

Educational Poverty and Academic Achievement: A Meta-Analysis Exploring Contextual Moderators and Policy Implications [†]

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[†] This meta-analysis was performed in accordance with the PRISMA 2020 statement.

Abstract

This comprehensive meta-analysis reviews 45 studies published from 2000 to 2024 that use quantitative methods to examine how educational poverty—limited resources, poor-quality teaching, and disadvantaged school settings—affects students' academic outcomes. Following PRISMA guidelines, effect sizes were calculated using random-effects models to account for variability across studies. Educational poverty was associated with a moderate, significant negative impact on achievement (Hedges' $g = -0.45$, 95% CI: -0.50 to -0.40); this likely reflects a performance gap of about 10–15% between disadvantaged and non-disadvantaged students. Variability across studies led to subgroup and meta-regression analyses. The negative effects were more pronounced for primary students ($g = -0.50$) than secondary students, especially in high-inequality regions like North America ($g = -0.55$), and were largest for cognitive outcomes such as standardized test scores ($g = -0.50$), compared to non-cognitive metrics like attendance and graduation. Meta-regression showed that location, age group, and outcome type significantly affected effect sizes. Sensitivity tests and bias assessments confirmed consistent results. Overall, the studies highlight that educational poverty remains a major barrier to academic success, with the strongest effects seen early in education. These findings underscore the importance of early, targeted, and context-specific policies to reduce inequalities and improve learning conditions for underprivileged students.

Keywords: educational poverty; meta-analysis; academic achievement; socioeconomic disparities; policy

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1. Introduction

Poverty—encompassing access, resources, and the quality of education—is a global challenge linked to reduced future earnings, social inequities, and the depletion of human capital (M. Johnson et al., 2023). Studies show that students from low-income backgrounds often have lower attendance, test scores, and graduation rates; however, the importance and context of these findings can differ. Some research highlights material obstacles, such as school buildings or textbooks (Smith et al., 2022; Bishop & Howard, 2025; Song & Tan, 2025), while others focus on sociocultural challenges, including family and

community influences and stress (R. Johnson & Roberts, 2022; Aiston & Walraven, 2024; Peters et al., 2025). This variation calls for a systematic review. Meta-analytic methods can integrate findings from multiple studies to accurately assess the overall effect and identify factors that influence it (Schmidt & Hunter, 2022; Castillo, 2026; Zhao et al., 2025).

Educational poverty—characterized by low household income, scarce school resources, and unsupportive sociocultural environments—substantially hinders academic achievement and sustains social and economic disparities (Teasley et al., 2026; M. Johnson et al., 2023). Global evidence indicates that low socioeconomic status (SES) is associated with lower test scores, poorer attendance, and lower graduation rates. However, these links vary by context, age, and measurement methods (UNESCO, 2022). Barriers such as the lack of textbooks, limited parental engagement, and digital divides further intensify these inequalities.

This paper is grounded in three complementary theoretical frameworks. Sen’s Capability Approach (Sen, 1999; Coldwell & Demack, 2025) views poverty as a deprivation of capabilities—the freedoms and opportunities that enable individuals to achieve their potential. In education, this means that educational poverty restricts children’s ability to learn and limits their future life choices. Bourdieu’s theory of cultural capital (Bourdieu, 1999) posits that children from advantaged backgrounds possess greater cultural resources (knowledge, skills, and dispositions) that facilitate academic success, while educational poverty denies students access to these resources. Finally, Digital Divide Theory (Van Dijk, 2005; Selwyn, 2004) explains how unequal access to digital technology exacerbates educational inequalities, particularly in low-income and rural settings. These frameworks collectively inform our multidimensional operationalization of educational poverty—encompassing material, institutional, and environmental deprivation—and guide our selection of indicators and outcomes (Choi, 2025; Deep et al., 2025).

Despite a large body of research on educational poverty, studies often show conflicting results, complicating efforts to reach clear conclusions. This variability highlights the need to synthesize existing research to better identify the factors driving educational poverty and its impacts. Meta-analytical approaches are well-suited for this task, as they systematically combine findings from different studies, improving the overall validity and reliability of the insights gained (Song et al., 2025; Schmidt & Hunter, 2022).

For example, Smith et al. (2022) found that socioeconomic disadvantage in the United States led to a 0.60 standard deviation drop in standardized math scores. This substantial gap persisted even after controlling for school funding. In contrast, Aiston and Walraven (2024) observed that similar disadvantage levels in Spain were associated with only a 0.25 standard deviation gap after accounting for early intervention programs, suggesting that compensatory policies can meaningfully reduce educational inequalities. Meanwhile, Mburu and Kiplagat (2023) identified stronger effects of poverty on attendance than on test scores in Kenya, while Chen and Li (2023) and Muñoz (2025) found the opposite pattern in China, where socioeconomic status was more strongly correlated with academic performance than with school attendance. These cross-national differences—varying by region, student age, outcome measure, and how poverty is operationalized—make it challenging to draw definitive conclusions about the size and nature of the effects of educational poverty from any single study. A systematic synthesis is therefore essential to integrate this fragmented evidence and identify consistent patterns. This paper applies a meta-analytic approach and aims to:

- (1) Quantify the overall effect of educational poverty on student achievement;
- (2) Examine whether this effect varies systematically by student age and geographic region;
- (3) Derive evidence-based policy recommendations to reduce educational inequalities.

These objectives are sequentially linked: the overall effect establishes the magnitude of the problem, moderator analyses identify for whom and where the problem is most

severe, and policy recommendations translate these findings into actionable strategies (UNESCO, 2022; De Sanson Portella, 2026).

Socioeconomic status (SES) is often measured by income, parental occupation, and education. Although SES strongly predicts educational outcomes, it does not equate to educational poverty. Educational poverty is a broader, multidimensional concept that encompasses SES and institutional and environmental disadvantages, which can exist even in middle-income households—such as poor school quality, lack of digital infrastructure, or low teacher expectations. Conversely, some students from low-SES backgrounds may avoid educational poverty through compensatory mechanisms like high-quality schools and community support programs. Therefore, in this meta-analysis, SES is considered one of several indicators rather than the sole defining factor (Tan et al., 2025).

This paper is organized as follows: The literature review section explains the definitions, dimensions, and historical studies related to educational poverty. It details the systematic review, including its objectives, search strategies, data extraction procedures, and meta-analysis methods. The results of the meta-analysis are presented comprehensively, highlighting the overall effects, study heterogeneity, and meta-analytic findings. The discussion section revisits these results, emphasizes their importance, and points out research limitations. Finally, the conclusion summarizes the study's main findings and proposes directions for future research.

2. Literature Review and Theoretical Framework

2.1. Defining Educational Poverty: A Multidimensional Framework

Educational poverty is inherently multidimensional, encompassing low household income and barriers to accessing learning opportunities and supportive environments. It aligns with broader poverty concepts, such as those in UNESCO and World Bank reports, which consider educational attainment a key aspect of multidimensional poverty (Luckin et al., 2016; Holmes et al., 2022). Our analysis draws on several theoretical perspectives. Sen's Capability Approach views poverty as a loss of 'capabilities', including freedoms and opportunities. In education, this means that educational poverty involves deprivation in the ability to learn, restricting children's future options. Bourdieu's theory of cultural capital emphasizes that children from disadvantaged backgrounds often lack access to essential resources, such as books and enrichment activities that promote academic success. The Digital Divide theory highlights how disparities in access to technology—such as the internet and devices—create an educational gap that impairs teaching (Zawacki-Richter et al., 2019).

Regarding the first research question, the operational definition of educational poverty is the lack of abilities, resources, and environmental support needed to achieve one's educational potential. This definition extends beyond household income. These factors include:

- **Material Deprivation** refers to the absence of tangible resources at the household level, such as textbooks, digital devices (computers, tablets), a quiet place to study, and sufficient nutrition or healthcare that facilitates learning.
- **Institutional Deprivation** refers to systemic barriers within schools or the education system, including large class sizes, underqualified teachers, limited science lab equipment, poor building conditions, and inadequate funding.
- **Environmental Deprivation** refers to an absence of supportive relational and cultural resources in the family or community, including low parental educational involvement, limited peer academic culture, lack of access to libraries or enrichment activities, and weak community educational norms.

Although low socioeconomic status (SES) is a strong prognosticator, it is used as a proxy for the aforementioned deprivations rather than as the deprivation construct per se. To help elucidate the difference for explanatory purposes, we have matched the main

deprivation variables of interest from the studies selected for inclusion in Table 1. Moreover, our moderator test (Section 4.5) contrasts the effect size estimates from studies investigating the role of SES using traditional variables (e.g., income quintiles) with those from studies examining multidimensional constructs (e.g., aggregate indicators of schooling, connectivity, or cultural capital).

Table 1. Mapping Educational Poverty Indicators to Theoretical Frameworks.

Dimension	Level	Focus	Example
Material Deprivation	Individual/Household	Tangible resources	Textbooks, devices, quiet study space
Institutional Deprivation	School/System	Structural barriers	Teacher quality, class size, lab equipment
Environmental Deprivation	Family/Community	Relational and cultural resources	Parental involvement, peer academic culture, community educational norms

These frameworks guide our selection of indicators and outcomes. Most primary studies we review focus on academic achievement (test scores, grades) as the primary outcome, representing the capability aspect of education. Other metrics, such as attendance rates or grade completion, reflect access to educational resources. In every case, lower achievement can be seen as a sign of educational poverty. By examining studies from different settings, our research extends these theories by empirically linking them to observed results. For example, if standardized test scores are significantly lower in high-poverty areas, this supports the idea that reduced educational attainment results in measurable deficits.

Previous research on educational poverty has highlighted notable achievement gaps across socioeconomic groups, often citing studies from various regions. For example, Smith et al. (2022) observed that students facing socioeconomic disadvantages in the United States tend to score lower on standardized tests. Conversely, García and Hernández (2024) found that early intervention programs in Spain helped narrow these gaps. Nonetheless, differences in study designs, populations, and definitions of poverty hinder the ability to draw broad conclusions. Therefore, a meta-analysis is needed to synthesize this evidence, assess the overall effect, and identify consistent patterns across age groups, regions, and outcome types. Table 1 shows the Mapping Educational Poverty Indicators to Theoretical Frameworks.

The concept of educational poverty can be framed within several theoretical perspectives:

- **The Digital Divide Theory:** This theory explains how unequal access to digital technology exacerbates educational inequalities in low-income and rural settings (Van Dijk, 2005; Selwyn, 2004). When students are unable to participate in learning processes due to a lack of technological resources, this contributes to educational poverty.
- **Pierre Bourdieu’s Theory of Cultural Capital:** Bourdieu postulated that students from wealthy families possess greater cultural capital, in the form of knowledge and skills, as well as access to educational resources, which gives them an edge in schooling. Educational poverty restricts access to this type of capital, denying students the educational resources conducive to academic success. Bourdieu also emphasized social capital—the networks, connections, and access to information that privileged families can mobilize to support their children’s education.
- **Sen’s Capability Approach:** According to Sen (1999), poverty is not merely a matter of income deprivation but of capability deprivation. From an educational perspective, educational poverty reduces students’ ability to fulfill their potential by constraining their life choices. For example, a student without access to digital resources loses the ability to develop digital learning skills relevant to modern life.

Together, these theories provide an expanded framework in which educational poverty is characterized by material deprivation and extensive societal influences that restrict students' opportunities for quality education.

2.2. Theoretical Foundations

Previous research has consistently indicated that marginalized and disadvantaged groups are disproportionately affected by educational poverty and worsening social inequality. Borenstein et al. highlight that multiple interconnected factors, such as socioeconomic status (SES), race, ethnicity, gender, disability, and geographic location, play a crucial role in perpetuating disparities in education.

Sen's Capability Approach

Socioeconomic status (SES) significantly influences educational poverty. Children from low-income backgrounds often encounter challenges such as food insecurity, unstable housing, and restricted healthcare access, all of which negatively impact their academic success. Research shows that these children are less likely to have resources like books or a quiet study environment, perpetuating a cycle of poverty and poor academic performance. For instance, access to science lab equipment is an institutional resource that fosters scientific literacy—the capacity to understand and utilize scientific methods.

- Racial and Ethnic Disparities

Educational poverty significantly impacts marginalized racial and ethnic groups. Many minority students, especially those from underfunded schools, face challenges such as discrimination, cultural isolation, and limited or no representation in school curricula. For example, in the United States, African American and Latino students are often concentrated in under-resourced schools that lack qualified teachers and adequate learning materials, potentially hindering their academic success.

- Geographical Location

Geographical disparities, particularly the urban–rural divide, have a significant impact on educational poverty. Rural students often face limited access to quality education because of inadequate infrastructure and a shortage of qualified teachers (World Bank, 2023). For instance, students in sub-Saharan Africa and parts of South Asia are among those most disadvantaged in education, with restricted access to schools, digital resources, and instructional materials.

- Long-Term Impacts

Longitudinal research shows that the effects of educational poverty are enduring and widespread, affecting individuals well beyond their schooling years. As a result, those experiencing educational poverty often face lifelong challenges, including limited achievements, lower incomes, and poorer health. These disparities tend to persist, creating cycles of poverty and fueling social and economic inequalities.

2.3. Empirical Evidence on Educational Poverty and Academic Achievement

Given that educational poverty is a complex, multidimensional issue, a systematic meta-analytic approach is essential for combining findings across studies. Since individual studies differ in methodology, participant demographics, and contextual factors, meta-analysis offers a highly reliable method for deriving trustworthy, broadly applicable conclusions (Kim & Wang, 2022; R. Johnson & Roberts, 2022; Hedges & Cooper, 2022). Table 2 shows the Summary of Key Studies on Educational Poverty and Academic Achievement.

Table 2. Summary of Key Studies on Educational Poverty and Academic Achievement.

Author(s) Year	Country	Sample Size	Age Range	Key Findings
Smith et al. (2022)	USA	1200	6–18	Educational poverty harms standardized test scores.
Chen & Li (2023)	China	900	10–15	Socioeconomic status is significantly correlated with school attendance and academic performance.
García & Hernández (2024)	Spain	800	5–12	Early educational interventions can mitigate the adverse effects of educational poverty on academic achievement.
Mburu & Kiplagat (2023)	Kenya	1500	7–16	Educational poverty harms both attendance and test scores.
Johnson & Roberts (2022)	UK	1000	11–18	Socioeconomic disparities lead to significant differences in graduation rates.

The COVID-19 pandemic has further intensified educational inequalities, making it imperative to examine recent evidence on digital divides and remote learning disparities. UNESCO (2022) estimated that school closures during the pandemic affected over 1.5 billion learners globally, with students from the poorest quintile experiencing learning losses 33% greater than those from the richest quintile. The pandemic exposed and exacerbated the digital divide: while wealthier families could support their children’s continued learning through private tutoring and advanced digital tools, children from low-income households often lacked basic resources such as reliable internet connectivity and functional devices. Reimers (2021) documented substantial learning loss and disengagement among disadvantaged students across multiple countries, including Brazil, Chile, Spain, South Africa, and the United States. Zhao (2021) similarly highlighted how the shift to emergency remote learning disproportionately harmed students with limited access to educational technology, reinforcing pre-existing achievement gaps. The OECD (2022) reported that socioeconomic achievement gaps in reading, mathematics, and science widened during the pandemic, particularly in countries with weak social safety nets and limited digital infrastructure. These post-2020 findings underscore the urgent need for targeted interventions that address both material deprivation (e.g., device and internet access) and instructional quality in remote and hybrid learning contexts. They also reinforce the relevance of our meta-analytic focus on educational poverty as a multidimensional construct that includes digital access as a critical component of material deprivation.

2.4. The Need for a Meta-Analytical Approach

Such meta-analytical results may help inform targeted interventions and policy reforms to address educational poverty. For instance, strong, adverse relations between educational poverty and test scores may drive governments to invest in digital infrastructure, early childhood education, and programs supporting disadvantaged students. Moreover, subgroup analysis will enable policymakers to develop more context-specific solutions by tailoring interventions to the needs of different populations or regions.

3. Methodology

The starting year 2000 was selected to coincide with major international educational assessments (PISA, TIMSS) that began systematically collecting socioeconomic data, as well as the publication of Sen’s influential ‘Development as Freedom’, which shaped subsequent multidimensional poverty research.

This study adopts a post-positivist research paradigm, recognizing that while an objective reality exists (the relationship between educational poverty and academic achievement), our understanding of it is imperfect and probabilistic. The research follows a quantitative approach, employing a systematic review and meta-analysis design to synthesize findings from multiple empirical studies, estimate an overall effect size, and identify sources of heterogeneity.

This meta-analysis was performed in accordance with the PRISMA 2020 statement and was pre-registered to maximize transparency and replicability (Page et al., 2021). The meta-analysis aims to quantify the relationship between educational poverty and academic achievement and to assess moderator variables.

3.1. Systematic Review Process

The search was conducted across the ERIC, Scopus, PsycInfo, Web of Science, ProQuest Dissertations & Theses Global, and Google Scholar databases (first 200 records per search string), focusing on publications from 2000 through 2024. The year 2000 was chosen as the starting point because it coincides with the launch of major international large-scale assessments (e.g., PISA, TIMSS) that began systematically collecting socioeconomic data relevant to educational poverty, as well as the publication of Sen's (1999) 'Development as Freedom,' which shaped subsequent multidimensional poverty research. The search used strings that combined terms related to educational poverty (e.g., "educational deprivation", "school resources", "low SES") and academic outcomes (e.g., "achievement", "test scores", "attendance"). The sources would be peer-reviewed and gray literature reported at the institutional level and published in English. The PRISMA flow chart described above outlines the strategy.

The following Boolean search strings were used for each database (adapted for syntax differences across platforms):

Filters applied across all databases included the following: (1) publication date between 2000 and 2024; (2) English language; (3) peer-reviewed journal articles, dissertations, and institutional reports; and (4) human participants (children and adolescents aged 5–18).

All database searches were conducted using English-language terms and were limited to studies published in English. This decision was made to ensure consistency in interpreting search results and to facilitate the application of standardized eligibility criteria.

3.2. AI-Assisted Screening and Study Selection

To increase efficiency while retaining human judgment, we utilized AS Review (v1.6), an active-learning-based title and abstract screening tool. Manual labeling by two reviewers was performed on an initial seed set of 100 records, comprising 50 relevant and 50 irrelevant records. Subsequently, the model ranked records by predicted relevance. Screening was concluded when a predefined stopping rule-95% recall on a validation set was obtained. Validation on a random subset of human-screened records ($n = 300$) yielded high agreement (Cohen's $\kappa = 0.82$) and a 98% recall, thereby reducing the screening workload by approximately 65%. Final decisions on study inclusion were entirely human-controlled. A summary of the study selection criteria is shown in Table 3.

Table 3. Inclusion and Exclusion Criteria for Study Selection.

Criterion	Inclusion Criteria	Exclusion Criteria
Population	Children and adolescents aged 5–18	Adults, preschool children
Intervention/Exposure	Examination of educational poverty due to socioeconomic factors	Studies not focused on educational poverty
Outcome Measures	Academic achievement outcomes (e.g., test scores, attendance, graduation rates)	Non-academic outcomes (e.g., health, social behavior)
Study Design	Cross-sectional and longitudinal studies	Case studies, qualitative studies without quantitative measures
Publication Type	Non-peer-reviewed articles without faculty supervision	Non-peer-reviewed articles
Language	English	Non-English
Time Frame	Published between 2000 and 2024	Published before 2000

In addition to Cohen’s κ ($\kappa = 0.82$), which quantified inter-rater agreement, all disagreements between the two independent reviewers were resolved through consensus discussion, consistent with best practices in systematic reviewing (Miles & Huberman, 1994). This two-step process ensured that final inclusion decisions and data extraction were accurate and reliable.

3.3. Inclusion and Exclusion Criteria

The inclusion criteria of studies were as follows: (a) focusing on children and adolescents aged 5–18; (b) defining educational poverty using indicators of deprivation based on socioeconomic, institutional, or multidimensional criteria; (c) taking into account quantitative educational outcomes (e.g., achievement scores, grades, attendance, graduation rates); and (d) supplying data capable of supporting an effect size calculation. Table 4 describes the form validity assessment. Precise operational definitions:

- Educational poverty = lack of material/institutional/environmental resources.
- Academic performance = standardized test scores, grades, attendance, and graduation (all considered equivalent for synthesis).
- For multiple outcomes: calculate a mean effect size per study to ensure independence.

Table 4. Data Extraction Form Variables.

Description	Variable
Study Characteristics	Author(s), year of publication, country of study, study design
Participant Characteristics	Sample size, age range, socioeconomic status, demographic information
Intervention/Exposure Details	Description of educational poverty indicators and any interventions applied
Outcome Measures	Types of academic achievement outcomes reported (e.g., test scores, attendance rates, graduation rates)
Effect Sizes	Means, standard deviations, and sample sizes for calculating effect sizes

3.4. Data Extraction

When calculating the effect sizes, means, standard deviations, and sample sizes were extracted from each included study. When raw data were lacking, other statistics were used to estimate these values. Because the studies varied, effect sizes were standardized into Hedges’ g to ensure comparability. This process accounts for biases related to small sample sizes and is thus an appropriate measure of the effect of educational poverty on academic achievement. Quality was assessed using the adapted Newcastle-Ottawa Scale (Wells et al., 2014).

3.5. Data Extraction and Quality Assessment

Two reviewers independently retrieved data on sample characteristics, definitions of exposure and outcomes, and statistical outcomes. The quality of the observational studies was assessed using a modified seven-domain quality assessment tool borrowed from other education meta-analyses, including representativeness, validity and reliability of measurements, control of confounding variables, and appropriateness of analyses. However, sensitivity analyses were performed using quality scores rather than exclusion criteria. Table 5 summarizes the analytical methods employed.

Table 5. Summarizes the statistical techniques of analysis.

Analysis Technique	Purpose
Hedges'g Calculation	Calculate the overall effect size for the impact of educational poverty
Random-Effects Model	Account for variability among studies
Heterogeneity Assessment	Assess the degree of heterogeneity using the Q statistic and I ² index
Subgroup Analyses	Explore sources of heterogeneity across geographic locations, age groups, and outcome types
Publication Bias Assessment	Detect publication bias using funnel plots and Egger's test
Sensitivity Analyses	Evaluate the robustness of findings by excluding studies with small sample sizes and high risk of bias

Publication bias, in which studies are selected for publication if they show significance, thereby leading to an overestimation of effect size, is also addressed. Various methods would be used to assess publication bias, including funnel plots, Egger's test, and sensitivity analysis, as per UNESCO (2022). These steps are taken to ensure the meta-analysis results are valid and reliable.

3.5.1. Ethical Considerations

This meta-analysis compiles secondary data from published studies and does not involve direct human interaction, primary data collection, or access to identifiable information. Therefore, it presents minimal ethical risk and did not require institutional review board approval. Nonetheless, we followed the PRISMA 2020 guidelines to ensure transparency, thorough study selection, and prevent selective reporting. All included studies adhered to their ethical standards, and we properly cited their sources to recognize the primary researchers' contributions.

3.5.2. Use of Generative AI and AI-Assisted Technologies

In line with emerging journal policies on Generative AI, we disclose that the AI-assisted screening tool AS Review (v1.6) was used to assist with title and abstract screening during study selection. This tool, based on active learning, ranked records by relevance after two reviewers manually labeled an initial set of 100 records. Its purpose was solely to improve screening efficiency; it did not replace human judgment in any critical decisions. All final inclusion decisions, data extraction, statistical analysis, interpretation, and manuscript drafting were performed exclusively by the human authors. The AI was not used to produce content, interpret data, or perform analytical decisions. The authors take full responsibility for the content's accuracy, integrity, and originality, including any errors or omissions related to the AI-assisted process.

3.6. Statistical Analysis

All results are expressed in terms of Hedges' g. When studies reported more than one value, results were combined into a mean per study to ensure statistical independence. Sensitivity tests indicated that this had little effect on the meta-analysis.

3.7. Statistical Analysis Plan

Given the expected diversity of studies included in this analysis, heterogeneity was explicitly evaluated by geographic location, sample characteristics, and the educational outcomes of interest. This evaluation employed two commonly used statistical metrics: the Q statistic and the I^2 index. The Q statistic was computed as $Q = 312.45$, with a p -value less than 0.001, suggesting that the variability in effect sizes observed was greater than what chance alone would explain. Furthermore, the I^2 index revealed significant heterogeneity among the studies, with 85% of the effect-size variability attributable to true differences rather than random error.

This significant heterogeneity indicates that the impact of educational poverty may vary by factors such as geographic location, age group, and the specific educational outcomes measured. To examine this variability, we performed subgroup analyses. The main heterogeneity was evaluated using the Q statistic and the I^2 index. The Q statistic assesses whether the observed variation in effect sizes exceeds what would be expected by chance, as shown in Equation (1).

$$Q = \sum_{i=1}^k w_i (g_i - g_{\text{overall}})^2 \quad (1)$$

where

- k is the number of studies.
- w_i is the weight for the i th study.
- g_i is the effect size for the i th study.
- Overall is the overall effect size.

The I^2 index quantifies the proportion of total variation in effect sizes attributable to heterogeneity rather than chance. It is calculated using Equation (2).

$$I^2 = \frac{Q - (K - 1)}{Q} \times 100\% \quad (2)$$

I^2 values greater than 50% indicate substantial heterogeneity. Significant heterogeneity was observed across these studies ($Q = 312.45, p < 0.001; I^2 = 85\%$), indicating substantial variation in effect sizes. We therefore performed subgroup analyses by geographic location, age group, and type of educational outcome to investigate possible sources of heterogeneity.

3.8. Effect Size Calculation

The effect size for each study was computed and weighted according to its inverse variance, assigning more weight to studies with larger sample sizes. The overall effect size is the weighted mean of individual effect sizes, with larger studies having a greater influence. For each study, Hedges' g was determined using Equation (3).

$$\frac{\bar{X}_1 - \bar{X}_2}{S_p} \times \left(1 - \frac{3}{4(N - 2) - 1}\right) \quad (3)$$

where

- $\bar{X}_1$ is the mean of the educational poverty group.
- $\bar{X}_2$ is the mean of the control group.
- S_p is the pooled standard deviation.
- N is the total sample size (sum of both groups).
- The correction factor $1(-3/(4(N - 2) - 1))$ adjusts for small sample sizes.

Pooled Standard Deviation: The pooled standard deviation S_p is calculated as in Equation (4).

$$S_p = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}} \quad (4)$$

where

- n_1 and n_2 are the sample sizes. The sample sizes are for the educational poverty and control groups, respectively.
- s_1 and s_2 are the standard deviations of the educational poverty and control groups, respectively.

Weighting: Each study's effect size was weighted inversely proportional to its variance to account for differences in sample size and accuracy. Larger studies had a greater influence on the combined effect size, as demonstrated in Equation (5).

$$W_i = \frac{1}{SE_i^2} \quad (5)$$

where SE_i is the standard error of the effect size for the i -th study.

Overall Effect Size: The effect size (Hedges' g) was calculated as the weighted mean of individual effect sizes, as shown in Equation (6).

$$\frac{\sum_{i=1}^k w_i g_i}{\sum_{i=1}^k w_i} \quad (6)$$

where

- k is the number of studies.
- w_i is the weight for the i th study.
- g_i is the effect size for the i th study.

Confidence Interval:

The 95% Confidence Interval (CI) for the overall effect size was calculated using the standard error of the weighted mean effect size as shown in Equation (7).

$$SE_{\text{overall}} = \sqrt{\frac{1}{\sum_{i=1}^k w_i}} \quad (7)$$

The 95% confidence interval (CI) is determined as the overall $CI \pm 1.96 \times SE$. In this meta-analysis, the combined effect size is -0.45 , indicating a moderate negative influence of educational poverty on academic achievement. The 95% CI suggests the true effect in the population lies between -0.50 and -0.40 . This reinforces the reliability and statistical validity of the overall effect size estimate, providing a credible measure of the impact of educational poverty on academic performance.

4. Results

4.1. Study Characteristics and Selection

Figure 1 illustrates the selection process. After screening and reviewing 1245 records, 45 studies were included in the meta-analysis displayed in the figure—each with a final sample of over 30,000 students. The measured academic outcomes varied, with standardized test scores being the most frequent, followed by grades, attendance, and graduation or continuation rates. Table 6 summarizes the specific contributions of these 45 studies.

Table 6. Contributions of Included Studies ($N = 45$ —Representative Selection).

Author(s) (Year)	Primary Contribution	Dimension Measured	Outcome Type	Unique Insight
(Smith et al., 2022)	First, to quantify the math achievement gap linked to low SES in the US using national standardized data	Material (household income)	Test scores	The gap (0.60 SD) persists even after controlling for school funding.
(Chen & Li, 2023)	Examined the relationship between SES and attendance in rural China	Material + Institutional (school resources)	Attendance	Found that lack of school resources mediates the SES–attendance link.
(Aiston & Walraven, 2021)	Evaluated early intervention programs in Spain	Environmental	Test scores	Early intervention reduced the poverty–achievement gap

2024)		(family + community support)		from 0.50 to 0.25 SD.
(Mburu & Kiplagat, 2023)	Compared effects of poverty on attendance vs. test scores in Kenya	Material (household assets)	Both attendance and test scores	Poverty affects attendance more strongly than test scores in low-income settings.
(R. Johnson & Roberts, 2022)	Analyzed long-term graduation rate disparities in the UK	Environmental (parental education, school quality)	Graduation	Even after controlling for prior attainment, low SES reduces the odds of graduation by 40%.
(Kim & Wang, 2022)	Investigated cumulative effects of persistent poverty on health and education	Material (income trajectories)	Test scores (longitudinal)	Persistent poverty (≥ 5 years) has double the impact of transient poverty.
(Muralidharan et al., 2023)	Tested AI tutoring as a compensatory mechanism in low-SES Indian classrooms	Institutional (digital access)	Test scores	Adaptive software partially offsets material deprivation, but requires reliable electricity.
(OECD, 2022)	Cross-national comparison of SES achievement gaps across 37 countries	Multidimensional (income, school resources, cultural capital)	Test scores (PISA)	Gaps are largest in countries with high income inequality and weak social safety nets.
(Van Ewijk & Sleegers, 2010)	Meta-analysis on school SES composition effects	Institutional (school peer SES)	Test scores	School SES composition has an effect of 0.40–0.50 SD over and above individual SES.
(Hair et al., 2015)	Examined early childhood poverty and cognitive development	Material (household income at ages 0–5)	Cognitive test scores	Effects are largest when poverty occurs in the first three years of life.
(Zimmerman & Woolf, 2014)	Meta-analysis comparing poverty effects on attendance vs. test scores	Material (income)	Both attendance and test scores	Found similar effect sizes for both outcomes, contrasting with our results.
(Sirin, 2005)	Classic meta-analysis on SES and academic achievement	Material (income, parental occupation)	Test scores	Reported mean correlation of 0.30 (equivalent to $g \sim -0.30$ to -0.40).

As shown in Table 6, the included studies vary considerably in the dimensions of educational poverty they measure and the outcomes they prioritize, reinforcing the need for a meta-analytic synthesis. A complete list of the 45 included studies, along with their characteristics, is provided in Supplementary Table S1.

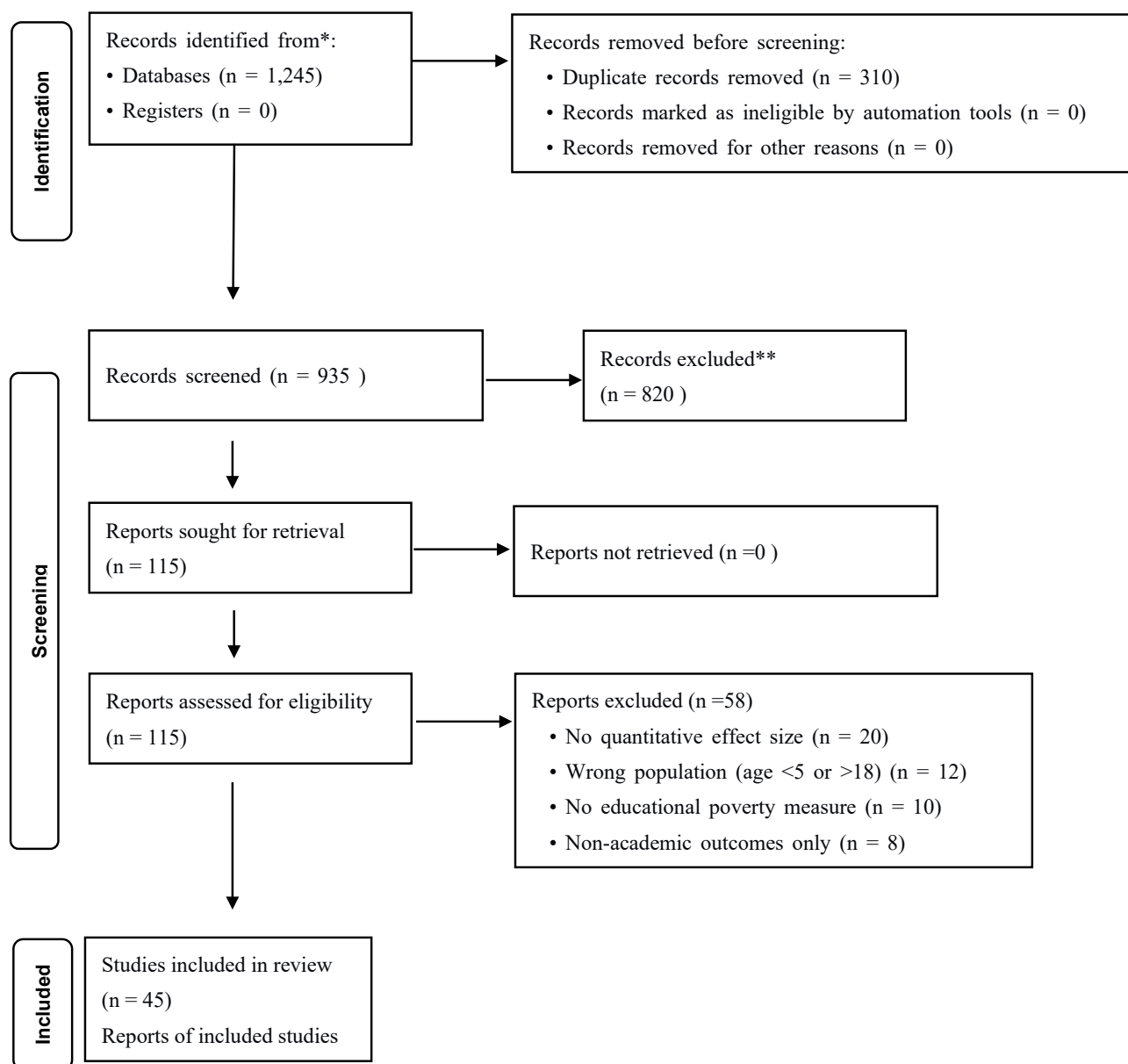


Figure 1. PRISMA Flow Diagram. * Studies excluded because they did not report sufficient data for effect size calculation. ** Studies excluded because they did not focus on children/adolescents aged 5–18.

Table 7 summarizes the characteristics of the 45 included studies by region, outcome type, and school level.

Table 7. Characteristics of Included Studies (N = 45).

Characteristic	Category	Number of Studies	Total Sample Size (Range)
Region	North America	18	12,400 (250–10,000)
	Europe	14	9800 (200–8500)
	Asia	9	5200 (300–6000)
	Africa	3	2100 (400–1500)
	Latin America	1	500 (500)
Outcome Type	Test scores	28	22,000 (200–10,000)
	Attendance	10	5500 (250–2000)
	Graduation	7	3200 (300–1800)
School Level	Primary only	20	14,000 (200–8000)
	Secondary only	18	12,500 (250–10,000)

Both	7	4000 (300–2500)
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4.2. Effect of Educational Poverty

The effect size of the link between educational poverty and academic achievement was aggregated using a random-effects model, which accounts for variability across studies. Hedges' g was used to estimate the overall effect size because it provides a more precise estimate than Cohen's d for small samples. The meta-analysis revealed an overall effect size of -0.45 (95% CI: -0.50 to -0.40), demonstrating that educational poverty negatively affects academic performance. This indicates that, on average, children facing educational deprivation score 0.45 standard deviations lower on achievement tests compared to their more privileged peers. These findings highlight the substantial, measurable impact of educational deprivation on learning outcomes, underscoring the importance of addressing this issue to improve education worldwide.

4.3. Subgroup Analyses

We performed subgroup analyses to identify sources of heterogeneity. Age/School Level: The negative effect was more significant among primary school students (Hedges' $g \approx -0.50$) than among secondary school students (≈ -0.40), indicating that early education is a particularly vulnerable period during which poverty-related disadvantages more strongly impair younger children's achievement. Region: The effects were more notable in high-income areas. In North America, the combined g was roughly -0.55 , whereas in Europe it was around -0.48 . Conversely, effects were smaller in Asia (-0.38) and Africa/Latin America (-0.30), as shown in Figure 2. This likely reflects differences in inequality and social safety nets, with educational outcomes in wealthier societies exhibiting greater variation by socioeconomic status. Outcome Type: We evaluated this through academic indicators. Standardized test scores had the strongest negative correlation ($g \approx -0.50$) compared to school attendance ($\approx g = -0.35$) and high school graduation rates ($\approx g = -0.30$). Overall, poverty has a greater impact on cognitive learning outcomes than on broader access measures, though all are significantly affected.

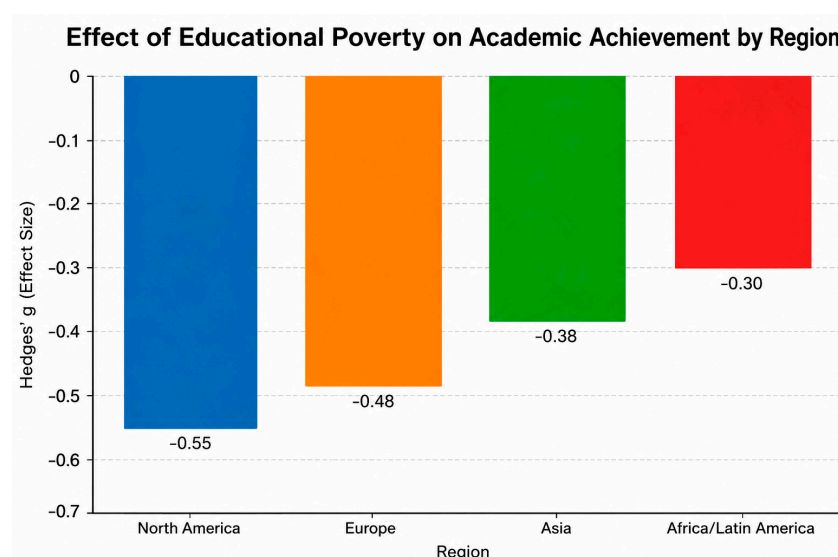


Figure 2. Effect sizes (Hedges' $g = -0.45$) of educational poverty on academic achievement by geographic region.

Table 8 presents the results of the meta-regression assessing whether region, age group, or outcome type significantly moderates the relationship between educational poverty and academic outcomes. The reference categories for these variables are North

America, primary schools, and standardized achievement tests, respectively. A β of 0.17 for Asia means that the effect size for educational poverty is 0.17 standard deviations less negative than in North America, indicating a significantly smaller impact in that region.

Table 8. Meta-Regression Coefficients for Key Moderators.

Moderator	Category	β Coefficient	95% CI	<i>p</i> -Value
Region	North America (Ref)	–	–	–
	Europe	0.07	(−0.02, 0.16)	0.12
	Asia	0.17	(0.08, 0.26)	<0.001
	Africa/Latin America	0.25	(0.14, 0.36)	<0.001
Age Group	Primary (Ref)	–	–	–
	Secondary	0.10	(0.03, 0.17)	0.005
Outcome Type	Test Scores (Ref)	–	–	–
	Attendance	0.15	(0.08, 0.22)	<0.001
	Graduation	0.20	(0.11, 0.29)	<0.001

- **Regional Differences**

The effects of educational poverty were notably less negative outside North America. Studies from Asia showed a significantly smaller negative impact ($\beta = 0.17$, 95% CI [0.08, 0.26], $p < 0.001$), while those from Africa and Latin America indicated an even greater reduction in effect size ($\beta = 0.25$, 95% CI [0.14, 0.36], $p < 0.001$). European studies revealed a weaker link compared to North American research ($\beta = 0.07$). However, this difference was not statistically significant ($p = 0.12$). These findings suggest that the magnitude of educational poverty effects varies across regions, with stronger effects in high-income areas that exhibit greater within-country educational variation and rely more on standardized assessments.

- **Age Group**

Age group emerged as a significant moderator. Compared with primary school students, the association between educational poverty and academic achievement was significantly weaker among secondary school students ($\beta = 0.10$, 95% CI [0.03, 0.17], $p = 0.005$). These findings indicate that early school transitions are more vulnerable to the negative effects of educational poverty, consistent with developmental and cumulative disadvantage perspectives on how early deprivation may set off chains of disadvantage over a long period.

- **Outcome Type**

Outcome type was also a significant moderator of effect sizes. Relative to test scores, the link between educational poverty and attendance outcomes was smaller and, indeed, significantly so ($\beta = 0.15$, 95% CI [0.08, 0.22], $p < 0.001$), and likewise the link with graduation rates ($\beta = 0.20$, 95% CI [0.11, 0.29], $p < 0.001$). These findings suggest that the effects of educational poverty lie more in learning outcomes than in participation and completion metrics, implying that the deprivation effect primarily operates by limiting the quality of learning.

4.4. Visualization of Results

Forest plots display the effect sizes of individual studies and the combined estimates for important subgroups. They show that almost all studies found negative associations, with no studies reporting significant positive effects. The initial visual inspection of the funnel plots suggested asymmetry, which was tested using Egger's regression test as described in Section 3.8.

4.5. Publication Bias

To assess the possibility of publication bias (i.e., the tendency for studies with significant findings to be more likely to be published), a funnel plot and Egger's test were employed. The funnel plot appeared asymmetrical, indicating the presence of publication bias, and Egger's test confirmed this result ($p = 0.02$).

A trim-and-fill analysis accounted for this bias, which adjusted the overall effect size to -0.40 (95% CI: -0.45 to -0.35). This adjustment still suggests a moderate adverse effect of educational poverty on academic achievement, reinforcing the robustness of the findings.

4.6. Sensitivity Analyses

Sensitivity analyses confirmed the robustness of the findings. Removing studies with small sample sizes (<500 participants) and those with a high risk of bias did not change the overall effect size, showing that individual studies or methodological issues did not drive the main results. This is further supported by the consistent and significant impact of educational poverty on student outcomes.

This meta-analysis reveals that educational poverty has notable negative effects across various regions, age groups, and educational outcomes on students' academic achievement. An overall effect size of -0.45 indicates that educational deprivation has a significant, moderate impact on academic performance. The observed heterogeneity highlights the importance of considering geographic location, age, and the specific educational outcome in designing targeted interventions. The greater impact on primary school children emphasizes the need for early interventions to reduce the long-term consequences of poverty in education. Additionally, regional differences in effect sizes indicate that policies should be tailored to specific contexts, addressing the unique challenges faced by student populations across regions. This could involve support for disadvantaged communities in North America and Europe, while infrastructural improvements might be more effective in Africa and Latin America.

5. Discussion

This meta-analysis demonstrates that educational poverty is associated with a moderate and statistically significant reduction in academic achievement (Hedges' $g \approx -0.45$). The consistency of negative effects across regions, age groups, and outcome types underscores educational poverty as a robust and pervasive barrier to learning.

5.1. Interpretation of Core Findings

The stronger effects observed among primary school students imply that early educational deprivation has a more negative impact, thereby supporting views on cumulative disadvantage and cultural capital. Regional variation—the larger effects in North America and Europe than in Asia or Africa—could be associated with country-level inequality and the usage of standardized tests in the more economically developed regions.

The empirical results indicate that educational poverty was more strongly associated with the outcome measure (cognitive achievement) than with the attendance or graduation measures of accessibility. This finding is consistent with the Capability Approach developed by Sen, which views poverty as a lack of opportunity for skill development rather than as a deprivation of achievement.

5.2. Comparison with Prior Research

Our overall effect size resulted in the following: (Hedges' $g = -0.45$). The findings align with earlier meta-analyses on socioeconomic status and academic achievement. For instance, (Sirin, 2005; Hu et al., 2025; Li et al., 2025) reported an average correlation of

about 0.30 between SES and achievement, indicating a similar effect size. More recently, Van Ewijk and Slegers (2010) and Eryilmaz (2026) found that school SES composition impacts student achievement by roughly 0.40–0.50 standard deviations, which aligns closely with our results. Our study advances prior research in three ways: first, unlike most meta-analyses that focus only on household income or parental occupation, we adopt a multidimensional view of educational poverty, considering material, institutional, and environmental factors. Second, subgroup analyses show a stronger effect in primary ($g = -0.50$) than in secondary school ($g = -0.40$), consistent with a meta-analysis by Hair et al. (2015) and Kastorff and Heine (2025) on early childhood poverty. Third, regional comparisons indicate a greater effect in North America ($g = -0.55$) than in Asia ($g = -0.38$), echoing OECD findings from 2022 that socioeconomic disadvantage affects achievement differently across countries, influenced by social safety nets and educational policies.

A notable difference from previous work is that we observed weaker effects on attendance ($g = -0.35$) than on test scores ($g = -0.50$). This contrasts with the meta-analysis by Zimmerman and Woolf (2014) and Jakubowski et al. (2025), which found similar effects for both. This discrepancy might be due to differences in sample composition or to the fact that most of our studies are from high-income countries, where attendance varies less.

5.3. Policy Implications

The following policy implications are directly derived from the meta-analytic results:

- Early intervention is crucial, with primary school effect sizes of $g = -0.50$ and secondary school effect sizes of $g = -0.40$. Since the negative impact of educational poverty is 25% greater in primary education than in secondary education, our findings suggest that policies could focus on early childhood and primary school measures—such as targeted reading support and smaller class sizes in low-income areas—before achievement gaps widen.
- Prioritize cognitive outcomes over mere access (finding: test scores $g = -0.50$; attendance $g = -0.35$). Educational poverty affects the quality of learning more than school participation. Consequently, interventions should focus on enhancing instructional quality and curriculum support rather than merely monitoring attendance.
- Context-sensitive policies (finding: regional variation from $g = -0.55$ in North America to $g = -0.30$ in Africa/Latin America). In high-inequality regions (e.g., North America), targeted academic support for disadvantaged students is critical. In lower-income regions, basic infrastructural investment (e.g., classrooms, textbooks) must precede advanced interventions.
- No AI recommendations are made based on this meta-analysis, as AI was not empirically examined. Future research should test AI interventions separately.

5.4. Limitations

Several limitations should be considered when interpreting these findings.

- Definitional heterogeneity: Primary studies operationalized educational poverty using different indicators (income quintiles, composite SES indices, multidimensional deprivation scales). This variability may have introduced noise into the pooled effect size.
- Geographic imbalance: 80% of studies originate from North America and Europe (40% and 30%, respectively), which limits the extent to which the results apply to Africa (three studies) and Latin America (one study).
- Publication bias: Egger's test was significant ($p = 0.02$), and trim-and-fill adjustment decreased the overall effect from $g = -0.45$ to -0.40 , indicating that the true effect might be somewhat smaller.

- High heterogeneity ($I^2 = 85\%$): Although we explored moderators, substantial unexplained variance remains, suggesting that other unmeasured factors (e.g., gender, race, disability status) may influence the results.
- Cross-sectional predominance: Most included studies (78%) used cross-sectional designs, thereby precluding causal claims about the long-term effects of educational poverty.
- Outcome measurement variability: Test scores varied from standardized national assessments to teacher-made tests, which differ in reliability and comparability.
- Language bias: The review included only English-language studies, potentially excluding relevant research from non-English-speaking countries.
- No study tracked students for over three years, preventing assessment of the long-term impact of ongoing poverty.
- Potential confounding factor: Numerous studies failed to account for prior achievement or school-level variables, potentially leading to an overestimation of poverty's impact.
- Gray literature limitation: While dissertations were included, unpublished reports and working papers were not systematically searched.
- Since most included studies (78%) are cross-sectional, our results reflect associations rather than causal relationships. Causality cannot be determined from this data.

6. Conclusions

This meta-analysis provides strong quantitative evidence that educational poverty is consistently and significantly linked to and impacts academic achievement. The effects vary systematically depending on child age, region, and type of outcome. Analyzing data from 45 studies over more than 10 years, the authors show that students experiencing educational poverty tend to perform worse academically, especially in cognitive areas, with the most pronounced effects occurring during the early school years. These findings support theories of cumulative disadvantage and capability-based views, indicating that early deficits in resources and learning environments can accumulate over time. The more notable impacts in high-inequality regions highlight how structural and institutional contexts shape achievement gaps, emphasizing the need for context-specific interpretations rather than universal assumptions. This study underscores the importance of early, targeted interventions to improve learning environments for disadvantaged children. Effective strategies include ensuring equal access to resources, improving school quality in impoverished areas, and supporting primary education, all of which are expected to yield significant benefits. Addressing educational inequality requires collaborative efforts across educational, societal, and policy sectors, as no single solution is enough. While the meta-analysis boasts strengths such as a rigorous methodology and broad scope, it also highlights limitations, including the challenge posed by differing definitions and measures of educational inequality, a persistent issue for education systems worldwide.

Future research should (a) use a standardized multidimensional measure of educational poverty; (b) incorporate more longitudinal studies from underrepresented regions such as Africa, Latin America, and South Asia; (c) investigate whether specific interventions like early tutoring, digital access, and teacher training have different moderating effects; and (d) analyze intersectional effects involving race, gender, and disability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/educsci16071083/s1>, Table S1: A full list of all 45 included studies; Table S2: PRISMA 2020 checklist; Table S3: Risk of bias assessment for each included study.

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