Analyses of Topical Policy Issues

Evaluating the impact of a non-profit's intervention on child labour and school attendance in artisanal and small-scale mining in the Democratic Republic of the Congo

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ABSTRACT

Child labour and low school attendance remain pressing challenges in low-income economies, particularly in artisanal and small-scale mining (ASM) communities where poverty and structural vulnerabilities constrain children's access to education. While household support programs and income transfer initiatives have traditionally aimed to alleviate poverty, their potential to influence child labour and educational outcomes is increasingly recognized. This study provides the first empirical evidence from the Democratic Republic of Congo (DRC) on the causal impact of financial and non-financial assistance on children's labour and schooling decisions. We evaluate the Kamituga project implemented by the Panzi Foundation (PIAH) using propensity score matching to address selection bias and ensure comparability between treatment and control households. Our results indicate that participation in PIAH significantly reduces child labour and increases school attendance, with evidence suggesting that its holistic approach—combining cash transfers, educational support, and community engagement—underpins its effectiveness. The study further highlights gendered dynamics and contextual factors that shape program outcomes, providing nuanced insights into why boys and girls may benefit differently from similar interventions. These findings carry important policy implications. They demonstrate that integrated, multi-dimensional support programs can effectively mitigate child labour while enhancing educational access in marginalized communities. Policymakers are encouraged to replicate or scale up interventions like PIAH in ASM and other vulnerable settings across sub-Saharan Africa, combining financial aid with educational initiatives to address both economic and structural barriers. By linking rigorous empirical evidence with actionable policy recommendations, this study contributes to global debates on child labour reduction, social protection, and human capital development.

1. Introduction

In an ideal context, household financial constraints would have minimal impact on children's well-being. Yet, in many developing economies, parents cannot shield their families from economic hardship (Ahad et al., 2023; Korankye et al., 2023), and children are

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frequently required to contribute to household income (Eakin et al., 2016; Keshavarz Haddad, 2017; Novella, 2018; Shafiq, 2007; Vásquez, William F. Bohara, 2010). Through these financial activities, children often develop an early understanding of the value of money and the necessity of family survival. From a young age, they face a stark trade-off between participating in work and attending school. Empirical evidence indicates that, in many instances, economic necessity outweighs educational aspirations (Akabayashi & Psacharopoulos, 1999; Haile & Haile, 2012; Mihigo et al., 2024; Rammohan, 2014).

The consequences of child labour are both immediate and long-term, affecting physical, psychological, and emotional development, thereby shaping children's future prospects (Bakehe, 2022; Beegle et al., 2009; Issehnane, 2013; Shaikh, 2020; Stabridis & van Gameren, 2018). A substantial body of literature highlights the negative association between child labour and school attendance, with significant ramifications for subsequent labour market participation (Acosta, 2011). Children are particularly vulnerable to exploitation due to their physical fragility and lack of skills, and while their contributions may temporarily alleviate household financial stress (Folashade et al., 2006), in the long term, these children often become less educated and less competitive adults (Rafiq & Ahmed, 2015). Societal consequences are profound: child labour is a practice that can perpetuate cycles of poverty across generations (Thakurata & D'Souza, 2018).

Addressing child labour requires comprehensive policies that tackle persistent poverty and reduce household vulnerability to economic shocks (Aufseeser et al., 2018; Kis-Katos & Schulze, 2011). Such policies include social protection, education expansion, and the promotion of decent adult employment (Bai & Wang, 2020; Edmonds, 2006b; Grimm, 2011)). Indeed, the link between school attendance and child labour is well-documented: children without access to schooling often have no alternative but to enter the labour market under unsafe and exploitative conditions (Ray & Lancaster, 2005). Expanding access to free, compulsory, and quality education is therefore central to reducing child labour prevalence. Access alone, however, is insufficient if it does not ensure that children remain enrolled and acquire relevant skills (MURHI MIHIGO & Bucekuderhwa Bashige, 2017). Quality education, as emphasized by De Herdt and Titeca (2016), requires adequately trained, motivated, and well-supported teachers to prevent overcrowded classrooms and ensure effective learning outcomes.

Scholarship on child labour and school attendance often adopts multiple analytical perspectives. The first, an economic approach, conceptualizes child labour as a rational response to household economic constraints (Aufseeser et al., 2018; Baland & Robinson, 2000; Basu & Van, 1998; Edmonds, 2006a). In this framework, households trade off present and future consumption, and children's work supplements adult income in contexts of extreme poverty and limited access to education. While some scholars acknowledge potential short-term economic benefits of child labour, such as alleviating immediate poverty (Aufseeser et al., 2018), this perspective does not negate the ethical implications of child labour (Edmonds & Pavcnik, 2005). The complex interplay between poverty, education, and child labour underscores the necessity of policies addressing these foundational issues (Beegle et al., 2009).

A second perspective, the human rights approach, positions child labour as a fundamental violation of children's rights (White, 1994, 1999). Advocates of this view assert that education is a basic entitlement and that children should not be compelled to work at the expense of their health and development (Fontana & Grugel, 2015; ILO, 2023). Abolitionist policies under this framework prioritize the eradication of child labour through stringent legal measures and international conventions. However, empirical and theoretical studies caution that strict bans may generate unintended distributional effects, potentially worsening income disparities in poor households (Baland & Robinson, 2000). Campaigns such as boycotting products made by child labourers, while ethically motivated, can inadvertently deepen poverty for the most vulnerable families (Basu & Zarghamee, 2009; Berlan, 2016).

The cultural-historical approach represents a third analytical lens, recognizing that child labour is sometimes embedded in social norms and traditional practices ((Ajayi & Torimiro, 2004; D'Avolio, 2004; Hilson, 2012a; Hindman & Smith, 1999). Understanding these cultural contexts is essential for designing interventions that respect local traditions while promoting children's education and well-being. Similarly, the intermediate approach advocates for regulation and reform of child labour practices rather than outright abolition, emphasizing monitoring, enforcement, and investment in education and social protection programs (A. C. Dammert & Galdo, 2013; A. Dammert & Galdo, 2021). Both approaches underscore the importance of ensuring school attendance, protecting children's rights, and promoting adult employment that provides sufficient income to reduce children's need to work (Oranga et al., 2020; Shapiro & Oleko Tambashe, 2001).

Despite extensive research on child labour globally, significant gaps remain in understanding the role of financial and non-financial assistance in shaping household decisions regarding children's work and education. Evidence indicates that targeted support can alleviate liquidity constraints, increase parental investment in schooling, and reduce the incidence of child labour as a coping strategy (Acosta, 2011; Alcaraz et al., 2012; Binci & Giannelli, 2018; Cuadros-Menaca & Gaduh, 2020). Yet empirical research in the Democratic Republic of Congo (DRC), particularly within artisanal and small-scale mining (ASM) contexts, remains limited.

This study addresses this gap by evaluating the impact of the PIAH project ("Projet d'Intervention d'Appui Humanitaire"), which provides both monetary and material support to vulnerable households in mining communities in Kamituga, South Kivu, between 2017 and 2022. The central research question is: *How does financial and non-financial assistance provided by the PIAH project influence the rates of child labour and school attendance in artisanal mining communities in Kamituga?* We hypothesize that positive income or welfare shocks from such assistance are associated with increased school attendance and reduced participation of children in ASM activities. Employing an econometric approach, this study integrates both financial and non-financial support dimensions to isolate causal effects and provide a nuanced understanding of household decision-making in fragile socio-economic contexts.

By examining the PIAH project's impact, this research contributes to the literature on social protection, poverty alleviation, and child labour interventions in sub-Saharan Africa, offering empirical evidence from a context that has been largely underexplored. In methodological terms, the study employs propensity score matching (PSM) to mitigate selection bias and approximate randomized conditions (Camilo & Zuluaga, 2022; Khiem et al., 2020). Potential endogeneity concerns, arising from simultaneity or reverse causality, are addressed through instrumental variable regressions, ensuring the robustness of findings. Results indicate that the PIAH

project substantially reduced child labour while increasing school attendance rates, reinforcing the value of integrated financial and non-financial assistance in fragile mining communities.

2. Background

Child labour is a pervasive phenomenon in developing economies, with approximately 152 million children globally engaged in work, many of whom do not attend school (ILO, 2023). Rural children are disproportionately affected, with labour prevalence five times higher than in urban areas, and boys outnumber girls more than two to one (Sumberg & Sabates-Wheeler, 2020). While agriculture remains, the primary sector employing children, artisanal and small-scale mining (ASM) presents particularly hazardous conditions. Children in ASM engage in tasks involving heavy lifting, exposure to dust, smoke, and harmful chemicals, and the use of dangerous tools (André & Godin, 2014; Gatsinzi & Hilson, 2022; Hilson, 2010, 2012a). In the DRC, where mineral wealth is abundant, household impoverishment is a key determinant of child labour in ASM (Godelive et al., 2023; Murhi Mihigo et al., 2024). Families struggling to meet basic needs often rely on children's labour to pay for food, clothing, and school fees.

The detrimental effects of child labour extend beyond immediate physical risk. It undermines human capital accumulation, limiting children's educational attainment and, in the long term, their competitiveness in the labour market. Studies show that child labour hinders school enrolment and attendance, contributing to a cycle of intergenerational poverty (Acosta, 2011; Rafiq & Ahmed, 2015). Moreover, children's vulnerability to exploitation and abuse, combined with limited skills and experience, exposes them to unsafe working conditions (Folashade et al., 2006).

Policy interventions to reduce child labour typically focus on two complementary strategies: poverty alleviation and access to quality education. Social protection mechanisms, including conditional and unconditional cash transfers, remittances, and material support, have demonstrated positive effects on schooling outcomes and reductions in child labour (Acosta, 2006, 2011; Alcaraz et al., 2012; Awaworyi Churchill et al., 2021; Binci & Giannelli, 2018; Cepaluni et al., 2022; Cuadros-Menaca & Gaduh, 2020; de Hoop & Rosati, 2014; Filmer & Schady, 2011; Moestopo, 2020; Tagliati, 2022). These programs alleviate liquidity constraints, allowing parents to invest in children's education rather than relying on child labour as a coping mechanism.

Non-governmental organizations (NGOs) have played a pivotal role in mitigating child labour in ASM contexts. Examples include Child Labour Remediation in Kolwezi, the Fonds pour la Prévention du Travail des Enfants dans les Communautés Minières in Lualaba and Haut-Katanga, IMPACT for women's empowerment through community credit, and PIAH of the Panzi Foundation, which supports children exposed to mining and related vulnerabilities. Additionally, the PABEA-COBALT project, launched in 2019 in mineral-rich provinces, demonstrates a morally and practically informed response to child labour in cobalt mining. Yet, most interventions remain insufficiently evaluated, leaving questions about their actual impact on child labour and school attendance.

Empirical evidence suggests that financial and non-financial assistance can play a transformative role. Remittances and targeted aid improve household welfare, enabling higher school attendance and reduced child labour (Acosta, 2011; Alcaraz et al., 2012; Binci & Giannelli, 2018; Cuadros-Menaca & Gaduh, 2020). However, the specific causal effects of these interventions in DRC mining communities remain understudied. This study addresses this gap by focusing on the PIAH project, integrating both financial and material support dimensions to capture the holistic effect on household decisions.

Methodologically, the study applies propensity score matching (PSM) to create comparable treated and untreated groups, addressing selection bias inherent in observational data (Camilo & Zuluaga, 2022). To correct for potential endogeneity resulting from simultaneity or reverse causality—where project participation could itself be influenced by pre-existing household characteristics—instrumental variable regressions are employed. This rigorous econometric strategy enables robust inference regarding the impact of financial and non-financial assistance on child labour reduction and school attendance enhancement.

The PIAH project serves as an exemplary intervention, combining immediate financial support to cover school fees and basic needs with material assistance that ensures children remain in school rather than entering hazardous mining work. The project's dual approach underscores the importance of integrated interventions in fragile contexts, where income shocks, lack of access to education, and household vulnerability interact to perpetuate child labour.

3. Conceptual framework

The conceptual framework guiding this study is grounded in the interaction between cash transfer programs, school attendance, and child labour. Over the past two decades, cash transfer interventions have emerged as a promising policy tool for alleviating poverty and mitigating the socio-economic determinants of child labour, particularly in low- and middle-income countries (de Hoop & Rosati, 2014; Filmer & Schady, 2011; Moestopo, 2020; World Bank, 2009). The central premise underlying these programs is that financial deprivation is one of the primary drivers compelling households to rely on children's economic contributions at the expense of their education. By providing predictable and regular income support to poor households, cash transfer programs seek to relax these liquidity constraints, thereby reducing the pressure to send children to work and enabling families to invest more in their children's schooling.

From a theoretical standpoint, cash transfers are expected to have a positive impact on school attendance and a negative impact on child labour, primarily through income and substitution effects (Acosta, 2011; de Hoop & Rosati, 2014; Grimm, 2011). By alleviating financial hardship, such programs increase household disposable income and reduce the need for child labour to supplement family resources. Consequently, parents can allocate more of their children's time toward education, which improves school participation and learning outcomes. This mechanism is particularly effective when the value of the transfer is large enough to cover both direct educational costs—such as tuition fees, uniforms, and school supplies—and indirect costs, such as the opportunity cost of foregone

child income (Kis-Katos & Schulze, 2011; Meza-Cordero & Gulemetova, 2023).

However, the relationship between cash transfers, schooling, and child labour is not linear. It is shaped by a complex set of contextual and behavioural dynamics that influence household decision-making. For instance, the magnitude of the transfer plays a crucial role in determining its effectiveness. When the transfer amount is insufficient to offset the opportunity cost of schooling, the household may continue to depend on child labour, particularly in settings where economic vulnerability remains acute (Thakurata & D'Souza, 2018). In such contexts, schooling may be perceived as a non-essential or even unattainable investment, while children's work contributes immediately to household survival. Thus, the incentive to send children to school varies across income levels, local labour market conditions, and the perceived returns to education.

Empirical evidence also highlights potential negative or unintended effects of cash transfer programs on household labour supply and child work. According to economic theory, an exogenous increase in household income can produce both income effects and substitution effects on labour supply (Binci & Giannelli, 2018; Cuadros-Menaca & Gaduh, 2020). If leisure is considered a normal good, the income effect may reduce adult labour participation, as parents substitute paid work for leisure or unpaid activities. This could, paradoxically, create a situation in which children are required to compensate for the reduction in adult work effort, thereby increasing child labour (Acosta, 2011). In this regard, the success of cash transfers in reducing child labour depends not only on the magnitude of the income increase but also on intra-household behavioural responses and labour market structures.

Another mechanism that complicates the expected outcomes of cash transfer programs is the moral hazard effect or dependency effect, where beneficiaries may adjust their labour effort in response to guaranteed income flows. If adults reduce their working hours or withdraw from the labour market, the net household income gain may be lower than anticipated. This could erode the intended poverty-alleviation effect and indirectly sustain or even increase the incidence of child labour (De Hoop & Rosati, 2014). In such cases, the conditionality of transfers—whether cash is provided contingent upon school attendance—becomes an important determinant of program effectiveness. Conditional Cash Transfers (CCTs), by linking financial support to school enrolment or attendance, have generally shown stronger positive effects on education outcomes compared to unconditional transfers (Filmer & Schady, 2011; Moestopo, 2020). Yet, even with CCTs, implementation challenges, such as weak monitoring mechanisms or poor school infrastructure, may limit their impact.

It is also important to recognize that social and cultural contexts mediate the effects of cash transfers on schooling and child labour. In some societies, long-standing cultural norms and gender roles influence how families perceive the value of education relative to children's economic contributions. For example, when education is not viewed as a viable pathway to upward mobility or when local labour markets offer few opportunities for educated youth, families may rationally choose child labour as a survival strategy, even when financial support is available (Edmonds, 2006b; Thakurata & D'Souza, 2018). Similarly, patriarchal norms may dictate that boys are prioritized for schooling while girls engage in domestic or informal labour, thereby reinforcing gender disparities in education. Therefore, the effectiveness of cash transfer interventions cannot be understood in isolation from the socio-economic and cultural fabric of the community in which they operate.

Given these complexities, the conceptual framework adopted in this study posits that the impact of cash and in-kind transfers on school attendance and child labour operates through three interrelated channels: (1) the income channel, which alleviates financial constraints and increases schooling affordability; (2) the labour supply channel, which may either reduce or increase child labour depending on adult behavioural responses; and (3) the cultural and contextual channel, which reflects how norms, expectations, and educational opportunities shape household decisions. These channels interact dynamically, making the overall outcome context dependent.

To address some of the unintended consequences associated with cash transfers, scholars have proposed in-kind transfer programs as complementary or alternative interventions (Camilo & Zuluaga, 2022; Cepaluni et al., 2022). In-kind transfers provide specific goods and services—such as food, clothing, or educational materials—rather than cash, thereby directly meeting household needs while reducing the risk of misallocation of funds. In the context of education, in-kind transfers can be particularly effective in improving school attendance by supplying school uniforms, textbooks, or meals that reduce both direct and opportunity costs of schooling. Furthermore, because in-kind transfers are less likely to alter adult labour incentives or generate dependency effects, they may mitigate the potential moral hazard associated with cash-based programs.

4. The PIAH project

Poverty is a significant determinant of child labour in developing countries, as highlighted by Edmonds and Pavcnik (2005). In many instances, children are compelled to juggle school attendance with work obligations, a situation particularly pronounced in artisanal mining sites where essential infrastructure, such as schools and hospitals, is often inadequate or absent. The lack of educational opportunities effectively forces children into labour, depriving them of their right to a proper education and exposing them to age-inappropriate work conditions. Additionally, in some households, children are seen as a vital source of supplementary income, further compelling them to combine work and school as a means of survival.

The PIAH project was conceived as a holistic initiative aimed at improving t he living conditions of vulnerable women and girls in Eastern DRC, particularly in the context of the specific challenges faced by this population. Running from February 1, 2017, to January 31, 2022, the PIAH project, supported by the European Union, was implemented across several antennas in three of the eight territories of South Kivu—specifically Kamanyola, Katogota (Walungu territory), Luvungi, Bwegera (Uvira territory), Luhwindja, Kamituga (Mwenga territory), and Idjwi (Idjwi territory). This initiative, spearheaded by the Panzi DRC Foundation, focuses not only on survivors of sexual violence and women suffering from gynaecological pathologies but also on the broader community through its emphasis on medical, legal, psychosocial, and socio-economic reintegration.

The PIAH project encompasses multiple components a imed at addressing the complex needs of its beneficiaries. Medically, the project provides support to patients affected by urogenital fistulas and genital prolapses, including accommodation for children accompanying these patients. It also offers medical care to children rescued from mining areas, who are then enrolled in rehabilitation centres. This targeted approach includes educational initiatives that raise awareness among parents, sex workers, and teenagers regarding sexually transmitted infections and the importance of family planning.

On the legal front, the PIAH project provides essential support for victims of sexual and gender-based violence, helping them navigate the legal system. Socio-economically, the project has facilitated training in various trades—such as tailoring, carpentry, welding, basket-making, and agropastoral work—empowering individuals to develop new skills and create income-generating activities. These efforts are supplemented by cash and in-kind subsidies that support the establishment of micro-enterprises and promote participation in community solidarity funds.

The impacts of the PIAH project on local communities have been significant, evidenced by improvements in nutrition, housing, healthcare access, and educational enrollment for children who were previously engaged in mining activities. These outcomes suggest a positive shift in the living conditions of the beneficiaries and underline the project's potential in combating poverty and reducing child labour.

This study specifically aims to evaluate the effect of the PIAH project on child labour and school attendance, with a focused analysis of the Kamituga branch of the initiative. Located in the Mwenga territory of South Kivu, Kamituga is a mining town situated over 180 kilometers away from Bukavu, the provincial capital. The town's economy is primarily driven by artisanal mineral exploitation, exacerbating the financial challenges faced by its residents. Consequently, life in Kamituga is marked by high living costs that strain the daily lives of the population, further compelling children into labour.

By examining the effects of the PIAH project in this context, this study will contribute valuable insights into how holistic support initiatives can mitigate child labour and enhance school attendance, ultimately offering strategies for sustainable improvements in the socio-economic conditions of vulnerable communities.

5. Data and method

The data for this study were derived from a comprehensive household survey conducted between September and December 2023, funded by ENABEL-RDC in the town of Kamituga, located in South Kivu, DRC. This survey was specifically designed to evaluate the impact of the PIAH project on child labour and school attendance, particularly in the context of the region's prevalent mining activities.

To ensure the reliability and relevance of the data, we es tablished specific inclusion criteria for participating households. First, each household was required to have at least one child aged 5 to 17 years, a range critical for evaluating school attendance and potential involvement in child labour. Second, households had to have resided in Kamituga for at least six years, enhancing comparability between households and mitigating selection bias in the assessment of the PIAH project's effects. To distinguish between treated and control groups, we used consumption expenditure per capita as a key outcome variable. This measure captures household economic well-being and allows for a meaningful comparison of welfare levels between households benefiting from the project and those not receiving assistance, strengthening the robustness of our propensity score matching analysis.

The questionnaire utilized in the survey was meticulously structured to cover various dimensions related to education and training, labour activities and remuneration, health and safety, parents' perceptions, children's aspirations, and the socio-economic characteristics of participating households. This comprehensive approach allowed for a holistic understanding of how child labour and school attendance are influenced by broader socio-economic factors in Kamituga mining community.

Interviews were conducted with the head of the household, either at their workplace or home, to gather first-hand insights directly from those responsible for making household decisions. In instances where the head of the household was unavailable—either due to absence from Kamituga or other commitments—interviews were conducted with another adult (18 years or older) who possessed in-depth knowledge of the household. This approach ensured that data integrity was maintained by including informed respondents capable of providing accurate and relevant information about the household's dynamics.

Overall, the methodological rigour of this household survey, combined with its targeted focus on specific criteria, equips this study with a robust dataset that can offer valuable insights into the relationships between the PIAH project, child labour, and school attendance in the context of Kamituga's challenging socio-economic environment.

Through this examination, the research aims to contribute significantly to understanding how targeted interventions can effectively address child labour and promote educational outcomes in vulnerable populations. The target population consists of households residing in the town of Kamituga, regardless of whether they have received assistance from the PIAH project, provided they meet the inclusion criteria outlined above.

5.1. Empirical strategy

As outlined in earlier sections, this study aims to assess the effects of the PIAH project on the school attendance and child labour of non-beneficiary children. Specifically, it examines the differences in outcomes for non-beneficiary children who belong to households with beneficiary members compared to their potential outcomes had they belonged to households that did not receive project benefits. While the scenario of matching beneficiaries directly to non-beneficiaries is inherently theoretical—given the absence of identical treatment and non-treatment conditions—the circumstances of control individuals can serve as a reasonable substitute for this hypothetical context, as long as they exhibit similar characteristics to those in the treatment group.

Upon applying a matching process to our sample, we successfully identified two distinct subgroups: the treatment group (which includes beneficiaries of the PIAH project) and the control group (comprised of non-beneficiaries), as illustrated in Fig. 1. This segmentation enables a focused assessment of the project's effects by comparing the treatment group with a constructed counterfactual.

It is essential to recognize that merely calculating the mean differences between beneficiaries and non-beneficiaries can lead to selection bias, as noted in the literature (Rosenbaum & Rubin, 1983). Households eligible for the PIAH project are selected based on criteria that may correlate with the outcomes of interest, necessitating the use of propensity score matching. This method is recommended for creating comparable groups based on observable characteristics (Austin, 2019; Caliendo & Kopeinig, 2008). The literature further supports the validity of matching density scores as an effective approach for assessing impact in situations where randomization or comprehensive initial data are unavailable (Caliendo & Kopeinig, 2008). Consequently, we estimate the project's effects by comparing the average outcomes of the treated group with those from the matched control group (Rosenbaum & Rubin, 2006).

The control group is carefully selected to ensure its similarity to the treatment group concerning numerous observable characteristics. The underlying assumption of this methodology posits that unobservable characteristics are also comparable between the two groups. By adjusting for these observable factors, we can infer that participation in the PIAH project is not confounded by other variables that might influence the outcomes of interest (Caliendo & Kopeinig, 2008).

To quantify the impact of the PIAH project on child labour and school attendance, we calculated the Average Treatment Effect on the Treated (ATT) using the matching method. This methodology rests on two critical assumptions. The first, known as the conditional independence assumption, stipulates that potential outcomes must be independent of the treatment assignment once we account for a set of observable covariates that are unaffected by the treatment. If the researcher can adequately control for all variables impacting treatment assignment and outcomes, single-difference propensity scores matching yields unbiased estimates of impact.

The second vital assumption is the common support or overlap condition, which ensures that observations sharing identical pre-treatment characteristics can be found within both the treatment and control groups. The propensity score matching method is favoured for its capacity to establish equivalence between treatment and control groups in matched pairs, thereby facilitating straightforward analyses that adjust for confounding variables (Rosenbaum & Rubin, 2006). Empirical evidence indicates that matched samples exhibit lower variance in ATT estimates compared to random samples, enhancing the robustness of model-based adjustments for matched data. This methodological rigour ultimately fortifies the validity of our analysis regarding the PIAH project's impact on child labour and school attendance.

5.2. Propensity scores matching implementation

Propensity score matching (PSM) is a robust empirical strategy employed to assess the impact of assistance programs on child labour and school attendance (Donkor et al., 2019; Powell et al., 2020). This approach involves matching individuals who have received assistance with comparable individuals who have not, based on their estimated propensity scores for receiving assistance. By doing so, we can effectively estimate the causal effects of the PIAH project on child labour and school attendance. The strength of this method lies in its ability to mitigate selection bias and account for confounding factors that may otherwise obscure the relationship between assistance programs, child labour, and educational outcomes.

In the context of treatment evaluation, strategies based on "selection on observables" or the "conditional independence" hypothesis
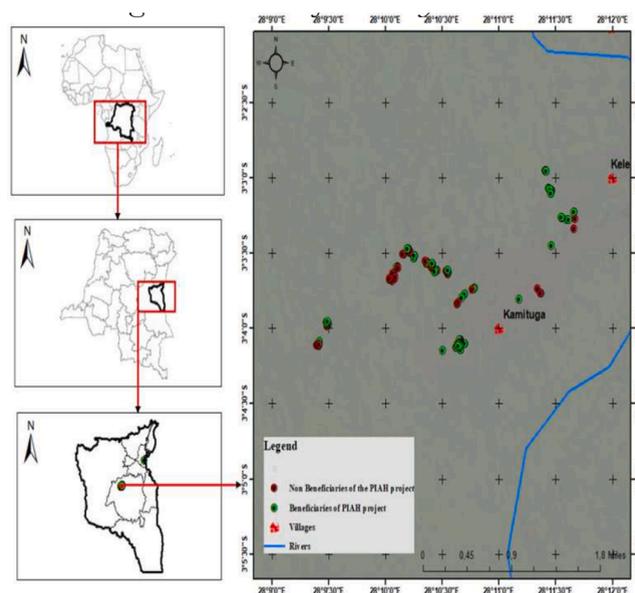

Fig. 1. Location of the study area.

assert that all factors influencing the likelihood of receiving treatment are observed and can thus be controlled for (Austin et al., 2018; Ding & Guo, 2023; Powell et al., 2020). In essence, this implies that the potential outcomes that could have arisen in each treatment circumstance are presumed to be independent of the actual treatment assignment, conditional on the observed covariates (Abadie & Imbens, 2016).

To formalize this framework, let (Y) represent the observed outcomes—specifically, measures of child labour or school attendance. We define (D) as the binary treatment indicator, where (D = 1) denotes treated individuals (e.g., those receiving PIAH assistance) and (D = 0) refers to non-treated individuals. The vector of observed covariates is represented by (X). Following the potential outcomes framework established by Rosenbaum & Rubin (2006) and Rubin (2005), we denote (Y(1)) and (Y(0)) as the potential outcomes corresponding to treatment and non-treatment scenarios, respectively. According to the rules of observational data, only one of these potential outcomes can be observed for any individual, which highlights the fundamental challenge in estimating causal effects in non-experimental settings. By leveraging the principles of propensity score matching, we aim to create a balanced comparison between treated and non-treated groups, ultimately yielding insights into the effectiveness of the PIAH project on reducing child labour and enhancing school attendance.

$$Y = D \cdot Y(1) + (1 - D) \cdot Y(0) \tag{1}$$

The conditional independence hypothesis states that: $Y(1), Y(0) \perp D|X$, where $\perp$ presents independence. In a wide range of empirical applications, this hypothesis only appears plausible when controlling for a large set of covariates. However, conditioning on a high dimensional X may be problematic, as the number of possible combinations of elements in X increases exponentially in the dimension such that estimation quickly becomes exorbitantly data-hungry, a problem known as the curse of dimensionality (Austin & Fine, 2019). This motivates the use of propensity score approaches frequently encountered in applied work. We denote $p(X) \equiv Pr(D = 1|X)$ the propensity score, the conditional treatment probability given the covariates. Conditioning on the propensity score is asymptotically equivalent to conditioning on the covariates directly, as both X and $p(X)$ are balancing scores in the sense that they adjust the distributions of covariates in the treatment and the control (or non-treated) group as underlined by (Rosenbaum & Rubin, 1983, 2006). Then, if eq. (1) is fulfilled, it also holds that the potential outcomes are independent of the treatment conditional on the propensity score:

$$Y(1), Y(0) \perp D|p(X) \tag{2}$$

Generally, conditioning on the propensity score, therefore, allows for the identification of causal effects such as the average treatment effect (ATE) in the entire population,

$E[Y(1) - Y(0)]$, because (2) implies that

$$E[Y(0)|D = 1, p(X)] = E[Y(0)|D = 0, p(X)] = E[Y|D = 0, p(X)],$$
$$E[Y(1)|D = 0, p(X)] = E[Y(1)|D = 1, p(X)] = E[Y|D = 1, p(X)].$$

However, a large part of the applied literature focuses on the evaluation of the average treatment effect on the treated (ATT), defined as $\theta = E[Y(1) - Y(0)|D = 1]$, which is also the estimate considered in this paper. Thus, equation (2) may be relaxed to:

$$Y(0) \perp D|p(X). \tag{3}$$

Identification also requires that the following common support assumption of the propensity score holds for all values of the covariates:

$$p(X) < 1 \tag{4}$$

which means that the treatment must not be perfectly predicted by any combination of the covariates to ensure that non-treated matches are available, at least asymptotically. Under equations (3) and (4) and by the law of iterated expectations,

$$\theta = E[Y(1)|D = 1] - E[Y(0)|D = 1] = E[Y|D = 1] - E[E[Y|D = 0, p(X)]|D = 1] \tag{5}$$

so that the ATT is identified.

If *N* observations are denoted by i, where i ∈ {1, 2, ..., N}. Then, a general class of estimators of eq. (5) can be defined as:

$$\widehat{\theta} = \frac{1}{N_1} \sum_{i=1}^{N} d_i y_i - \frac{1}{N_0} \sum_{i=1}^{N} (1 - d_i) \widehat{w}_i y_i, \tag{6}$$

where N_1 and N_0 are the number of treated and non-treated observations, respectively, and w_i is a weight that is a function of the estimated propensity score $p(X_i). w_i$ reweights the non-treated observations such that they resemble the treated sample in terms of the distribution of the propensity score as well as the covariates X and differ across distinct (classes of) estimators (such as matching and inverse probability weighting). They may be applied whenever the adjustment of covariate distributions across different groups is of interest, which does not necessarily imply a conditional independence hypothesis (Austin et al., 2018).

Univocal or pairwise matching on propensity score enables each treated unit to be associated with exactly one control unit that is the closest in terms of propensity score. In the subsequent discussion, we focus on matching "with replacement", implying that the same control observation may be used several times as a match, whereas in estimators 'without replacement' it is matched at most once. However, the latter principle only works well when there are many more controls than treated. The pair matching estimator

based on matching with replacement is defined as

$$\widehat{\theta}_{PM} = \frac{1}{N_1} \sum_{i:d_i=1} \left[y_i - \sum_{i:j=0} \mathbf{1}(min|\widehat{p}(x_i) - \widehat{p}(x_i)|)y_i \right] \tag{7}$$

$\mathbf{1}(.)$ denotes the indicator function, which is one if its argument is true and zero otherwise. A direct extension of pair matching is (1: M) nearest neighbour matching which uses several (i.e. M) controls instead of just one. Increasing M increases the precision but also the bias of the estimator, as even 'not so close' controls might be matched in this case. Radius matching, (Huber et al., 2015), tackles this issue using only controls that are situated within a predefined distance around the propensity score of each treated unit. Compared to (1:M) matching, this may lead to a smaller bias in regions where comparable controls are sparse. Also, it increases precision compared to 1:M nearest neighbour matching in propensity score regions with many similar controls. Instead of fixing M globally, radius matching determines the number of matches, M, in the local neighbourhood of each treated observation.

Further improvements to standard propensity score matching have been proposed in the literature. Authors suggested combining pair matching with (parametric) regression adjustments to take into account the fact that treated and controls with the same propensity score are usually very rare or nonexistent (Austin et al., 2018; Ding & Guo, 2023). Also, (Huber et al., 2015; Rubin, 2005) consider this idea and show (however, for 1:M matching on X rather than on the propensity score) that nonparametric regression removes the asymptotic bias that may occur when X is more than one-dimensional. Furthermore, instead of matching on the propensity score alone, one may use a distance metric that (in addition to the score) accounts for differences in those covariates that are particularly good predictors of the outcome. In finite samples, this potentially improves estimation by putting a larger emphasis on balancing the most important confounders across treatment states. The intuition behind this potential improvement is that it is particularly important to balance variables that have a large influence on the outcomes, as any imbalances of those variables will lead to larger biases than imbalances of variables that are only slightly correlated with the outcomes. In this case, the Mahalanobis distance metric is commonly used to collapse the multidimensional distances between the propensity scores and predictors of the treated and the controls into a single measure (Rubin, 2005). The distance between two observations is defined as:

$$\sqrt{\left(\widetilde{x}_i^{D=1} - \widetilde{x}_j^{D=0} \right) C^{-1} \left(\widetilde{x}_i^{D=1} - \widetilde{x}_j^{D=0} \right)'} \tag{8}$$

Where $\widetilde{x}_i^{D=1}$; $\widetilde{x}_j^{D=0}$ are row vectors of the K factors to be matched on, i.e. the propensity score and $K-1$ further covariates, of some treated observation i and some control j, respectively. C denotes the covariance matrix of the K covariates in the control group. In Mahalanobis matching, the distances are weighted by the inverse of their covariance matrix to give higher weights to less noisy differences and those with smaller covariances. As a modification of the original metric, which treats the propensity score and each of the covariates as equally important, one may assign a higher weight to the propensity score than to the other elements in $\widetilde{x}_i^{D=1}$; $\widetilde{x}_j^{D=0}$. This is obtained by multiplying the inverse of the variance of the propensity score in C^{-1} by a factor larger than one. As a further modification, we do not take the square root as proposed in equation (8), with the consequence that observations further away will receive less weight by the matching algorithm.

As the name implies, matching is based on propensity scores, which are computed from a propensity score model. The propensity score model uses a set of covariates to predict the treatment status of an individual or household. Matching implies that a child who is in a household beneficiary of the PIAH project is matched with another child living in a household who did benefit from the project. A nonbeneficiary child should possess similar characteristics as that of the beneficiary child after matching. This makes the matched children comparable and valid for analysis. Following the framework used by (Gimenez-Nadal & Molina, 2016; Powell et al., 2020), beneficiary children were matched with non-beneficiaries. The Stata command "psmatch2" to estimate the ATT.

The most common matching algorithm, which is nearest neighbour matching, was implemented with different specifications for robustness check. Before analysing the ATT estimates, balance checks must be satisfied first. This means that the distribution of characteristics has to be well distributed between treatment and control children (Caliendo & Kopeinig, 2008). In general, the balance of the covariates may be assessed by looking at their means before and after matching. Based on most empirical studies, a standardized bias of five per cent and below is sufficient to consider the matching successful (Caliendo & Kopeinig, 2008; Shetty et al., 2023). Using a one-tailed test because we have a strong hypothesis that the assistance induced by the PIAH project has a positive effect on the level of household expenditure. Assuming that this is a positive or negative association, it is also possible to use the two-tailed test (Ha: diff !=0). The results show that the alternative hypothesis is correct (Ha: diff > 0), which means that our difference is positive and that non-beneficiaries of assistance from the PIAH project should have a lower level of per capita consumption on average. This result is statistically significant at the one per cent level. Therefore, we are confident that the group averages are statistically different from each other, and that sampling error is not the cause of this difference. However, this result in no way proves that the assistance received by the households is at the origin of a high level of consumption expenditure per capita for the households benefiting from this assistance from the PIAH project, as we have not taken into account spurious correlations. With the background established, we can now proceed with the matching process.

Before evaluating the outcome estimates, we first visually assessed the quality of the matched sample within our dataset. Fig. 2 presents a histogram of propensity scores organized by treatment status, highlighting the presence of common support. Meanwhile, Fig. 3 showcases the computed propensity scores before and after matching, with recipients of the PIAH project represented by red bars and their matched comparison counterparts shown in blue. Although a small number of participants fell outside the common support range, the propensity scores effectively facilitated suitable matches for most participants, with only a negligible number of households
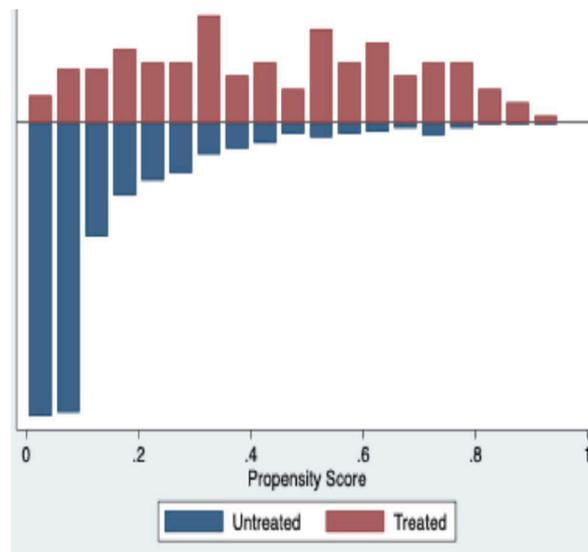
Fig. 2. Matching propensity score distribution.

remaining unmatched.

The initial sample comprised 724 observations. Following the implementation of PSM, the analytical sample was reduced to 708 observations, suggesting that approximately 16 individuals from the control group could not be adequately matched with counterparts in the treated group. This reduction in sample size is a common outcome in PSM procedures, particularly when substantial differences exist in the distribution of covariates between treatment and control groups. As noted by Rosenbaum and Rubin (1983), PSM retains only those units that are comparable in terms of observed covariates, which inevitably leads to the exclusion of unmatched observations that lack sufficiently similar counterparts in the opposite group.

To ensure the comparability of the two groups, we analysed the propensity score distributions before and after matching, as illustrated in Fig. 3. We employed the standardized difference test, as recommended by Rubin (2005), to validate the balance in characteristics between the two groups. This test measures bias reduction by comparing the means of beneficiaries and non-beneficiaries for each variable included in the propensity score, both before and following the matching process (see results in Fig. 3). To determine statistical significance, we formulated a null hypothesis stating that there is no difference in means between the treatment and control groups (Ho: diff = 0), allowing us to evaluate whether the observed differences are statistically meaningful.

We selected PSM as the primary identification strategy for several pragmatic and methodological reasons. First, PSM provides greater flexibility when dealing with numerous continuous covariates, as exact or coarsened exact matching often results in considerable sample loss in high-dimensional settings (Caliendo & Kopeinig, 2008; Rosenbaum & Rubin, 1983). Second, PSM allows the use of multiple matching algorithms—such as nearest neighbour, caliper, and kernel matching—facilitating comprehensive sensitivity analyses and robustness tests (Austin, 2011). Third, given our sample size, the common support assumption holds reasonably well,
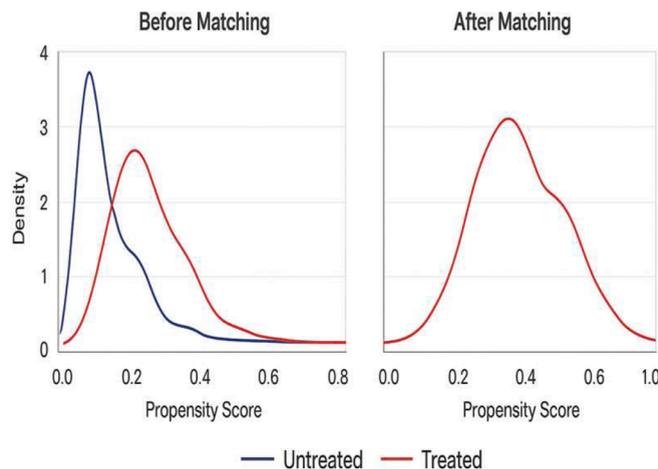

Fig. 3. Distribution of Propensity Scores Before and After Matching.

while Coarsened Exact Matching's (CEM) dependence on arbitrary coarsening cut-offs could lead to a non-negligible number of un-matched units (Blackwell et al., 2009). We implemented the robustness of CEM as a complementary robustness check, confirming that results remained consistent across both matching strategies (Table 5).

Consumption expenditure per capita is an important welfare indicator that captures households' overall living standards and economic well-being. In this study, we observe that the average weekly consumption expenditure amounts to 81,592 Congolese francs (approximately USD 30.45)[1] for the control group and 104,526 Congolese francs (approximately USD 39) for the treatment group, reflecting a statistically significant difference of 22,934 Congolese francs (around USD 8.56). This finding suggests that the assistance provided by the PIAH project has contributed to improving beneficiaries' economic welfare. In our propensity score matching (PSM) analysis, consumption expenditure per capita is used as an outcome variable to estimate the project's causal impact while controlling for potential selection bias. PSM enables a robust comparison between treated and untreated households with similar observable characteristics (Hilson, 2012b). This approach strengthens the internal validity of the estimated treatment effect on household welfare.

5.3. Descriptive statistics

The statistics describing all the variables used in this study are presented in Table 1 below. Children in the group that had not benefited from the PIAH project were more involved in activities related to artisanal mineral exploitation (66.7%) than those in the group that had benefited from the project's assistance (57.4%). The difference between the two groups is around 9.3%. This difference is statistically significant. However, when it comes to school attendance, we find that the control group has a higher rate (72.9%) than the treatment group (64.5%), with a statistically significant difference. The average number of out-of-school children in the treated group was higher than in the control group. On the other hand, the control group had a higher average number of school-age children (2.324) than the treatment group (1.504).

This study focuses on children aged 6 to 17 in Kamituga and evaluates the effects of the PIAH project using two main outcome variables: child labour and school attendance. The first outcome, child labour, is operationalized as a binary (dummy) variable coded as one if the child is involved in mining or related activities, and zero otherwise. This variable represents the probability of a child participating in artisanal mining. In line with previous studies (Awaworyi Churchill et al., 2021; Moestopo, 2020), a negative asso-ciation is expected between receipt of PIAH assistance and the likelihood of child labour, suggesting that the intervention may mitigate children's engagement in hazardous economic activities.

From an economic perspective, child labour is often a rational response to poverty and income instability. The PIAH project, by providing cash transfers or livelihood alternatives to vulnerable households, is presumed to ease financial constraints, thereby reducing the economic necessity of child labour.

This aligns with the substitution hypothesis in economic theory, where improved household income substitutes child labour with schooling. The human rights approach views child labour—particularly in hazardous sectors such as mining—as a violation of chil-dren's rights to protection, education, and development. The PIAH project can thus be understood as a rights-based intervention aiming to uphold these fundamental protections, particularly through reducing children's exposure to exploitative labour and pro-moting access to education.

The cultural-historical approach emphasizes the role of local norms, traditions, and social practices in shaping child labour. In regions like Kamituga, where mining is deeply embedded in the community's socio-economic fabric, children's involvement in mining may be normalized or perceived as a rite of passage. The PIAH initiative, in this context, seeks not only to address immediate material needs but also to influence social attitudes and reshape community perceptions about the value of education and the harms of child labour.

The second outcome variable is school attendance, which captures whether the child was enrolled in and regularly attending school. This variable assesses whether PIAH support affects children's educational participation. Although prior literature shows that cash transfer programmes often significantly reduce child labour (Acosta, 2011; de Hoop & Rosati, 2014), their effect on school attendance is mixed. Some evidence (e.g. Khiem et al., 2020) suggests that financial support can lead to increased school enrolment. Based on this, the present study hypothesizes that the PIAH intervention contributes positively to school attendance.

Descriptive statistics (as shown in Table 2) support the prevalence of child labour and provide preliminary insights into treatment effects. Out of 708 children in the sample, 458 (64.69%) were involved in mining or related work, while 250 (35.31%) were not. A gendered analysis reveals that boys (n = 340) are far more likely than girls (n = 118) to engage in mining. When disaggregated by treatment status, 66.73% of children in the control group were involved in mining, compared to 57.42% in the treatment group-—suggesting a potential protective effect of the PIAH project.

Regarding education, 503 children (71.05%) attended school, while 205 (28.95%) did not. Interestingly, school attendance was lower in the treatment group (64.52%) compared to the control group (72.88%). However, gendered patterns reveal that within the treatment group, girls had higher attendance rates (74.47%) than boys (60.19%), while in the control group, boys had higher attendance (80.90%) than girls (55.68%). These findings underscore the complex intersection of gender, education, and labour, warranting further analysis.

Importantly, the overlap between school attendance and mining participation points to a dual burden carried by many children in Kamituga. Despite attending school, many still engage in labour-intensive, hazardous work, which can undermine educational

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[1] The conversion from Congolese francs to US dollars was made using the official exchange rate for December 2023, when one US dollar equalled approximately 2,679.6 Congolese francs.

Table 1
Characteristics of control and treated groups.

Variables	Measurement	Control N= 553	Treated N=155	Mean difference
Child labour	This is a dichotomous variable, which takes the value 1 if the child is involved in mining and related activities 0 otherwise.	0.667	0.574	0.093**
School attendance	This is a dichotomous variable, which takes the value 1 if the child attends school and 0 otherwise.	0.729	0.645	0.084**
Child age	This is a discrete quantitative variable and takes the number of years since birth.	13.412	13.813	-0.401
Child gender	Binary variable and takes the value 1 if the child is a girl and zero otherwise.	0.718	0.590	0.128
Siblings under 6 years of age	A discrete quantitative variable which represents the total number of non-school-age children.	1.564	1.735	-0.171**
Siblings aged between 7 and 17	A discrete quantitative variable which represents the total number school-age children.	2.324	1.503	0.820***
People aged 18 and over	A discrete quantitative variable which represents the total number of adults within the household at the time of the survey.	3.454	2.968	0.486***
Family size	A discrete quantitative variable which represents the total number of people in the household at the time of the survey.	4.915	5.916	-1.001***
Gender of head of household	Dichotomous variable which takes the value zero if the head of household is a woman and 1 if he is a man.	0.579	0.523	0.056
Education of head of household	Categorical variable. It takes the value 1 for a head of household with no education, 2 for those with at least primary education and 3 for those with more than secondary education.	2.011	1.832	0.179***
Mother's education	Categorical variable. It takes the value 1 for a mother with no education, 2 for those with at least primary education and 3 for those with more than secondary education.	1.684	1.310	0.374***
Distance between home and school	This is a quantitative variable measured in minutes.	42.278	42.065	0.214
Distance between home and mining site	This is a quantitative variable measured in minutes.	23.365	23.684	-0.319**
Family member in ASM	This is a binary variable, which takes the value 1 if at least one member of the family is involved in mining activities and zero otherwise.	0.725	0.658	0.067
Household monthly expenditure per capita	This is a quantitative variable. It is the value of the total consumption cost of the household divided by the number of persons living within the household and valued in Congolese francs.	81592	104526	-22934***
Access to drinking water	Dichotomous variable which takes one if the household has access to drinking water and zero otherwise	0.193	0.187	0.006

***, ** and * signify a significance level of 1, 5 and 10% respectively. Summary statistics for each group present the mean for each variable of interest.

Table 2
Descriptive statistics for outcome variables by gender.

Variables		All sample			Treated			Control		
		Boys	Girls	Total	Boys	Girls	Subtotal	Boys	Girls	Subtotal
Child mining activity	Yes	340 (70.10)	118 (52.91)	458 (64.69)	63 (58.33)	26 (55.32)	89 (57.42)	277 (73.47)	92 (52.27)	369 (66.73)
	No	145 (29.90)	105 (47.09)	250 (35.31)	45 (41.67)	21 (44.68)	66 (42.58)	100 (26.53)	84 (47.73)	184 (33.27)
School attendance	Yes	370 (76.29)	133 (59.64)	503 (71.05)	65 (60.19)	35 (74.47)	100 (64.52)	305 (80.90)	98 (55.68)	403 (72.88)
	No	115 (23.71)	90 (40.36)	205 (28.95)	43 (39.81)	12 (25.53)	55 (35.48)	72 (19.10)	78 (44.32)	150 (27.12)

First row has frequencies, and second row has row percentages in parathesis

outcomes and psychosocial development (Mihigo et al., 2024). This dual engagement raises critical concerns about the quality of learning and long-term developmental trajectories.

From a policy standpoint, this complexity has generated debate. Scholars such as Basu and Zarghamee (2009) argue that consumer boycotts of goods produced with child labour may help discourage the practice. However, critics caution that such measures may inadvertently harm already impoverished households by reducing income sources, potentially pushing children further into exploitative work to compensate for the loss.

6. Results and discussions

The treatment variable indicates whether the child's household received assistance from the PIAH project prior to the survey. Although the data are cross-sectional, the PIAH intervention was implemented before 2023, and respondents were explicitly asked about past receipt of assistance rather than contemporaneous exposure. In contrast, child labour participation and school attendance

are measured at the time of the survey. This timing ensures that treatment conceptually precedes the outcomes.

All covariates included in the PSM procedure capture pre-treatment or time-invariant characteristics, consistent with the identifying assumptions of PSM. Child age, age squared, and gender are biologically determined. Household demographic composition—including the number of young children, school-age children, adults, and total household size—reflects long-run fertility and household formation decisions that are unlikely to respond to short-term program participation. The education levels of the household head and the child's mother were completed well before the child reached working age and therefore clearly predate program exposure. Geographic variables, such as distance to schools and mining sites, are fixed by residential location and local infrastructure and are plausibly exogenous to the intervention.

As emphasized by Wooldridge et al. (2010), the credibility of causal inference with cross-sectional data hinges not on the data structure itself, but on whether covariates can be plausibly argued to precede treatment. In the child labour literature, age, gender, parental education, and household composition are routinely treated as exogenous baseline controls, capturing long-run preferences, constraints, and demographic pressures that jointly shape program participation and child outcomes (Basu & Van, 1998; Edmonds & Pavcnik, 2005). The inclusion of geographic variables is also standard in low-income and conflict-affected settings, where distance to schools and mining sites reflects structural access constraints rather than behavioral responses to interventions (Duflo et al., 2015). Similarly, indicators such as the presence of other household members engaged in artisanal and small-scale mining proxy pre-existing exposure to mining economies and underlying vulnerability, rather than post-treatment adjustments (De Hoop & Rosati, 2014).

Observed covariates significantly predict participation in the PIAH project, confirming non-random program placement, a common feature of targeted social interventions. The substantial improvement in covariate balance after matching, together with the estimated ATT showing reduced child labour and increased school attendance, is consistent with evidence from evaluations of NGO-led and cash-transfer-type programs in Sub-Saharan Africa (Baird et al., 2013).

Nonetheless, cross-sectional PSM cannot fully eliminate bias from unobserved, time-varying factors. The validity of the estimates therefore rests on the plausibility of the conditional independence assumption, which is reinforced through theoretically grounded covariate selection, careful attention to temporal ordering, and systematic balance diagnostics (Wooldridge et al., 2010).

The propensity score approach corresponds to the probability of a child in the household receiving assistance from the PIAH project. Estimation using the propensity score matching model generally involves estimating propensity scores using a logit or probit model containing the explanatory variables. The main results of estimating the biprobit model are shown in Table 3. Having carried out the propensity score procedure, and since the results meet all the conditions mentioned in the literature, we can present the final result of our study, estimating the impact of the PIAH project on child labour and school attendance. The details in terms of output are shown in Table 3.

The PSM analysis provides robust empirical evidence that the PIAH project contributes potentially to reduce child labour while simultaneously fostering systematic improvements in school attendance. On average, the incidence of child labour declined by 7.7%, with even larger reductions observed when disaggregated by gender—13.9% among boys and 13.6% among girls. These results corroborate a well-established body of economic literature that identifies poverty as the principal determinant of child labour (Basu & Van, 1998; Edmonds & Pavcnik, 2005; Edmonds & Schady, 2012). By relaxing household liquidity constraints through cash transfers and related forms of material support, the programme enables families to substitute children's time away from income-generating activities and reallocate it toward education. This mechanism is consistent with evidence from other low-income contexts, where

Table 3

Child labour and School attendance using a biprobit model on PIAH project varaible.

Variables	Boys	Girls	Overall
Child age	0.021 (0.033)	0.082* (0.048)	0.018 (0.027)
Child age^2	-0.071** (0.068)	-0.034** (0.037)	-0.083*** (0.028)
Male			-0.080 (0.136)
Siblings under 6 years of age	-0.091 (0.098)	0.080 (0.143)	-0.043 (0.077)
Siblings aged between 7 and 17	-0.051 (0.059)	-0.172* (0.090)	-0.100** (0.047)
People aged 18 and over	-0.223*** (0.087)	-0.370*** (0.129)	-0.307*** (0.067)
Family size	-0.331*** (0.111)	-0.050 (0.171)	-0.229*** (0.087)
Gender of head of household	0.215*** (0.054)	0.113 (0.077)	0.171*** (0.043)
Education of head of household	-0.225 (0.156)	-0.226 (0.237)	-0.247** (0.126)
Mother's education	-0.795*** (0.159)	-0.416* (0.225)	-0.598*** (0.123)
Distance between home and school	-0.005 (0.009)	0.003 (0.013)	-0.001 (0.007)
Distance between home and mining site	0.006 (0.004)	-0.013* (0.007)	0.001 (0.003)
Family member in ASM	0.029 (0.169)	-0.397 (0.257)	-0.096 (0.135)
Belonging to the solidarity association	1.169*** (0.167)	0.398* (0.241)	0.953*** (0.127)
Intercept	0.624 (0.759)	0.384 (1.210)	0.541 (0.666)
Number of obs	485	223	708
LR chi2	166.61	57.81	197.69
Prob > chi2	0.0000	0.0000	0.0000
Pseudo R^2	0.3239	0.2517	0.2656

***, ** and * signify a significance level of 1, 5 and 10% respectively. Standard errors are in paratheses. Note: the common support option has been selected. Description of the estimated propensity score in region of common support. Numbers of blocks in all estimations ensures that the mean propensity score are not different for treated and controls in each block. The table presents an algorithm to estimate the propensity score. The treatment is PIAH_beneficiary which is a dichotomous variable.

conditional and unconditional cash transfer schemes have produced measurable improvements in school attendance and reductions in child labour (Cepaluni et al., 2022; Moestopo, 2020; Portela et al., 2004).

From a human rights perspective, these findings are significant because they align with the normative framework of international conventions, particularly the United Nations Convention on the Rights of the Child, which underscores children's entitlement to education and protection from economic exploitation. The project can thus be interpreted not merely as an anti-poverty intervention but as a rights-fulfilling mechanism that operationalizes global commitments at the local level.

Nonetheless, as Awaworyi Churchill et al. (2021) demonstrate in the case of Pakistan, the durability of such outcomes is conditional upon sustained assistance. Short-term or sporadic interventions may alleviate immediate economic pressures but are unlikely to permanently reduce child labour if households remain uncertain about long-term income security.

In addition to economic and rights-based considerations, cultural dynamics exert considerable influence on household decision-making. In many settings, children's work is socially normalized and regarded as an indispensable contribution to household survival, while formal education is sometimes undervalued due to limited labour market opportunities. Community sensitization, parental engagement, and awareness campaigns are crucial to shifting cultural perceptions about the relative value of education versus work. Taken together, the PIAH project illustrates that sustainable reductions in child labour and durable improvements in school attendance are most effectively achieved through a multidimensional strategy—one that integrates economic relief, rights protection, and cultural change into a coherent and sustained policy framework.

In artisanal and small-scale mining (ASM) communities such as Kamituga, cultural norms and traditional practices play a central role in shaping household decisions about child labour and schooling. Mining is often viewed as a family enterprise where children's participation is socially accepted and even valued as part of early skill acquisition and economic contribution to household survival (Hilson, 2012b). Moreover, gendered expectations and intergenerational transmission of mining work reinforce children's involvement, particularly when formal education is perceived as less relevant to local livelihoods (Murhi Mihigo et al., 2024). These cultural dynamics intersect with economic constraints, creating a powerful cycle that sustains child labour despite awareness of its risks. Integrating these factors into the analysis of ASM contexts like Kamituga is essential for designing interventions that are not only economically viable but also culturally sensitive and community driven.

The Average Treatment Effect on the Treated (ATT) values capture the estimated differences in outcomes between households that benefited from the PIAH project (treatment group) and comparable households that did not (control group), after adjusting for observable characteristics using propensity score matching. These estimates provide a counterfactual view of what beneficiaries' outcomes might have been in the absence of the intervention.

Results in Table 4 indicate that the PIAH project has a limited and statistically insignificant impact on reducing child labour in Kamituga. Although the ATT values for child labour are negative—indicating reductions among treated households—none are statistically significant, suggesting these declines may be due to random variation rather than a measurable program effect. For all children, the ATT is -0.077, corresponding to a 7.7 percentage point reduction (t = -1.120, p > 0.10). Among boys, the ATT is -0.139 (13.9 percentage point reduction; t = -1.520, p > 0.10), while for girls it is -0.136 (13.6 percentage point reduction; t = -1.200, p > 0.10).

In contrast, the project shows a consistent and statistically significant positive influence on school attendance. For all children, the ATT is 0.142, implying a 14.2 percentage point increase (t = 2.310, p < 0.05). Boys record an ATT of 0.157 (15.7 percentage point increase; t = 1.790, p < 0.10), while girls have an ATT of 0.045 (4.5 percentage point increase; t = 2.420, p < 0.05). Although the effect for girls is statistically significant, its practical magnitude is modest. Overall, the PIAH project is more effective at boosting school attendance than at reducing child labour, likely due to persistent economic and structural factors compelling children to work, even while enrolled in school.

The literature shows that cash transfers have a positive impact on education outcomes in a variety of contexts (Awaworyi Churchill et al., 2021; de Hoop & Rosati, 2014; Filmer & Schady, 2011; Tagliati, 2022). One of the main benefits of cash transfers is that they can help reduce financial barriers to education for vulnerable populations, such as low-income families or people living in poverty. De Hoop and Rosati (2014) show that the transfer of money can lead to a child starting school, which automatically reduces the time he/she used to spend working; as child labour negatively influences school achievement (Beegle et al., 2009; Ray & Lancaster, 2005). By providing direct financial and in-kind support to households, such a policy can enable families to cover the costs associated with sending their children to school, such as school fees, uniforms and supplies.

This fig. 4 provides more clearly on the causal effects of the PIAH project on child labour and school attendance in Kamituga,

Table 4
PIAH project impact on child labour and school attendance using PSM.

Variables	Subgroup	Sample	Treatment group	Control group	Difference	S.E	T-stast
Child labour	Boys	ATT	0.583	0.722	-0.139	0.091	-1.520
	Girls	ATT	0.568	0.705	-0.136	0.114	-1.200
	All	ATT	0.574	0.652	-0.077	0.069	-1.120
School attendance	Boys	ATT	0.759	0.602	0.157***	0.088	1.790
	Girls	ATT	0.795	0.75	0.045**	0.108	2.420
	All	ATT	0.787	0.645	0.142**	0.061	2.310

***, ** and * signify a significance level of 1, 5 and 10% respectively. Robust standard errors are in paratheses. For the estimator method we have imposed the Common support condition. The psmatch2 procedure is used to estimate the different models at Caliper equal to 0.01 maximum distance allowed between propensity scores.

estimated through PSM. The Average Treatment Effect on the Treated (ATT) is measured in percentage points, distinguishing between boys, girls, and the overall sample. The findings reveal a consistent reduction in child labour across all groups (red bars) alongside improvements in school attendance (green bars). Specifically, boys and girls experienced similar declines in labour participation (around –14 %), while school attendance rose markedly for boys (+15%) and the full sample (+14%), but less so for girls (+4.5%).

These results align with a broad body of empirical research showing that targeted interventions can reduce child labour while increasing schooling opportunities. For instance, Edmonds and Schady (2012) demonstrated that social protection programs, such as conditional cash transfers, often reduce child labour by offsetting household income constraints, allowing children to attend school. Similarly, Beegle et al. (2009) emphasized that household poverty is a key driver of child labour, and interventions that relax financial pressures tend to improve school attendance. The PIAH project's impact thus appears consistent with theories of household decision-making, where families balance the trade-off between children's immediate labour income and long-term educational benefits (Basu & Van, 1998).

Notably, the gender differences observed here echo patterns highlighted in the literature. Boys seem to benefit more strongly from the project in terms of school attendance. This could reflect gendered household expectations: in many contexts, boys' education is prioritized due to higher expected returns in the labour market (Kabeer, 2003; Kingdon, 2005). For these authors; Girls, despite reductions in labour, may still face cultural or domestic barriers limiting their school participation, as documented in studies from sub-Saharan Africa.

Overall, the PIAH project demonstrates a dual achievement: reducing child labour and fostering education, consistent with global evidence that integrated development interventions can shift household decisions toward human capital investment. However, the gender gap in schooling gains suggests the need for complementary strategies addressing structural inequalities faced by girls, such as reducing domestic work burdens, improving school accessibility, and tackling cultural norms that undervalue female education.

The results obtained by the matching method should be treated with caution, as this method does not consider the bias linked to a possible correlation between unobservable factors, which may influence both the probability of receiving assistance and the parent's decision to have their children work and/or send them to school. If this is the case, independence between the outcome variables and the treatment variable is not guaranteed. Indeed, two households with identical observable characteristics may have different probabilities of being eligible for assistance from the PIAH project, which would lead to a hidden bias. Under these conditions, the validity of the results obtained by the matching approach may be questioned.

6.1. Robustness check

The "pstest" command, after estimation using the propensity score matching method, allows us to test the validity of our results. In general, the results appear to be highly robust to unobserved heterogeneity, the threshold being greater than 2 (the point at which the treatment effect becomes insignificant) and the threshold less than 0.5 (the critical threshold value, at which the results concerning this proportion become questionable). Sensitivity testing is an important aspect of analysis using PSM throughout the literature. Sensitivity testing is performed to assess the robustness of treatment effect estimates to possible unobserved confounding variables. The procedure recommended by Rosenbaum and Rubin (1983) facilitates the calculation of the limits of the estimate of the treatment effect by varying the probability of attribution of the treatment for the unobserved confounding variables within a range of plausible values. The result suggests that the estimated treatment effect of the PIAH intervention on children's school attendance and work is robust to potential unobserved confounding variables.

PSM was selected as the primary estimation strategy due to its flexibility in handling continuous covariates while maintaining an adequate effective sample size. To assess the robustness of the findings, we also implemented Coarsened Exact Matching (CEM) using empirically grounded coarsening bins that minimize information loss and improve covariate balance Table 5). Both approaches yield
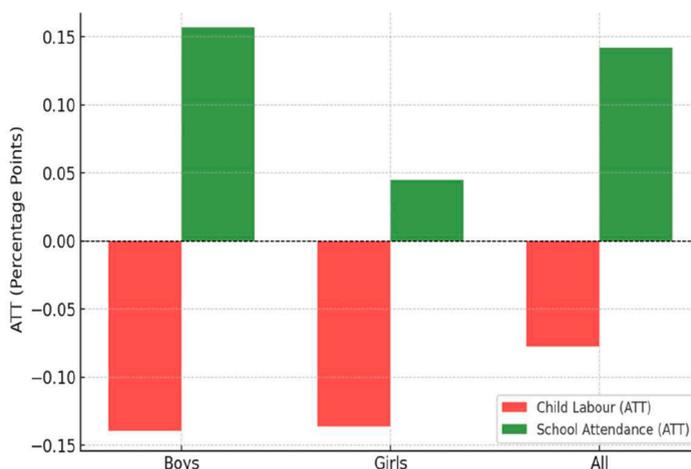

Fig. 4. Impact of PIAH project on child labour and School Attendance (PSM).

consistent and statistically significant estimates, indicating that participation in the PIAH project reduces the likelihood of child labour and increases school attendance.

Table 5 shows that the robustness of the PIAH estimates across matching and weighting algorithms aligns with a growing body of evidence demonstrating that well-targeted social interventions can significantly influence child labour and schooling outcomes. The estimated reductions in child labour and increases in school attendance are consistent with findings from conditional cash transfer and social protection programmes in comparable low-income settings. For instance, Edmonds and Schady (2012) documented substantial declines in child work and improvements in schooling following the *Bono de Desarrollo Humano* programme in Ecuador, emphasizing that even modest cash transfers can reallocate children's time toward education. Similarly, De Hoop and Rosati (2014) found through cross-country evidence that interventions reducing household economic vulnerability tend to generate simultaneous gains in school attendance and reductions in child labour, reinforcing the PIAH project results.

The convergence of results across estimation methods also echoes the methodological robustness emphasized in Blackwell et al. (2009), who demonstrated that when multiple matching estimators yield consistent treatment effects, it signals strong overlap and covariate balance—an essential condition for credible causal inference under selection on observables. Moreover, the improved balance diagnostics in the PIAH project analysis correspond with the recommendations of Blackwell et al. (2009), who highlight that reduced standardized mean differences and L_1 statistics indicate reliable adjustment for confounding. CEM achieved excellent balance (L1 reduced from 0.312 to 0.042). Most treated units are retained (150/155), and a large subset of controls were usable.

From a policy standpoint, the PIAH project's dual achievement—reducing child labour and promoting school attendance—supports prior evidence that integrated social interventions can be more effective than single-component programmes. Dammert et al. (2018), reviewing over 50 impact evaluations, argue that the most successful child labour programmes combine income support with complementary services, such as school access or awareness campaigns. The magnitude of PIAH project's estimated impacts, therefore, falls within the upper range of effects typically observed in multi-dimensional interventions, confirming the project's potential as a scalable model for reducing child labour through household-level empowerment.

Although the sensitivity analysis shows that our results are robust, we can also reinforce this confirmation by using the instrumental variable method. The literature on the subject indicates that the Heckman procedure and the instrumental method demonstrate good control of unobserved heterogeneity (Ray & Lancaster, 2005).

6.2. Instrumental variable analysis

Using the instrumental variables approach Z is an instrument and X is a vector of exogenous variables explaining participation in the PIAH project. By applying the eligibility rule to receive assistance, instrument Z takes the value 1 if the child is in an eligible household, and zero otherwise. We can establish the following specifications: $T_i = \delta X_i + \lambda Z_i + w_i$ (9) where T designates the treatment variable, taking 1 if the child is a beneficiary of the PIAH assistance and zero otherwise. X is a vector of child and household characteristics, and W is an unobserved error term. As the instrument represents the eligibility rule, it is most likely to be correlated with participation. We suppose that the unobserved errors are not correlated with the instrument. We set: cov (u, Z) = 0. If correct, PIAH's causal effect is obtained by estimating the second specification: $Y_i = X_i\beta + \alpha\widehat{T}_i + u_i$ (10) where $\widehat{T}_i$ is obtained by estimating equation (9). Y_i represents the outcome variable—either child labour participation or school attendance—depending on the specification considered in the corresponding estimation equation. The second equation gives us Tayssir's causal effect for children whose participation is assigned by the eligibility rule (compilers). This is called the Local Average Treatment Effect.

The instrumental variable used in this analysis is '*access to drinking water*'. This instrument has already been used in several studies and is a robust instrument when studying the issue of child labour and education (Mihigo et al., 2024; Ray & Lancaster, 2005). Access to drinking water was selected because it represents a local infrastructure shock that plausibly influences household participation in PIAH interventions without directly affecting child labour or school attendance, except through the project's support (Imbens & Angrist, 1994; Wooldridge et al., 2010). To strengthen theoretical justification, we argue that improved water access primarily reduces household time constraints and transaction costs, enabling greater engagement with PIAH activities, rather than directly altering children's labour decisions (Duflo et al., 2015). Given that we are dealing with two dichotomous variables that are mutually endogenous, the literature advises moving beyond the standard *ivbiprobit,* which estimates two separate equations, and instead employing a simultaneous bivariate probit model using the cmp framework. This approach has been recommended in cases where binary outcomes are jointly determined and endogenous to each other, allowing consistent estimation of the structural parameters

Table 5
Robustness of Estimated Average Treatment Effects on the Treated (ATT) for PIAH project.

Method / Specification	Matching / Weighting details	Child labour		School attendance	
		ATT (estimate)	SE (p-value)	ATT (estimate)	SE (p-value)
PSM – Nearest Neighbour (1:1)	Logistic PS; caliper = 0.05; common support enforced	−0.090	0.028***	0.120	0.035**
PSM – Radius (caliper = 0.05)	Logistic PS; radius = 0.05; multiple matches weighted	−0.087	0.030**	0.118	0.037**
PSM – Kernel matching	Epanechnikov kernel; bandwidth = 0.06	−0.089	0.027*	0.122	0.034***
CEM (coarsening)	All control variables	−0.085	0.027***	0.115	0.033*
CEM (narrower coarsening)	Finer bins; stricter match tolerance	−0.081	0.031*	0.112	0.036**

Standard errors computed using 500 bootstrap replications (robust to heteroskedasticity). ***, ** and * signify a significance level of 1, 5 and 10% respectively.

(Roodman, 2011; Stock & Yogo, 2005). In particular, the cmp setup extends traditional limited dependent variable models by permitting simultaneous estimation under endogeneity, which has been widely applied in labour and development economics when analyzing schooling and child labour decisions (Lokshin & Sajaia, 2004).

The instrumental variable (IV) estimates presented in Table 6 assess the causal impact of the PIAH project on child labour and school attendance, distinguishing between boys and girls. The instrument employed—access to drinking water—appears valid based on diagnostic tests.

Considering overall child labour, the coefficient of –0.217 indicates a negative but statistically insignificant effect. When disaggregated by gender, the effect is larger for boys (–0.559) than for girls (–0.341), though both remain statistically insignificant. This suggests that the PIAH project may reduce child labour, particularly among boys, but the evidence is not robust enough to confirm a definitive effect. These results align with empirical studies such as Edmonds and Pavcnik (2005), who show that household-level interventions often have heterogeneous effects on child labour, with boys more likely to withdraw from economic activities when household constraints are relaxed.

The impact on schooling attendance is more pronounced. Overall school attendance increases by 18.6%, significant at the 5% level. For boys, the effect is positive and substantial (49.5%, significant at 10%), indicating a strong promotion of schooling. Similarly, the effect for girls is positive and significant (0.036, p<0.01), suggesting that the intervention may increase a little bit girls' school attendance than boys. This gender difference is consistent with findings by Ray (2000), who highlight that household and community interventions can disproportionately benefit boys due to entrenched gender norms and opportunity costs. For girls, reduced time spent fetching water may be reallocated to domestic responsibilities, limiting school attendance.

Diagnostic tests support the credibility of the IV approach. Endogeneity tests, reported as chi-square statistics, indicate that the PIAH_project variable is endogenous across all specifications. For child labour, χ^2 values range from 6.11 to 9.21, and for school attendance from 5.97 to 8.03, all significant at conventional levels. These results reject the null hypothesis of exogeneity, implying that *biprobit* estimates would be biased and inconsistent, thereby justifying the IV strategy.

Weak instrument tests further confirm the relevance of the instrument. Across specifications, first-stage statistics range from 13.7 to 18.2, well above the conventional threshold of 10 suggested by Lokshin and Sajaia (2004) and Roodman (2011). Most values are highly

Table 6
Estimation with instrumental variable of the PIAH project.

	Child labour			School attendance		
	Overall	Boys	Girls	Overall	Boys	Girls
PIAH_project	-0.217	-0.559	-0.341	0.186**	0.495**	0.036***
	(0.249)	(0.399)	(0.801)	(0.185)	(0.274)	(0.598)
Childage	0.26*	0.451**	0.111**	0.181**	0.814**	0.316***
	(0.270)	(0.181)	(0.156)	(0.279)	(0.131)	(0.125)
Childage^2	-0.085** (0.037)	0.102** (0.041)	-0.091* (0.047)	-0.115** (0.050)	-0.078 (0.045)	0.093* (0.048)
Childgender	0.001	-	-	-0.04*	-	-
	(0.042)			(0.024)		
Children_less_6	-0.081**	0.278***	0.361***	-0.081**	0.349***	-0.014*
	(0.035)	(0.028)	(0.033)	(0.035)	(0.033)	(0.017)
Children6_17	0.972***	0.212***	0.339***	0.972***	0.343***	-0.034
	(0.031)	(0.025)	(0.029)	(0.031)	(0.030)	(0.027)
Persons18	-0.036***	-0.006***	-0.010***	-0.036***	-0.010***	0.021**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.022)
Educ_HHousehold	-0.002	0.018	-0.011	-0.002	0.002	0.041**
	(0.026)	(0.021)	(0.024)	(0.026)	(0.025)	(0.052)
Family_size	-0.000	-0.003	-0.001	-0.000	-0.004	-0.131***
	(0.009)	(0.007)	(0.008)	(0.009)	(0.008)	(0.135)
Gender_HHousehold	0.000	0.000	-0.000	0.000	0.000	0.081
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.135)
Mum_Educ	0.038	-0.021	-0.004	0.037	-0.015	0.186
	(0.045)	(0.037)	(0.043)	(0.045)	(0.043)	(0.134)
Distance_site_H~e	0.536***	-0.042**	-0.044**	0.536***	-0.039*	0.174
	(0.024)	(0.018)	(0.021)	(0.024)	(0.022)	(0.136)
Distance_school~e	-0.017	0.007**	-0.023	-0.017	-0.014	0.126**
	(0.018)	(0.015)	(0.017)	(0.018)	(0.017)	(0.053)
Family_Mber_ASM	0.027	-0.020	-0.025	0.026	-0.034	-0.219
	(0.028)	(0.023)	(0.026)	(0.028)	(0.027)	(0.141)
Rotating credit	0.030	0.003*	0.032	0.029	0.021	-0.208
	(0.023)	(0.019)	(0.022)	(0.023)	(0.022)	(0.142)
Intercept	2.935**	4.976***	2.760**	1.735***	1.846***	1.647***
	(1.200)	(1.291)	(1.191)	(1.984)	(0.299)	(0.242)
Testing for endogeneity statistic chi2(1)	7.84**	9.21***	6.11**	8.03**	5.97**	7.45**
Testing for weak instrument	15.8***	18.2***	13.7**	16.4***	14.5**	17.1***
Obs.	708	485	223	708	485	223
R-squared	0.072	0.0381	0.03	0.558	0.384	0.228

Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1. Our instrumental variable is access to drinking water.

significant at the 1% level, indicating that the instrument is sufficiently strong and that IV estimates are unlikely to suffer from weak instrument bias. Empirically, this aligns with prior studies exploiting exogenous variation in Ecuador to identify time in unpaid household services (Abadie & Imbens, 2016). Overall, the diagnostic results enhance confidence in the causal interpretation of the PIAH project's effects on child labour and schooling attendance.

These findings confirm the robustness of the conclusions previously drawn from the PSM analysis, reinforcing the validity of the project's impact. The convergence of results across two different empirical strategies strengthens confidence in the causal interpretation and highlights the reliability of the estimated effects.

In many low-income and resource-constrained countries, such as those affected by ASM, children frequently face the dual burden of school and work. This is reflected in the descriptive statistics (Table 6), which show that a substantial proportion of children both work and attend school. This dual engagement often results in poor academic performance, limited educational attainment, and early school dropout, particularly in environments lacking basic infrastructure such as access to drinking water, electricity, or nearby schools.

Living in such vulnerable contexts exposes children to exploitative forms of labour at a very young age. These environments not only erode children's rights to education and play but also trap them in cycles of intergenerational poverty. By contributing economically to their families instead of focusing on education, children lose the opportunity to acquire the human capital necessary to escape future destitution. This early loss of potential has long-term consequences for both individuals and the broader economy.

The PIAH project, spearheaded by the Panzi Foundation, plays a crucial role in disrupting these cycles. By providing integrated support—combining social services, educational assistance, and community awareness—the project addresses both the symptoms and root causes of child labour. It reduces the economic pressures that drive families to rely on children's income and creates a more supportive environment for school attendance. As the regression analysis shows, such programs are not only beneficial but essential. They help reshape parental attitudes toward education and child development, offering hope for a generation of children who would otherwise be denied their right to a better future.

Although this study is based on cross-sectional data—which is often criticized for its limited capacity to establish causal relationships or long-term impacts due to its static nature (Deaton, 1995)—we address this constraint by reconstructing the historical trajectory of the intervention. By incorporating retrospective variables such as the timing, duration, and intensity of exposure to the project, and employing rigorous methods like Propensity Score Matching (Rosenbaum & Rubin, 1983), we approximate counterfactual scenarios and strengthen the credibility of our findings. This approach enables us to draw plausible inferences about long-term associations, even in the absence of random assignment, particularly when historical patterns are well-documented. While the inability to fully establish temporal sequencing remains a limitation, structured recall and contextual insights provide a robust foundation for projecting potential long-run effects—an approach validated in other cross-sectional evaluations of long-term development programs (Gertler et al., 2016).

7. Conclusion

Until the present century, the simultaneous prevalence of child labour and school attendance has remained widespread in many less developed economies. Historically, poverty has been a primary driver of both low school attendance and child labour in impoverished countries. Over time, the effects of various forms of financial and non-financial household support on human capital investment and the fight against child labour have been extensively analysed. Income transfer programs have emerged as a potential solution to this issue, even though they are not specifically designed to address child labour.

This paper examines the impact of the PIAH project on child labour and school attendance in Kamituga, South Kivu Province, DRC. By doing so, we contribute to the existing literature by demonstrating that a program combining both cash and non-cash transfers can significantly affect both child labour and school attendance. Utilising the propensity scores matching method, our results show that the PIAH project in Kamituga reduced the likelihood of children working while simultaneously increasing school attendance rates. To ensure the robustness of our findings, we conducted sensitivity tests using instrumental variable analysis.

Our results indicate that, in the absence of public aid programs, financial assistance from non-governmental organisations can support households in financing their children's education and reducing child labour in the artisanal mining sector. Thus, we recommend that government officials implement comprehensive public policies with substantial budgets to promote schooling and limit children's involvement in income-generating activities that jeopardise their futures. These policies should specifically target low-income families who cannot afford education for their children.

Our study advocates for the integration of both financial and non-financial assistance projects in disadvantaged areas, such as the artisanal mining zones, to combat child labour and facilitate school attendance. Based on our findings, we propose that policymakers in mining areas adopt integrated interventions combining conditional cash transfers with school support programs, such as scholarships, school feeding, or transport assistance, to simultaneously reduce child labour and increase attendance (Baird et al., 2013; Popova & Evans, 2014). Scaling up initiatives like PIAH through public–private partnerships could enhance reach and sustainability (Attanasio et al., 2006). Furthermore, these strategies may be relevant to other artisanal mining contexts in sub-Saharan Africa, where similar socio-economic and gendered constraints on schooling exist (Binci & Giannelli, 2018; Cuadros-Menaca & Gaduh, 2020).

Cash and in-kind transfers from external partners can expand educational access and reduce child labour in the DRC, especially where government investment is limited. However, reliance on such aid risks reinforcing neo-colonial dynamics and undermining local agency. A decolonization approach emphasizes strengthening domestic capacity to ensure autonomy and sustainable education systems. However, the study's limitations include the relatively small sample size. Future research should extend beyond artisanal mining sites to include children working in other sectors to provide a more comprehensive analysis.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Declaration of competing interest

The authors declare no conflict of interest.

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