
Child Labour Participation (CLP)	.763	.884	—

Government Welfare Support (GWS)	−.299	−.412	−.501
HTMT: HEV	—		
HTMT: SD	.851	—	
HTMT: CLP	.763	.884	—
HTMT: GWS	.299	.412	.502

Note. Upper section: latent factor correlations from CFA. HTMT rows: Heterotrait-Monotrait ratios. All HTMT < .90 confirms discriminant validity (Henseler et al., 2015). All correlations significant at $p < .001$.

Table 5

HTMT Ratio Summary for Discriminant Validity

Construct Pair	HTMT Ratio	Threshold	Decision
GWS – CLP	0.502	< 0.90	Confirmed
GWS – SD	0.412	< 0.90	Confirmed
GWS – HEV	0.299	< 0.90	Confirmed
CLP – SD	0.884	< 0.90	Confirmed
CLP – HEV	0.763	< 0.90	Confirmed
SD – HEV	0.851	< 0.90	Confirmed

Note. HTMT = Heterotrait-Monotrait ratio. All values below .90 threshold confirm discriminant validity between all construct pairs (Henseler et al., 2015).

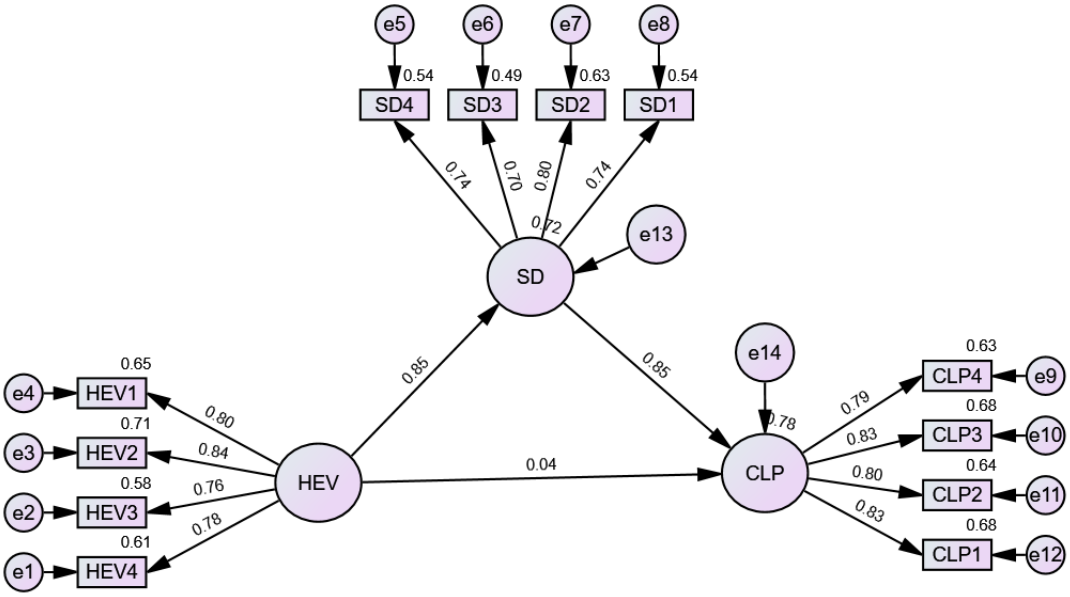
4.3 Structural Model: Direct Effects and Mediation (H1–H4)

The structural model yielded excellent fit: $\chi^2(51) = 69.979$, $p = .040$; $\chi^2/df = 1.372$; CFI = .994; TLI = .992; NFI = .978; GFI = .975; RMSEA = .029 (90% CI [.007, .045]; PCLOSE = .988). The full SEM path diagram is presented in Figure 2.

HEV significantly and positively predicted SD ($\beta = .851$, SE = .058, $p < .001$), supporting H2. SD significantly and positively predicted CLP ($\beta = .849$, SE = .117, $p < .001$), supporting H3. The total effect of HEV on CLP was significant ($\beta = .763$, $p < .001$), supporting H1. The direct path from HEV to CLP controlling for SD was non-significant ($\beta = .040$, SE = .098, $p = .675$), indicating full mediation. The standardized indirect effect was .723 (95% CI [.539, .969], $p < .001$), supporting H4. Results are summarized in Table 6.

Figure 2

Structural Equation Model (SEM) Depicting Full Mediation of School Dropout Between Household Economic Vulnerability and Child Labour Participation



Note. Standardized path coefficients shown on structural paths. Numbers near indicator arrows are standardized factor loadings. The direct path HEV → CLP (β = .04, p = .675) is non-significant, confirming full mediation by SD. Indirect effect of HEV on CLP via SD: β = .723, 95% CI [.539, .969]. HEV = Household Economic Vulnerability; SD = School Dropout; CLP = Child Labour Participation. ***p < .001.

Table 6

Structural Path Coefficients and Hypothesis Testing Results

H	Predictor	Outcome	β	SE	p	Decision
H1	HEV	CLP – Total Effect	.763	—	< .001	Supported
H2	HEV	School Dropout (SD)	.851	.058	< .001	Supported
H3	School Dropout (SD)	Child Labour Participation	.849	.117	< .001	Supported
—	HEV	CLP – Direct (with SD)	.040	.098	.675	Not Supported
H4	HEV → SD → CLP	Indirect Effect	.723	.105	< .001	Supported

Note. β = standardized coefficient. SE = standard error. Bootstrap 95% CI for indirect effect (H4): [.539, .969], based on 5,000 bias-corrected bootstrap samples. Non-significant direct path with significant indirect effect indicates full mediation.

4.4 Moderation Analysis: Government Welfare Support (H5)

The moderating role of GWS was examined using Hayes PROCESS macro (Version 4.2, Model 1) with 5,000 bootstrap samples. The model explained 52.7% of variance in CLP (R^2 = .527, F(3, 436) = 161.65, p < .001). Both main effects were significant: HEV (β = .612, SE = .035, t = 17.73, p < .001) and GWS (β = −.293, SE = .037, t = −7.96, p < .001). The HEV × GWS interaction approached but did not reach conventional significance (β = −.052, SE = .030, t = −1.75, p = .082, ΔR^2 = .003), providing marginal support for H5. The negative interaction directionally indicates that higher GWS attenuates the positive HEV–CLP relationship. Results are in Tables 7–8 and Figure 3.

Table 7

Moderation Analysis: Government Welfare Support Moderating HEV → Child Labour Participation

Predictor	β	SE	t	p	LLCI	ULCI

Constant	2.982	.042	71.88	< .001	2.901	3.064
Household Econ. Vulnerability (HEV)	.612	.035	17.73	< .001	.544	.680
Government Welfare Support (GWS)	−.293	.037	−7.96	< .001	−.366	−.221
HEV × GWS (Interaction)	−.052	.030	−1.75	.082	−.111	.007
R^2 = .527; F(3, 436) = 161.65, p < .001; ΔR^2 = .003						

Note. Outcome: Child Labour Participation (CLP). Predictors mean-centered prior to computing the interaction term. N = 440. Hayes PROCESS macro Version 4.2, Model 1, 5,000 bootstrap samples.

Table 8

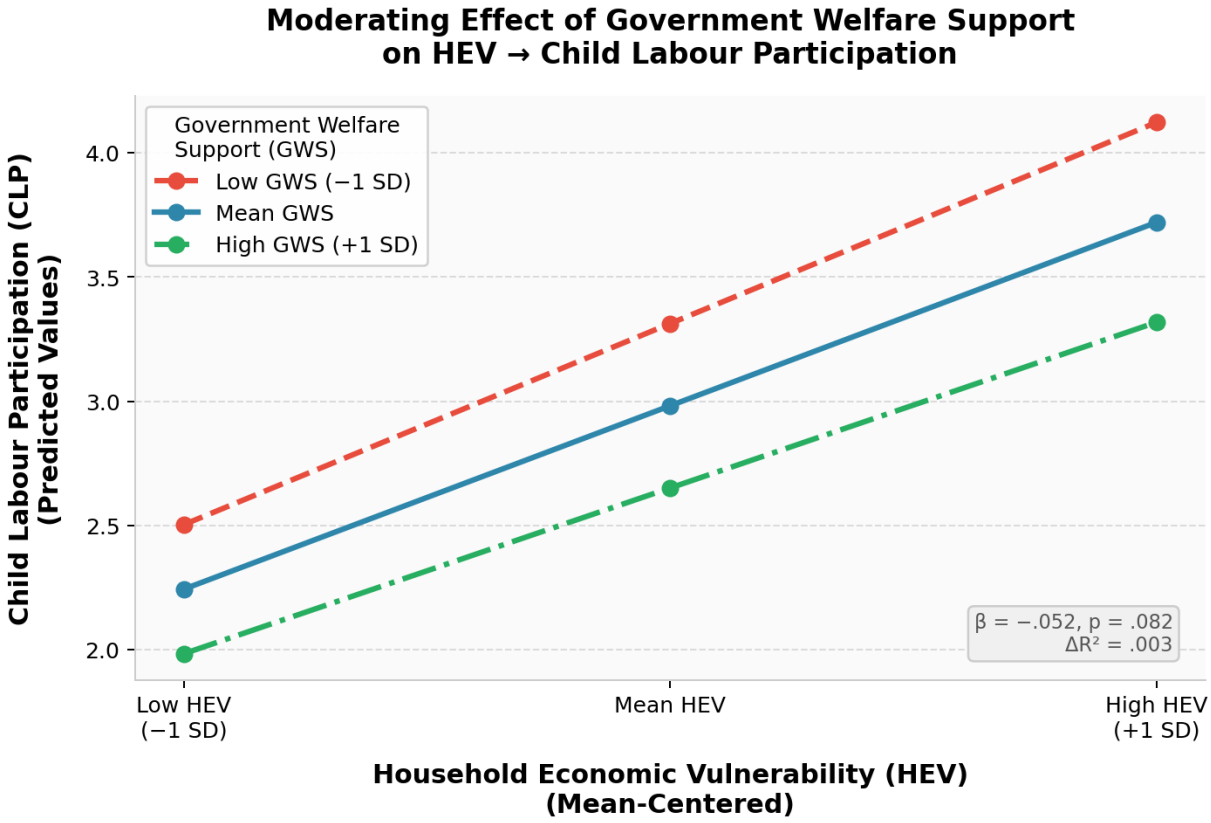
Conditional Effects of HEV on CLP at Three Levels of Government Welfare Support

GWS Level	GWS Value	Effect (β)	SE	t	LLCI	ULCI
Low GWS (−1 SD)	−1.129	.671	.047	14.16	.578	.764
Mean GWS	0.000	.612	.035	17.73	.544	.680
High GWS (+1 SD)	+1.129	.553	.049	11.24	.456	.650

Note. Conditional effects represent the slope of HEV → CLP at each level of GWS. All three conditional effects are statistically significant (p < .001). Magnitude is directionally attenuated at higher GWS. SD = standard deviation from mean-centered GWS.

Figure 3

Interaction Plot: Moderating Effect of Government Welfare Support on the HEV–Child Labour Participation Relationship



Note. Conditional effect of Household Economic Vulnerability (HEV) on Child Labour Participation (CLP) at three levels of Government Welfare Support (GWS): low (−1 SD), mean, and high (+1 SD). Predicted values derived from Hayes PROCESS macro (Version 4.2, Model 1). Converging lines illustrate that higher GWS directionally attenuates the positive HEV–CLP relationship. Interaction coefficient: β = −.052, p = .082, ΔR^2 = .003.

Table 9

Summary of Hypothesis Testing Results

H	Hypothesis Statement	Statistical Result	Decision
H1	HEV → CLP (significant positive effect)	Total β = .763, p < .001	Supported
H2	HEV → SD (significant positive effect)	β = .851, p < .001	Supported
H3	SD → CLP (significant positive effect)	β = .849, p < .001	Supported
H4	SD fully mediates HEV → CLP	Indirect β = .723, 95% CI [.539, .969]	Supported
H5	GWS moderates HEV → CLP	β = −.052, p = .082 (marginal)	Partial

Note. HEV = Household Economic Vulnerability; SD = School Dropout; CLP = Child Labour Participation; GWS = Government Welfare Support. H1–H4 fully supported at p < .001. H5 partially supported (marginal moderation at p = .082).

5. DISCUSSION

5.1 Overview of Findings

This study examined the impact of household economic vulnerability on child labour participation among 440 households in Karnataka, India. Four of five hypotheses were fully supported. Household economic vulnerability increases school dropout (H2), which in turn increases child labour participation (H3), with school dropout fully mediating the overall HEV–CLP relationship (H1, H4). Government welfare support

marginally moderated the HEV–CLP link (H5), directionally attenuating the positive effect without reaching conventional significance thresholds.

5.2 Household Economic Vulnerability and Child Labour (H1)

The significant total positive effect of HEV on CLP ($\beta = .763$, $p < .001$) is consistent with foundational theoretical frameworks and empirical evidence across developing contexts (Basu & Van, 1998; Edmonds, 2008; Gupta, 2000). The magnitude of this effect underscores the pervasive influence of economic precarity on child labour decisions in Karnataka, where agricultural seasonality, daily wage dependence, and limited formal employment characterize the economic landscape for the majority of sampled households. The high concentration of respondents in the below Rs. 10,000 income bracket (35.5%) and predominantly rural profile (59.1%) contextualizes these structural conditions.

5.3 School Dropout as Full Mediator (H2, H3, H4)

The finding that HEV significantly increases school dropout ($\beta = .851$, $p < .001$) extends evidence from Filmer and Pritchett (1999) and Tansel (2002) to the contemporary Karnataka context. The large path coefficient suggests economic vulnerability is among the most powerful antecedents of school dropout in this region, consistent with evidence that direct and indirect schooling costs represent prohibitive barriers despite the Right to Education Act mandate. School dropout's strong positive effect on CLP ($\beta = .849$, $p < .001$), combined with the non-significant direct HEV → CLP path ($\beta = .040$, $p = .675$), demonstrates full mediation. Bootstrap CIs entirely excluding zero [.539, .969] confirm that school dropout is the primary mechanism through which economic vulnerability converts into child labour participation—a finding that provides a theoretically and methodologically rigorous basis for focusing interventions on educational retention.

5.4 Moderating Role of Government Welfare Support (H5)

The marginal HEV × GWS interaction ($\beta = -.052$, $p = .082$, $\Delta R^2 = .003$) provides directional but not statistically conclusive evidence for the buffering role of government welfare support. The small effect size suggests current welfare programs are insufficient to substantially disrupt the vulnerability-to-child-labour pathway. Even at high GWS levels, HEV remains a highly significant positive predictor of CLP (conditional $\beta = .553$, $p < .001$), pointing to the need for more targeted, higher-intensity interventions—particularly conditional cash transfers explicitly tied to school attendance verification.

5.5 Theoretical Contributions

This study advances Human Capital Theory and the Social Exclusion Framework by empirically demonstrating the sequential pathway through which household economic vulnerability erodes child labour protection: depleting educational investment capacity, then removing school enrollment as the institutional barrier against child labour entry. Establishing school dropout as a full mediator provides theoretically rigorous justification for prioritizing educational retention interventions over or alongside direct income transfer mechanisms. The simultaneous testing of mediation and moderation responds to calls for integrated, boundary-condition-specifying models in the child labour literature.

6. CONCLUSION

6.1 Summary of Findings

This study provides robust empirical evidence that household economic vulnerability exerts a significant positive influence on child labour participation in Karnataka, India, with school dropout serving as a full mediator and government welfare support providing a directional but statistically marginal buffer. The findings underscore the critical role of educational retention as the primary mechanism through which economic vulnerability translates into child labour, and highlight the inadequacy of current welfare programs in sufficiently disrupting this pathway.

6.2 Practical Implications

Several actionable recommendations emerge. First, policymakers should prioritize conditional cash transfers (CCTs) explicitly tied to school attendance verification. Second, state administrations should strengthen Right to Education Act implementation through residential schools and bridge education centers for dropout children. Third, the National Child Labour Project (NCLP) should be expanded with

enhanced rehabilitation components targeting children already in labour. Fourth, welfare program coverage should be concentrated on households with irregular income streams in agricultural labour categories. Fifth, social welfare officers should implement regular household-level screenings to identify at-risk children before dropout occurs.

6.3 Limitations and Future Directions

Several limitations warrant acknowledgement. The cross-sectional design precludes causal inference; longitudinal panel studies are needed to confirm directional relationships and assess the causal impact of welfare program enrollment. The purposive sampling strategy and geographic focus on Karnataka limit generalizability. Self-report measures introduce potential social desirability bias. Future research should use objective administrative data, longitudinal designs, and samples from diverse Indian states. Additionally, community-level factors, child-specific characteristics (gender, birth order), and household resilience mechanisms warrant investigation as additional boundary conditions in the vulnerability-to-child-labour pathway.

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