Effects of electricity access on learning outcomes in Ghana: the role of digital technology

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Thomas Boampong, Alhassan Atta-Quayson and Abraham Gyamfi Ababio
Department of Economics Education, University of Education Winneba, Winneba, Ghana

Abstract

Purpose – This article investigates the relationship between electricity access and learning outcomes in Ghana, emphasizing the mediating role of digital technology in this relationship.

Design/methodology/approach – This study employs a cross-sectional descriptive research design to analyze the effects of electricity access on learning outcomes in Ghana, with digital technology as a mediator. Secondary data were sourced from the sixth (2012/2013) and seventh (2016/2017) rounds of the Ghana Living Standards Survey (GLSS), conducted by the Ghana Statistical Service. The data were analyzed using probit regression estimation technique to assess direct and indirect relationships among variables.

Findings – The results show that electricity access positively influences learning outcomes. In addition, digital technology usage mediates this relationship. Households with electricity access showed significantly higher adoption of educational digital tools, correlating with improved academic performance.

Research limitations/implications – This study relies on secondary data from the Ghana Living Standards Survey (GLSS6 and GLSS7), which, while comprehensive, lacks measures of children's cognitive aptitude and inherent learning abilities. The absence of these variables limits the ability to account for individual-specific traits that may influence learning outcomes.

Practical implications – The findings highlight the importance of addressing energy poverty to improve educational outcomes. Policymakers are encouraged to prioritize rural electrification programs and promote the integration of digital technology in education.

Originality/value – This study contributes to the literature by modelling the mediating role of digital technology in the relationship between electricity access and learning outcomes. It provides actionable insights for policymakers and educators seeking to improve educational equity in developing countries.

Keywords Electricity access, Energy poverty, Digital technology, Learning outcomes, Probit regression

Paper type Research article

1. Introduction

Education is a universally acknowledged driver of economic growth, poverty alleviation and societal well-being. As a cornerstone of sustainable development, it is enshrined in the United Nations' Sustainable Development Goals (SDGs), particularly SDG 4, which emphasizes inclusive and equitable quality education for all by 2030 (UNESCO, 2014). Attaining this goal is vital for addressing critical global challenges, such as economic disparities, gender inequality and social exclusion (World Bank, 2022). Beyond fostering cognitive and technical skills, education empowers individuals socially and economically, enhancing mobility and reducing poverty (Barro and Lee, 2013).

Despite significant strides in enrolment, Ghana faces severe educational quality challenges. Assessments like the 2023 Early Grade Reading Assessment (EGRA) reveal that only 5% of Primary 2 pupils read proficiently, while 45% fail to recognize a single word. Similarly, the Early Grade Maths Assessment (EGMA) shows that nearly 60% of pupils struggle with conceptual mathematics, with urban students outperforming their rural counterparts (MOE, 2023; GSS, 2023). The 2022 National Education Assessment (NEA) further highlights a grim reality: 35% of Primary 4 pupils lag in reading, and 55% are below the minimum mathematical competence (MOE, 2023; World Bank, 2022). These statistics underscore that enrolment gains have not translated into corresponding improvements in skills acquisition and

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productivity. This study posits that energy poverty, a lack of access to affordable, modern energy services like electricity, is a fundamental barrier to improving educational outcomes in Ghana (Burlinson *et al.*, 2022; Fry *et al.*, 2023).

In 2013, 82.5% of Ghanaians were energy-poor, a figure only marginally reduced from 88.4% in 2006 (GSS, 2013). The repercussions are severe: in 2016 alone, approximately 55,000 Ghanaians died from indoor air pollution, with 76.4% of households relying on inadequate energy sources for lighting and only 23.6% accessing electricity (WHO, 2022). Such energy deficiencies limit the integration of information and communication technologies (ICT) in education, perpetuating rural–urban disparities and restricting students' access to modern learning tools.

Energy poverty disproportionately impacts rural communities, where unreliable or nonexistent electricity makes it difficult for children to study in the evenings or access digital learning resources (Khandker *et al.*, 2012; Lipscomb *et al.*, 2013). Digital tools such as computers, the Internet and e-learning platforms have revolutionized education, providing students with access to a wealth of resources and opportunities to enhance their learning outcomes (Ofosu-Asare,2024).

Though various initiatives aim to address energy poverty and promote digital literacy, their impact on learning outcomes remains underexplored. This study seeks to bridge this gap by examining the relationship between electricity access, digital technology, and learning outcomes in Ghana. It aims to evaluate how improved electricity access can enhance the effective use of digital technologies to support education, particularly in underserved regions. Understanding these dynamics is crucial for shaping policies that foster a more equitable and productive education system.

1.1 Theoretical foundation and hypothesis development

1.1.1 Electricity access and educational outcomes. Electricity access has been recognized as a foundational component for improving educational outcomes, particularly in resource-constrained settings. The Education Production Theory underpins this study, positing various inputs such as child, family, peer and school inputs combine to produce educational outputs, like student achievement (Hanushek, 1979). Electricity access serves as a vital input in this model, facilitating extended study hours, the use of educational technologies and enhanced learning environments.

Empirical evidence highlights its transformative potential. For instance, Khandker *et al.* (2012) demonstrated that electrification in rural India significantly increased children's study time, leading to improved academic performance. Similarly, Barron and Torero (2014) found that electrified households in El Salvador experienced a substantial increase in time spent on school-related activities. However, Squires (2015) showed that in some contexts, such as Honduras, electricity access could lead to unintended consequences like increased child labor, thereby reducing educational attainment Ghana's focus on educational technology suggests a net positive effect.

Electricity access also indirectly benefits education by attracting better teachers and improving school infrastructure (Cabraal *et al.*, 2005). However, the effective utilization of electricity for education may depend on additional factors like parental support, educational policies and digital infrastructure integration.

1.1.2 Digital technology in education. Digital technology has emerged as a critical enabler of modern education. Drawing from Constructivist Learning Theory, which emphasizes the active construction of knowledge, digital tools facilitate personalized learning and critical thinking (Criollo-C *et al.*, 2021). Technologies like interactive apps, virtual reality and AI-powered platforms offer immersive and tailored educational experiences, making learning more engaging and accessible (Foutsitzi and Caridakis, 2021).

However, the adoption of digital technology is fraught with challenges, particularly in developing contexts. Disparities in access to devices and connectivity exacerbate existing inequalities (Zeng and Mayr, 2019). Moreover, unregulated use of technology can lead to distractions, such as excessive gaming or social media use (Bulman and Fairlie, 2016).

Despite these challenges, research suggests that integrating electricity access with digital technologies can amplify educational outcomes. For instance, Lee *et al.* (2020) found that rural electrification in Kenya facilitated the use of digital tools, leading to better educational results when coupled with active integration into the learning process.

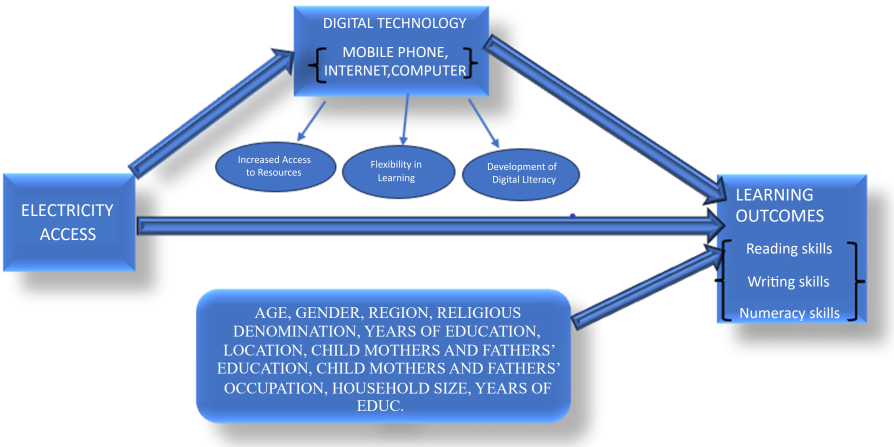
1.2 Conceptual framework

This study integrates insights from the Education Production Theory and Constructivist Learning Theory to examine how electricity access and digital technology interact to influence educational outcomes. Electricity access serves as an enabling factor for digital technology use, while digital tools mediate the relationship between electricity access and learning outcomes. Figure 1 presents the conceptual framework of the study, showing electricity access as the primary explanatory variable, digital technology as a mediating mechanism and learning outcomes as the final outcome variable.

1.2.1 Effects of electricity access on learning outcomes. Numerous studies have highlighted the transformative role of electricity in improving students' educational outcomes. Electrification enhances learning environments by enabling extended study hours and improving school infrastructure. The Independent Evaluation Group (IEG, 2008), in its comprehensive review, found that electrification directly enhanced school infrastructure and extended study hours, especially in rural areas, enabling students to study in the evening. The presence of reliable electricity also improved access to secondary education by fostering better school facilities. Similarly, Grogan and Sadanand (2013) employed a difference-in-differences (DiD) approach in Uganda and found that electrified schools experienced higher enrolment and completion rates, indicating a direct and significant link between electricity access and educational outcomes.

Lighting, a critical benefit of electrification, facilitates extended classroom hours, improving both attendance and learning outcomes. UNDESA (2014) reported that in Argentina, electricity enabled schools to start classes earlier in the day, while in Kenya, electrification allowed teachers to provide additional instruction during mornings and evenings (Kirubi *et al.*, 2009).

However, the direct effects of electrification are contingent on the quality and reliability of electricity.



Source: Author's Construct, 2024

Figure 1. Conceptual framework.

Building on this foundation, recent West African work has begun to explore how energy interventions translate into educational gains. Nano (2022) exploited lightning-strike frequency as an instrumental variable to demonstrate that rural electrification in Nigeria increased school enrolment and narrowed grade-for-age gaps, a proxy for improved academic performance, but emphasized that grid expansion must be coupled with targeted educational policies to achieve learning improvements. In a similar vein, Frempong *et al*. (2021) examined the adoption of clean cooking gas in rural Ghana and attributed modest improvements in children's test scores to time freed from domestic chores, thereby broadening our understanding of energy poverty's indirect effects on education.

The empirical evidence establishes a robust relationship between electricity access and improved learning outcomes. Therefore, this study hypothesizes that Electricity access has a direct and significant positive effect on learning outcomes.

1.2.2 Mediation role of digital technology in the relationship between electricity access and learning outcomes. While electricity access provides the foundation for educational improvements, digital technology serves as a key mediator that amplifies its benefits. Electrification facilitates the adoption and use of digital tools like computers, mobile phones and Internet resources, which directly enhance learning outcomes. Kouassi and Yao (2019) highlighted that regions with consistent access to electricity and digital technology reported better educational outcomes than regions lacking these resources. The study underscores that electricity alone is insufficient; the availability and effective use of digital technologies are crucial for realizing the full benefits of electrification.

Khandker *et al*. (2012) illustrated this dynamic in Bangladesh, where electrified households were more likely to own digital devices such as televisions and radios, which enriched children's learning experiences. Similarly, Bernard and Torero (2015) emphasized that the integration of ICT tools in classrooms significantly improved engagement and academic performance, demonstrating the mediating role of digital technology in linking electrification to better educational outcomes.

Empirical evidence also underscores the importance of ensuring the quality of digital interventions. Aker and Ksoll (2019), through a Randomized Controlled Trial (RCT) in Niger, found that mobile phones enhanced learning outcomes in mathematics and literacy by increasing access to digital educational content.

The critical mediating role of digital technology emerges most clearly in Lee *et al*.'s (2020) randomized controlled trial in Kenya. They found that while rural electrification substantially increased household ownership of mobile phones and computers, it did not improve learning outcomes unless these devices were actively integrated into teaching and learning processes. In Ghana, Ofosu-Asare (2024) similarly reports that schools with reliable electricity and Internet connectivity attain higher student engagement and test scores, but that rural schools continue to lag due to frequent outages and lack of hardware.

Global statistics on the digital divide further contextualize these findings. UNESCO (2020) warns that unequal access to information and communication technologies exacerbates educational inequalities, as students without Internet or digital tools are excluded from e-learning opportunities. Likewise, the World Health Organization and International Telecommunication Union (2020) reports that only 28% of households in Sub-Saharan Africa have Internet access, compared to 72% globally, illustrating the infrastructural barriers to ICT adoption in education.

Despite this growing body of evidence, no study has yet quantified how electricity access enables digital-technology usage, which in turn mediates improvements in learning outcomes at the micro (student or school) level in Ghana. By estimating both the direct effect of electricity access on academic performance and the indirect effect channeled through digital-technology use, the present study fills this critical gap and provides actionable insights for integrated energy-ICT education policies.

Therefore, this study hypothesizes that; digital technology mediates the relationship between electricity access and learning outcomes, as illustrated in Figure 1.

1.3 Methodology

1.3.1 Study design and approach. This study employed a quantitative, cross-sectional descriptive research design to examine the effects of electricity access on learning outcomes in Ghana, with a focus on the mediating role of digital technology. The design allowed for the systematic analysis of objective data collected at two time points, providing insights into key patterns and relationships without manipulating variables.

A positivist research philosophy underpinned the study, ensuring objectivity and the use of measurable data to investigate relationships between electricity access, digital technology and learning outcomes.

1.3.2 Data sources. The study analyzed secondary data from the sixth (GLSS6, 2012–2013) and seventh (GLSS7, 2016–2017) rounds of the Ghana Living Standards Survey (GLSS). The sample comprised 3,622 individual observations from GLSS6 and 7,616 observations from GLSS7, which included expanded metrics on electricity access and digital technology usage. A merged longitudinal dataset of 11,238 observations was created to capture temporal and regional trends.

1.3.3 Variables and measures. This study utilizes several key variables to comprehensively analyze the determinants of learning outcomes in children. These include Learning Outcomes as the dependent variable, with Digital Technology and Electricity Access as the primary independent variables. Learning outcomes were assessed through parental reports on children’s ability to perform age-appropriate tasks (e.g. reading a sentence, writing a short paragraph, solving basic arithmetic problems), as captured in the GLSS questionnaires. Control variables are also incorporated to account for potential confounding factors.

Learning Outcomes, the dependent variable, are measured by assessing whether a child can read, write and perform basic numeracy tasks. These binary indicators (i.e. “yes” or “no”) capture fundamental cognitive skills critical for academic and life success. The study posits that access to electricity and digital technology is positively associated with learning outcomes by enhancing educational opportunities, extending study time and providing access to supplemental learning resources.

Digital Technology, critical independent variable, is measured by whether a household has access to digital technology devices such as mobile phones, computers or tablets. This binary measure captures the basic presence or absence of these tools, which are increasingly recognized as critical facilitators of learning in modern educational systems. Digital technology is hypothesized to positively influence learning outcomes by offering children access to diverse educational content, fostering engagement and supporting self-directed learning.

Electricity Access is a key independent variable, measured by whether a household is connected to the national electricity grid. This binary indicator reflects the availability of reliable power, which is essential for using digital devices, extending study hours through adequate lighting and creating a supportive learning environment. Empirical evidence strongly supports a positive association between electricity access and improved learning outcomes, highlighting its role in increasing learning outcomes.

The study also incorporates other control variables to isolate the effects of the primary independent variables. These include age, gender, household size, rural–urban residence and parental education and occupation.

These variables were selected based on theoretical and empirical literature, ensuring a comprehensive analysis of cognitive skill development and its determinants.

1.4 Theoretical model

This study investigates the effects of electricity access on learning outcomes in Ghana, focusing on reading, writing and numeracy skills. The research builds on the education production theory and the skill formation model (Cunha and Heckman, 2007) to explore how various inputs influence educational outcomes.

The education production function models the relationship between educational outputs (learning outcomes) and key inputs.

G_{it}: Genes: Inherited characteristics influencing cognitive abilities and learning potential.

I_{it}: Investment: Resources allocated to a child's education, including access to electricity, money and educational materials.

P_{it}: Parental Inputs: Parents' contribution to a child's education, for instance parents' education and occupation

E_{it}: Environment: Broad context of a child's upbringing, encompassing socio-economic status, community resources.

These inputs are integrated into the production function:

$$Y_{it} = f(\boldsymbol{G}_{it}, \boldsymbol{I}_{it}, \boldsymbol{P}_{it}, \boldsymbol{E}_{it})$$

The model emphasizes electricity access (EA) as a critical input, essential for effective educational investments like study materials, conducive environments and digital tools. In areas with energy poverty, limited electricity hinders these investments, thereby restricting learning opportunities. By introducing EA into the education production function, the study highlights its pivotal role:

$$I_{it} = f(EA_{it}, \ldots, X_{it})$$

$$Y_{it} = \mathrm{f}\,(G_{it}, P_{it}, E_{it}, EA_{it})$$

This theoretical framework underpins the study's econometric analysis, represented by:

$$Y_i = \alpha_0 + \alpha_1 EA + \sum_{k=2}^{n} \alpha_k X_{ik} + \varepsilon_i$$

where Yi denotes learning outcomes, EA is Electricity Access, X_{ik} represents other inputs and ϵi is the error term.

To estimate this objective, the study employs the probit regression technique, which allows us to model the binary nature of the dependent variables and estimate the probability of electricity access and the other independent variables affecting it.

The Probit model was selected for its theoretical alignment with the assumption that latent learning ability conceptualized as an unobserved variable follows a normal distribution. This assumption is grounded in the Central Limit Theorem, which posits that the aggregation of numerous small, independent influences (e.g. socio-economic factors, pedagogical quality and cognitive inputs) converges toward a normal distribution with mean zero and variance one. In educational research, such latent constructs as "learning ability" or "academic proficiency" are often theorized as cumulative outcomes of multifaceted determinants, making the normality assumption inherent to Probit models particularly appropriate (Hanushek, 1979; Wooldridge, 2010).

While the Logit model, which assumes a logistic distribution, is frequently employed in binary outcome analyses and yields comparable marginal effects in practice, the Probit framework offers a more coherent fit with the theoretical underpinnings of this study. Specifically, the normal distribution of the error term in Probit models aligns with education production theories that treat learning outcomes as emergent properties of normally distributed latent abilities (Cameron and Trivedi, 2005). This is consistent with empirical precedents in educational economics, where Probit is often preferred for modeling proficiency thresholds (e.g., reading or numeracy benchmarks) that reflect underlying, normally distributed competencies (Glewwe and Kremer, 2006).

The Probit specification harmonizes with the study's conceptual framework, which draws on Hanushek's Education Production Function to interpret learning outcomes as a function of distributed inputs (e.g. electricity access, digital resources).

The binary probit model is specified as follows

$$P(Y=1|X)=\Phi(Z_i)=\int_{-\infty}^{z}\varnothing(\beta_0\,\beta_1X_i)d(z)$$

Where.

$P(Y=1|X)$ is the probability of the outcome being 1 given the value of the independent variables X.

$\Phi(Z_i)$ is the standardize normal CDF

$\varnothing(Z_i)$ is the standardize normal PDF

Z_i is a linear combination of the independent variables, $Z_i=\beta_0\,\beta_1X_i$

Electricity access serves as the focal independent variable. Learning outcomes are categorized into three components: reading, writing and numeracy skills. Our empirical model for objective two is specified as follows:

$$\begin{aligned}\Pr(\text{Reading}\,_i/writing_i/numeracy_i=1)\\ &=\Phi\big(\beta_0+\beta_1Elec\_Access_i++\beta_2Age_i\\ &\quad+\beta_3Household\_size_i+\beta_4Years\_of\_edu_i+\beta_5Gender_i\\ &\quad+\beta_6Loc_i+\beta_7mothers\_educ_i+\beta_8fathers\_educ_i\\ &\quad+\beta_9mothers\_occup_i+\beta_{10}fathers\_occup_i+\varepsilon_i\end{aligned}$$

The coefficients (β_0, $\beta_{1\,\ldots,}$ β_{10}) are the parameters to be estimated through the probit regression analysis. They quantify the effects of each independent variable on the probability of learning outcomes while holding other variables constant.

By estimating this model using maximum likelihood estimation (MLE), the study would obtain the coefficient estimates (marginal effects) and assess their statistical significance to understand the relationship between electricity access and learning outcomes in Ghana.

The next objective of this study is to assess the mediating role of digital technology in the relationship between electricity access and learning outcomes in Ghana. This objective aims to understand how access to digital technology, influenced by electricity access, affects educational achievements such as reading skills, writing skills and numeracy skills.

Digital technology serves as a critical mediator between electricity access and learning outcomes. Access to reliable electricity enhances the ability of students to utilize digital resources, which can positively influence their educational outcomes. Therefore, understanding the relationship between electricity access, digital technology and learning outcomes is essential.

In this framework, we incorporate digital technology as an additional input that interacts with electricity access to influence educational outcomes. The education production function can be represented as:

$$Y_{it} = \mathrm{f}(G_{it}, P_{it}, E_{it}, EA_{it} * DT_{it})$$

Where: DT_{it} represents digital technology usage, which can enhance learning outcomes.

To assess the mediating role of digital technology, we can examine the following relationships:

Direct Effect of Electricity Access on Learning Outcomes:

$Y_{it} = \mathrm{f}(EA_{it})$

This equation highlights how electricity access directly influences learning outcomes.

Direct effect of electricity access on digital technology usage:

$$DT_{it} = \mathrm{f}(EA_{it}),$$

This equation shows how electricity access affects the usage of digital technology.

The mediation effect can be summarized as:

$$Y_{it} = \mathrm{f}(EA_{it} * DT_{it})$$

This captures the indirect pathway through which electricity access influences learning outcomes via digital technology usage.

The mediating role of digital technology can be expressed empirically as:

$$\Pr\left(Dig\_Tech_i = 1\right) = \Phi(\beta_0 + \alpha_1 Elec\_Access_i + \varepsilon_i)$$

$$\Pr(\text{Reading}_i / writing_i / numeracy_i = 1) = \Phi\left(\beta_0 + \beta_1 Dig\_Tech_i + \varepsilon_i\right)$$

The indirect effect would be calculated as:

Indirect Effect $= \alpha_1 * \beta_1$ Baron and Kenny (1986).

Given the study's reliance on secondary GLSS data, the study also recognizes potential limitations in data quality and representativeness. Although the Ghana Living Standards Survey is nationally representative and employs internationally validated instruments, some constructs, such as innate ability, cannot be directly measured and must be proxied (e.g., through parental-input).

Finally, to ensure the rigor of the study's mediation analysis, the study employed generalized structural equation modeling (GSEM) with maximum likelihood estimation, examined model stability indices and conducted supplementary sensitivity tests (CFI, TLI and RMSEA). These procedures confirm that the estimated direct and indirect effects of electricity access and digital-technology usage on learning outcomes are both statistically robust and substantively meaningful.

All data management, descriptive statistics, probit regressions and mediation analyses via GSEM were performed using *Stata 17* (StataCorp, 2021). This software choice ensures reproducibility and transparency in our statistical pipeline.

1.5 Data analysis and results

1.5.1 Descriptive statistics. This section discusses descriptive statistics of variables included in the study. Here, the average tendencies and distribution of variables in the samples and how they compare with the population are discussed. (Table 1)

1.5.2 Children's learning outcomes, electricity access and digital technology usage across locations and genders in Ghana. Table 2 integrates learning outcomes, electricity access and digital technology usage, disaggregated by urban/rural locations and gender for both GLSS6 and GLSS7 datasets.

1.5.3 Probit regression outputs. This section displays the empirical estimations of the probit regression results. The estimation deals with the effects of electricity access on learning

Table 1. Descriptive statistics

Variable	Categories	GLSS6 (Freq/ Mean)	GLSS6 Percent/ SD	GLSS7 (Freq/ Mean)	GLSS7 Percent/ SD	Min	Max
Continuous variables							
Age	–	13.00	1.373	12.95	1.408	11	15
Years of Education	–	7.44	2.959	7.98	3.504	0	15
Household Size	–	3.77	2.280	2.57	3.342	1	15
Categorical variables							
Mother's Education	No Education	1,300	35.89%	1,139	14.96%	–	–
	Primary Education	2,053	56.68%	1,038	13.63%	–	–
	Secondary Education	263	7.26%	5,435	71.36%	–	–
	Tertiary Education	6	0.17%	4	0.05%	–	–
Father's Education	No Education	114	3.15%	617	8.10%	–	–
	Primary Education	2,708	74.77%	4,778	62.74%	–	–
	Secondary Education	722	19.93%	2,042	26.81%	–	–
	Tertiary Education	78	2.15%	179	2.35%	–	–
Mother's Occupation	Unemployed/Retired	52	1.44%	97	1.27%	–	–
	Public Sector	1,016	28.05%	1,893	24.86%	–	–
	Self-Employed	2,554	70.51%	5,626	73.87%	–	–
Father's Occupation	Unemployed/Retired	99	2.73%	194	2.55%	–	–
	Public Sector	943	26.04%	1,996	26.21%	–	–
	Self-Employed	2,580	71.23%	5,426	71.24%	–	–

Source(s): Authors' computation using GLSS6 and GLSS7 datasets

outcomes, which is measured by reading, writing and numeracy skills, the mediating role of digital technology and other explanatory variables. The marginal effects are in Table 3.

1.6 Discussion of findings

Table 1 provides a comprehensive summary of the descriptive statistics for the key continuous and categorical variables from the GLSS6 (2012/2013) and GLSS7 (2016/2017) datasets. The table highlights changes in demographic and socio-economic characteristics across the two survey periods, offering valuable insights into the sampled populations.

For the continuous variables, the average age of children in the GLSS6 dataset was 13 years, with a standard deviation of 1.373, while in GLSS7, the average age was slightly lower at 12.95 years, with a standard deviation of 1.408. The minimum and maximum ages for both datasets remained consistent at 11 and 15 years, respectively, demonstrating that the focus was on a comparable age range across the two surveys. The years of education recorded an increase from an average of 7.44 years in GLSS6 to 7.98 years in GLSS7, suggesting an improvement in educational attainment. This trend may reflect enhanced access to education and the implementation of national policies aimed at increasing educational participation. Household size, on the other hand, declined significantly, with an average size of 3.77 members in GLSS6 compared to 2.57 members in GLSS7. This reduction may indicate changes in family structure, urbanization or socio-economic conditions.

For the categorical variables, there were notable shifts in parental education levels. Among mothers, the proportion with no education decreased sharply from 35.89% in GLSS6 to 14.96% in GLSS7. Similarly, the percentage of mothers with secondary education rose dramatically from 7.26% in GLSS6 to 71.36% in GLSS7, reflecting significant progress in maternal educational attainment. Fathers' education also showed improvements, with an increase in the proportion attaining secondary education from 19.93% in GLSS6 to 26.81% in GLSS7. However, tertiary education remained uncommon among both mothers and fathers in both datasets.

Table 2. Children's learning outcomes, electricity access and digital technology usage across locations and genders

Variable	Reading skills (Yes)	Reading skills (No)	Writing skills (Yes)	Writing skills (No)	Numeracy skills (Yes)	Numeracy skills (No)	Electricity access (Yes)	Electricity access (No)	Digital tech usage (Yes)	Digital tech usage (No)
GLSS6: Urban	880	1,075	880	1,078	472	1,323	1,465 (55.28%)	493 (50.72%)	1,722 (62.96%)	236 (26.61%)
GLSS6: Rural	589	1,078	584	1,080	341	1,486	1,185 (44.72%)	479 (49.28%)	1,013 (37.04%)	651 (73.39%)
GLSS6: Male	726	1,021	723	1,024	393	1,354	1,267 (47.81%)	480 (49.38%)	1,396 (51.04%)	479 (54%)
GLSS6: Female	743	1,132	741	1,134	420	1,455	1,383 (52.19%)	492 (50.62%)	1,339 (48.96%)	408 (46%)
GLSS7: Urban	6,529	14	6,512	15	6,576	96	5,824 (98.39%)	95 (1.61%)	1,281 (68.87%)	5,720 (99.37%)
GLSS7: Rural	601	472	600	489	519	425	1,177 (69.36%)	520 (30.64%)	579 (31.13%)	36 (0.63%)
GLSS7: Male	6,855	444	6,838	461	6,810	489	1,532 (90.28%)	5,767 (97.43%)	290 (15.59%)	27 (0.47%)
GLSS7: Female	275	42	274	43	285	32	165 (9.72%)	152 (2.57%)	1,570 (84.41%)	5,729 (99.53%)

Source(s): Authors' computation using GLSS6 and GLSS7 datasets

Table 3. Marginal effects of probit regression output

Variables	GLSS6			GLSS7			GLSS6 and GLSS7 pooled		
Coefficients	Reading skills	Writing skills	Numeracy skills	Reading skills	Writing skills	Numeracy skills	Reading skills	Writing skills	Numeracy skills
Electricity access	0.7257***	0.7253***	0.1020***	0.0670***	0.0732***	0.0517***	0.1864***	0.1829***	0.1605***
	(0.0376)	(0.0374)	(0.0165)	(0.0216)	(0.0219)	(0.0105)	(0.0079)	(0.0080)	(0.0089)
Age	0.0016	0.0014	0.0040	0.0026	0.0012	0.0019	0.0028	0.0017	−0.0003
	(0.0051)	(0.0051)	(0.0049)	(0.0018)	(0.0019)	(0.0020)	(0.0022)	(0.0022)	(0.0023)
Household-size	0.0251***	0.0252***	0.0166***	0.0036	0.0046	0.0112***	0.0152***	0.0156***	0.0015
	(0.0030)	(0.0030)	(0.0031)	(0.0030)	(0.0031)	(0.0022)	(0.0012)	(0.0012)	(0.0013)
Years of education	0.0001	0.0001	0.0007	0.0008	0.0009	0.0047**	0.0057***	0.0058***	0.0057***
	(0.0024)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0011)	(0.0011)	(0.0012)
Gender (ref. Female)									
Male	0.0279**	0.0275**	0.0002	0.0353	0.1075***	0.0663***	0.0238***	0.0225***	0.1233***
	(0.0140)	(0.0139)	(0.0136)	(0.0232)	(0.0276)	(0.0130)	(0.0076)	(0.0077)	(0.0101)
Location (ref.urban)									
Rural	−0.1730***	−0.1763***	−0.0020	−0.0314**	−0.0287**	−0.2223***	−0.0777***	−0.0785***	−0.1644***
	(0.0138)	(0.0137)	(0.0138)	(0.0128)	(0.0137)	(0.0314)	(0.0084)	(0.0084)	(0.0098)
Mother's education (ref. None)									
Primary Education	0.0307**	0.0306**	−0.0239	0.1313**	0.1368**	0.0375	0.0196	0.0189	0.0129
	(0.0155)	(0.0155)	(0.0152)	(0.0527)	(0.0536)	(0.0427)	(0.0133)	(0.0133)	(0.0139)
Secondary Education	0.6336***	0.6354***	0.2384***	0.4513***	0.4836***	0.3372***	0.5812***	0.5850***	0.5017***
	(0.0152)	(0.0151)	(0.0145)	(0.0855)	(0.0826)	(0.0455)	(0.0118)	(0.0117)	(0.0131)
Tertiary Education	0.3605**	0.3622**	−0.0881	0	0	0	0.4425***	0.4448***	0.2391*
	(0.1706)	(0.1700)	(0.1535)				(0.1016)	(0.1021)	(0.1246)
Father's education (ref. None)									
Primary Education	0.0768**	0.0751**	0.0441	0.0051	0.0100	0.0045	0.0278*	0.0324**	0.0517***
	(0.0377)	(0.0376)	(0.0371)	(0.0109)	(0.0113)	(0.0115)	(0.0144)	(0.0144)	(0.0144)
Secondary Education	0.1184***	0.1186***	0.0503	0.0052	0.0099	0.0066	0.0417***	0.0465***	−0.0197
	(0.0408)	(0.0407)	(0.0399)	(0.0116)	(0.0120)	(0.0124)	(0.0154)	(0.0155)	(0.0155)

(*continued*)

Table 3. Continued

Variables	GLSS6			GLSS7			GLSS6 and GLSS7 pooled		
Coefficients	Reading skills	Writing skills	Numeracy skills	Reading skills	Writing skills	Numeracy skills	Reading skills	Writing skills	Numeracy skills
Tertiary Education	0.0071	0.0077	0.0201	−0.0114	−0.0027	−0.0013	−0.0134	−0.0055	−0.0473*
	(0.0577)	(0.0576)	(0.0572)	(0.0203)	(0.0202)	(0.0204)	(0.0244)	(0.0245)	(0.0249)
Mother's occup. (unemploy/rt)									
Public Sector	−0.1922***	−0.1928***	−0.0255	0.0101	0.0142	0.0079	−0.0706***	−0.0746***	−0.0376
	(0.0653)	(0.0651)	(0.0537)	(0.0218)	(0.0218)	(0.0258)	(0.0252)	(0.0252)	(0.0311)
Self-Employed	−0.0002	0.0008	0.0591***	−0.0010	0.0015	0.0024	0.0046	0.0072	0.0361***
	(0.0165)	(0.0165)	(0.0156)	(0.0062)	(0.0063)	(0.0069)	(0.0072)	(0.0072)	(0.0078)
Father's occup. (unemploy/rt)									
Public Sector	0.1929***	0.1933***	−0.0802**	0.0118*	0.0112*	0.0066	0.0637***	0.0665***	−0.0187
	(0.0472)	(0.0471)	(0.0407)	(0.0062)	(0.0063)	(0.0070)	(0.0180)	(0.0181)	(0.0221)
Self-Employed	0.0262	0.0253	−0.0158	0.0067	0.0105	0.0018	−0.0011	−0.0010	−0.0040
	(0.0179)	(0.0179)	(0.0181)	(0.0172)	(0.0168)	(0.0199)	(0.0077)	(0.0077)	(0.0080)
Indirect Effect (EA and DT)	0.0442***	0.0434***	0.0267***	0.0156***	0.0145***	0.0430***	0.0637***	0.0626***	0.0340***
	(0.0057)	(0.0058)	(0.0046)	(0.0045)	(0.0045)	(0.0046)	(0.0031)	(0.0031)	(0.0029)
P *seudo* R^2	0.2329	0.2357	0.0566	0.2141	0.2193	0.5499	0.4115	0.4098	0.3804
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
VIF	2.08	2.08	2.08	4.47	4.47	4.47	2.74	2.74	2.74
Wald Test of Exogeneity (*p*.value)	0.9989	0.9984	0.9988	0.9999	0.9999	0.9999	0.9900	0.9910	0.9949
No of observation	3,622	3,622	3,622	7,616	7,616	7,616	11,238	11,238	11,238

Note(s): Robust standard errors in parentheses ***$p < 0.01$ **$p < 0.05$ *$p < 0.1$
Source(s): Authors' computation using GLSS 6, GLSS 7 and pooled dataset of GLSS6&7

Parental occupation data revealed that self-employment was the predominant occupation for both mothers and fathers across both surveys. For mothers, self-employment increased slightly from 70.51% in GLSS6 to 73.87% in GLSS7, while for fathers, it remained stable at approximately 71%. The proportion of parents employed in the public sector also showed little change, accounting for about 25% of mothers and fathers across the datasets. Parents classified as unemployed or retired constituted a very small percentage of the total sample in both surveys, remaining below 3%.

These descriptive statistics illustrate important trends and variations in the sampled populations. The observed improvements in educational attainment, especially among mothers, and the reduction in household size may have implications for learning outcomes and access to digital technology. The dominance of self-employment highlights the informal nature of Ghana's economy, while changes in educational and occupational patterns provide a broader context for understanding electricity access, digital inclusion and their effects on learning outcomes in Ghana.

The results in Table 2 also reveal significant patterns in children's learning outcomes, electricity access and digital technology usage across urban and rural locations as well as gender.

Urban children consistently outperform their rural counterparts in reading, writing and numeracy skills in both GLSS6 and GLSS7 datasets. For instance, in GLSS7, urban children exhibited markedly higher literacy rates, with 6,529 children demonstrating reading skills compared to 601 in rural areas. Similarly, urban areas report near-universal electricity access (98.39%) compared to rural areas (69.36%). This gap in access reflects underlying infrastructural disparities and the challenges faced by rural households in benefiting from essential services. Furthermore, urban children exhibit greater adoption of digital technology, likely due to better connectivity and access to devices, with 68.87% using digital tools in GLSS7 compared to 31.13% in rural areas.

Gender-wise, the findings highlight interesting trends. Males demonstrate slightly higher numeracy skills, with 6,810 boys excelling in this area in GLSS7 compared to 285 girls. On the other hand, females show a comparable performance in reading and writing skills, suggesting less of a gender divide in these domains. However, females lag behind males in digital technology adoption in GLSS7, with only 15.59% of males having no access to digital technology, compared to 84.41% of females. This imbalance suggests the need for targeted interventions to bridge the digital gender gap and empower girls to leverage technology for learning.

Comparing GLSS6 and GLSS7 reveals marked improvements over time. Electricity access in urban areas grew significantly, with near-universal coverage reported in GLSS7. Similarly, rural electricity access increased from 44.72% in GLSS6 to 69.36% in GLSS7, reflecting the positive impact of electrification initiatives. Digital technology usage also saw an uptick across both urban and rural areas, with urban areas maintaining a significant lead. This temporal shift indicates the growing integration of technology in households and its potential to influence educational outcomes positively.

Table 3 presents a comprehensive analysis of the influence of electricity access on children's learning outcomes in Ghana, based on data from GLSS6, GLSS7 and pooled datasets. The analysis explores the relationship between electricity access and three key learning metrics: reading, writing and numeracy skills. The findings underscore the transformative role of electricity in enhancing educational outcomes, as indicated by the marginal effects derived from the probit regression analysis.

The results from the GLSS6 dataset reveal a substantial positive impact of electricity access on children's learning outcomes. Children with access to electricity are 72.57% more likely to achieve proficiency in reading, as shown by the marginal effect of 0.7257. This relationship is statistically significant at the 1% level, emphasizing the importance of electricity in fostering literacy. Similar patterns emerge for writing skills, with a marginal effect of 0.7253, reflecting a 72.53% increase in the probability of achieving writing proficiency. These consistent findings highlight the critical role of electricity in creating enabling environments for literacy development.

For numeracy skills, the marginal effect of 0.1020 indicates a 10.20% increase in the likelihood of numeracy proficiency for children with electricity access. Although smaller compared to literacy outcomes, this effect remains significant at the 1% level. These results align with findings by Dinkelman (2011), who highlights that electrification fosters improved educational attainment through enhanced study environments, and UNESCO Institute for Statistics (2014), which links electricity access to improved cognitive skill development and digital engagement.

Research supports the notion that electricity reduces time poverty for households, allowing children more hours for homework and study (World Bank, 2022). This is further corroborated by Practical Action (2014), which emphasizes that rural electrification improves study conditions, enabling better learning outcomes.

In the GLSS7 dataset, the marginal effects, though slightly lower than those in GLSS6, still indicate a positive and significant relationship between electricity access and learning outcomes. For reading and writing skills, electricity access increases the probabilities by 6.70% and 7.32%, respectively, both significant at the 1% level. The marginal effect for numeracy skills is 5.17%, also statistically significant.

The reduced marginal effects in GLSS7 compared to GLSS6 may reflect evolving socio-economic conditions or improvements in baseline access to educational resources over time, which could dilute the observed impact of electricity. However, the consistent statistical significance underscores the enduring importance of electricity access in supporting education. These findings are consistent with the assertion by UNESCO Institute for Statistics (2014) that electricity access enhances the ability of children to engage effectively with their studies, providing better lighting and opportunities for learning beyond daylight hours.

The pooled analysis provides further confirmation of the pivotal role of electricity access in improving learning outcomes. Children with electricity access are 18.64% more likely to achieve reading skills, 18.29% more likely to achieve writing skills, and 16.05% more likely to demonstrate numeracy proficiency. These effects are all significant at the 1% level, reinforcing the robustness of the relationship across different datasets.

Globally, access to electricity is recognized as essential for quality education. Studies in sub-Saharan Africa reveal that over 90% of children in primary schools without electricity face significant learning disadvantages (Davies *et al.*, 2015). Electrification programs, such as those in Zambia and Tanzania, have shown that solar energy and mini-grids can sustainably support education by improving lighting and facilitating technology integration (Mfune and Boon, 2008; UNDESA, 2014).

The consistent findings across datasets underscore that electricity access is a cornerstone of educational success. Enhanced lighting and access to digital learning tools contribute to better academic engagement and improved outcomes, particularly in literacy and numeracy. These results emphasize the need for continued investments in rural electrification to bridge educational disparities (World Bank, 2022; EFA, 2015).

The analysis of indirect effects highlights the critical role of digital technology in mediating the relationship between electricity access and educational outcomes, consistent with existing literature. Studies have shown that electricity access creates the infrastructure needed for the effective use of digital technologies, which significantly contribute to cognitive and educational advancements. Digital tools, such as e-learning platforms, multimedia resources and online tutorials, foster engagement and improve literacy and numeracy skills, confirming findings from earlier studies on the synergy between technology and education (Aker and Fafchamps, 2015; UNESCO Institute for Statistics, 2014).

For instance, research suggests that access to digital resources enhances student engagement and motivation, particularly when these technologies are integrated into teaching environments with adequate support (Nordhaus, 2015; PLOS ONE, 2023). Such integration is pivotal for maximizing the benefits of educational technology, which not only supplements traditional learning methods but also introduces innovative practices like gamified learning experiences that have been linked to increased academic performance and engagement (Hawlitschek, 2017; PLOS ONE, 2023).

The significant indirect effects observed in GLSS6 and GLSS7 datasets further support these findings. Electricity access facilitates digital inclusion by enabling households and schools to adopt educational technologies, bridging learning gaps and improving equity in education. This relationship mirrors evidence from global studies emphasizing the role of stable digital infrastructure in fostering improved learning outcomes, especially in contexts with limited access to conventional educational resources (World Bank, 2022; PLOS ONE, 2023).

The pooled analysis consolidates these insights, confirming that electricity access enables the use of digital technology to amplify educational outcomes. This dual benefit, direct improvement in study environments and indirect enhancement through digital tools, highlights the multifaceted impact of electricity on education. Such findings are critical for policy considerations aimed at scaling up digital education initiatives in regions with limited electricity access (Nordhaus, 2015; PLOS ONE, 2023).

The analysis also examines the potential issue of multicollinearity among the explanatory variables. The VIF (Variance Inflation Factor) values reported in Table 3 range from 2.08 to 4.47 across the datasets. According to Wooldridge (2010), VIF values below 5 indicate that multicollinearity is not a significant concern. This finding supports the robustness of the model estimates, ensuring that the relationships identified between the explanatory variables and children's educational outcomes are reliable and not unduly influenced by multicollinearity.

The Wald test of exogeneity was conducted to assess whether electricity access is endogenous to learning outcomes in the probit models. For all cognitive skill development (reading, writing and numeracy) across GLSS6, GLSS7 and the pooled datasets, the Wald test results indicate a high probability value (Prob > χ^2) well above the conventional significance level of 0.05. This outcome suggests we cannot reject the null hypothesis of no endogeneity, meaning electricity access does not show significant endogenous relationships with the measured learning outcomes. Therefore, the probit regression estimates are likely to be consistent and unbiased, reflecting a credible association between electricity access and learning outcomes. These results align with econometric guidance that cautions against unnecessary instrumental variable (IV) adjustments in the absence of endogeneity, which could lead to efficiency losses in estimates (Wooldridge, 2010).

The Pseudo R^2 values from the probit model analysis provide insights into how well the explanatory variables account for children's learning outcomes in reading, writing, and numeracy skills. A higher Pseudo R^2 value of 0.5499 suggests that the model effectively captures over half of the variance in children's learning outcomes. This indicates that the explanatory variables play a significant role in understanding the factors that influence children's educational achievements.

The Prob > χ^2 values for all models are 0.0000. This result signifies that the overall model is statistically significant, as the *p*-value is well below the conventional threshold of 0.05. This indicates that at least one of the independent variables has a significant relationship with the outcome variable.

The statistical significance of the model reinforces the conclusion that electricity access likely plays a crucial role in influencing children's learning outcomes. It suggests that interventions targeting electricity access could have meaningful impacts on learning outcomes.

1.7 Conclusions and policy recommendations

This study highlights factors influencing children's learning outcomes in Ghana, with a particular focus on the roles of electricity access, and digital technology usage. The analysis underscores the relationship among these variables, revealing how disparities in electricity access and digital resources shape educational achievements.

The results provide strong evidence that electricity access significantly enhances children's learning outcomes in Ghana. Access to electricity improves the probabilities of achieving proficiency in reading, writing and numeracy, reaffirming the importance of electrification as a cornerstone for educational development. These findings reinforce the need for policies that prioritize expanding electricity access to underserved communities, ensuring all children have the foundational resources necessary for academic success.

The study also highlights the critical mediating role of digital technology in the relationship between electricity access and learning outcomes. Electricity access facilitates the effective use of digital tools, which significantly enhance educational achievements by supporting literacy and numeracy skill development. These results underscore the transformative potential of electricity and technology in shaping future generations, advocating for integrated approaches that couple electrification initiatives with investments in digital infrastructure and digital literacy programs.

To translate research insights into sustainable educational equity, we propose the following actionable steps:

Accelerate Rural Electrification via the Ministry of Energy.

Expand grid coverage to underserved rural schools and households through the National Electrification Scheme (NES). Prioritizing schools in energy-poor districts will enable evening study, extend digital access and narrow rural–urban learning gaps.

Integrate Digital Technology in Education via Ghana Education Service (Ministry of Education).

Equip all public basic schools with solar-powered devices (tablets, projectors) and mandate ICT-pedagogy training for teachers under the Ghana Digital Acceleration Project. This leverages the evidence that digital tools mediate electricity's impact on learning, ensuring technology access directly translates to cognitive skill development.

1.8 Research limitations/recommendations for future research

This study relies on secondary data from the Ghana Living Standards Survey (GLSS6 and GLSS7), which is *the lack of direct cognitive aptitude measures (e.g., baseline IQ tests) limits our ability to control for innate learning capacity, which may confound the estimated effects of electricity access and digital technology.* Future research could incorporate direct measures of cognitive ability to deepen the understanding of these relationships.

Data availability

The datasets analyzed in this study (GLSS6 and GLSS7) are publicly available from the Ghana Statistical Service:

GLSS6: http://www.datafirst.uct.ac.za/Dataportal/index.php/catalog/854
GLSS7: https://catalog.ihsn.org/index.php/catalog/7967

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Corresponding author
Thomas Boampong can be contacted at: thomasboampong555@gmail.com