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IS MOBILE PHONE BAD FOR KIDS? EVIDENCE FROM THE INDONESIAN FAMILY LIFE SURVEY

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Abstract

Over the past decade, the use of mobile phones among children has become increasingly prevalent, extending even to those from lower socioeconomic backgrounds. This trend has prompted growing concern regarding the potential adverse effects of mobile phone use on children's development and well-being. This study aims to provide empirical evidence of the effect of phone ownership and usage among school-age children under 15 years old on their cognitive ability. The primary dataset used in this study is the fifth wave of the Indonesian Family Life Survey (IFLS). To estimate causal relationships, this study employs household fixed effects and an instrumental variable (IV) approach to address selection bias and other sources of endogeneity. The results indicate that, after controlling for household fixed effects, this study does not find statistically significant associations between mobile phone ownership or usage among children and cognitive outcomes, as measured by fluid and crystallized intelligence. The instrumental variable estimates also fail to detect a statistically significant causal effect.

INTRODUCTION

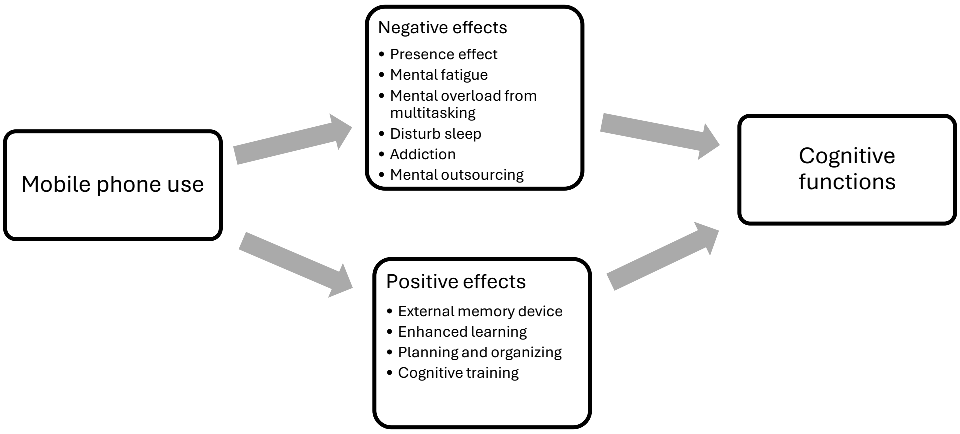
Over the past decade, advances in technology and industrialization have substantially reduced the cost of digital technologies, making them an integral part of everyday life. Among children and adolescents, the pervasive presence of digital technologies has generated growing concern regarding their potential impacts on psychosocial and cognitive development. Among several forms of digital technologies, mobile phones (including smartphones) are of special interest because of their portable and personal nature, which results in a major potential impact on the daily activities of children. Further, mobile phones are also the ones that have the relatively lowest price among the technologies, hence the highest adoption rate even in the lower socio-economic groups, making this problem universal.

The statistics on mobile phone usage among children show remarkable figures. As early as 2012 when the mobile phone was only about a decade after its widespread use by the public, 65 percent of children aged 8-18 years old from several countries (Japan, India, Indonesia, Egypt, and Chile) were reported to use a mobile phone, with the most common age to get it of 12 years old (GSMA and NTT Docomo, 2013). In India and Indonesia, the ownership rate of smartphones among children was twice the rate from their parents. These facts are followed by diverging opinions of parents about the harm and benefits of mobile phone use by children. A survey in the United States shows that, generally speaking, 71 percent of parents feel that the use of smartphones among children has a net potential harm to them, while 27 percent say its potential benefit outweighs potential harm (Auxier et al., 2020).

At the theoretical level, mobile phone use can affect cognitive function in several ways. First, the presence of mobile phones (especially smartphones) can distract users' attention even when the user does not interact with them. This is because smartphones' presence produces notifications in the form of vibration, sound, etc. that may attract users' attention and drain their cognitive resources (Dekker et al., 2025; Upshaw et al., 2022), and even the mere presence of a mobile phone can distract users' minds (Böttger et al., 2023; Skowronek et al., 2023). Second, acute and prolonged mobile phone use can induce mental fatigue (Jacquet et al., 2023). Third, operating a mobile phone while at the same time doing other cognitive-demanding tasks (such as learning or working), or phone multitasking, may overload and harm cognitive capacity (Leonhardt et al., 2025; Suhail et al., 2025). Fourth, the use of mobile phones, especially during bedtime, may disturb sleep patterns and quality, leading to impaired attention, working memory, and learning in the subsequent days (Fiore et al., 2025; Nagata et al., 2023). Fifth, mobile phone use can create addiction to instant gratification (Al-Amri et al., 2023). Last but not least, the habit of mobile phone usage (especially smartphones) may induce users to "outsource" their cognitive tasks (such as remembering, computing, etc.) into the phones and weakening the mind's internal capacity and knowledge acquisition from experience (Magen & Tomer-Offen, 2025).

On the other hand, the previous mobile phone usage could also possibly have a positive impact on cognitive functions and educational outcomes through several mechanisms. Shanmugasundaram & Tamilarasu (2023) provide an excellent summary of these mechanisms. In short, mobile phone use can benefit cognitive function in several ways. First, they act as an external memory device and hence reduce the mental costs of users. Second, they enhance learning by inducing sustained attention, especially using a gamification of a learning platform. Learning through software can also give students practical knowledge (Kusmira et al., 2025). Third, they enhance access to knowledge and information. Fourth, they enhance task planning and organizing. Lastly, they enhance cognitive training through application or games that improve cognitive performance. In the longer run, the use of mobile phones can also enhance digital literacy, which is beneficial to economic aspects such as investment and financial literacy (Lestari et al., 2025; Lisnayanti & Sukma, 2025).

The multiple potential transmission channels through which mobile phone usage may influence cognitive outcomes, both positively and negatively, are summarized in Figure 1. Cognitive ability is a multidimensional construct, and different dimensions may be affected in different ways. This study focuses on general intelligence, with particular attention to its fluid and crystallized components. Fluid intelligence, as measured by Raven's Progressive Matrices, captures abstract reasoning and pattern recognition, which may be influenced by visually intensive, interactive, and attention-related aspects of mobile phone use. In contrast, crystallized intelligence, proxied in this study by arithmetic ability, reflects knowledge and skills that depend heavily on formal instruction and cumulative learning. As a result, mechanisms such as distraction, multitasking, and sleep disruption may plausibly have different implications for these two dimensions of cognitive ability.



Source: Research Data, 2025

Figure 1. Conceptual Framework

Despite the abundance of empirical studies on this topic, in general, many of the studies are correlational in nature, and the direction of the effects is likely to be nuanced (Mallawaarachchi et al., 2022). Moreover, most of the studies only look at the cross-sectional correlation between mobile phone usage and cognitive outcomes, even with a small sample size, and provide no measures to establish causality. Except for studies that use randomized trials, the correlation between mobile phone usage and cognitive outcomes should not be interpreted directly as a causal connection since there are almost certainly confounding factors that affect both mobile phone usage (or ownership) and cognitive or academic outcomes, such as motivation, general ability, and intelligence (Baert et al., 2020). Among the exceptions to this are Dempsey et al. (2020), which utilized longitudinal data and controlled for individual heterogeneity, and Baert et al. (2020), which employed the instrumental variable technique. Many studies of this topic also focus on the developed country context with a sample of college students.

Considering the limited evidence on the causal relationship between mobile phone adoption and cognitive outcomes, this study attempts to contribute a new empirical finding to this discussion. To be specific, this study tries to fill the gap on this topic in a developing country context, with a focus on children (as opposed to college students who are significantly older). By utilizing rich survey data from Indonesia, this study finds that there is no effect of mobile phone ownership or usage among school-age children on their general intelligence.

RESEARCH METHOD

This study utilizes data from the Indonesian Family Life Survey (IFLS), which is a longitudinal survey of individuals, households, and communities who live in Indonesia. IFLS was first administered in 1993 (IFLS 1) and since then has been followed by four resurvey waves with additional samples in each wave, hence a growing number of samples. In its first wave, IFLS was designed to represent 83 percent of the Indonesian population in 1993. IFLS asked a vast range of topics regarding personal and household characteristics and dynamics—expenditure, wealth, income, education, employment, and health, to name a few.

In the last wave of IFLS, which is IFLS5 (fielded in 2014 until early 2015), a new set of questions related to mobile phone and internet adoption and usage was added to the questionnaire book for children under 15. These questions were asked conditional on the children being of school age. There are two mobile phone-related questions asked. The first is whether the child has a mobile phone or not. The second is the usage of mobile phone conditional on owning a mobile phone, with a multiple response categories of: A. private conversation, B. business conversation, C. text message, D. email, E. social media (chatting, Facebook, Twitter), F. mobile banking, G. transferring phone credit, and H. entertainment/ multimedia (games, ringtones, TV, radio, MP3). Both questions are utilized in the analysis of this study.

To measure cognitive ability as the outcome of interest of this study, a cognitive test module from the IFLS5 is utilized. IFLS5 administered two booklets of cognitive tests, one for 7-14-year-old respondents and the other one for 15-year-olds or older respondents. The first age group booklet contains two sets of questions. The first set is 12 items subset of Raven's Progressive Matrices (henceforth referred to simply as the Raven test), which measures fluid intelligence. The second set is 5-item arithmetic questions, ranging from simple subtraction to fraction operations, which is a proxy for crystallized intelligence. To construct the measure of cognitive ability from the Raven test and arithmetic test items, this study uses standardized predicted latent ability calculated from Item Response Theory (specifically, a Rasch model) estimation.

The Rasch model, which is a specific type of Item Response Theory (IRT) model, provides a relationship between individuals latent ability, the item difficulty parameter being tested, and the probability of the individual correctly answering each test item. Formally, the probability of individual i correctly answering item n with a difficulty of δ, given her/his latent ability of δ, is

$$\Pr(X_{in} = 1 \mid \theta_i, \delta_n) = \frac{e^{(\theta_i - \delta_n)}}{1+e^{(\theta_i - \delta_n)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

The use of predicted latent ability instead of a simple sum of correct items scoring ensures that the variable is in interval scale instead of an ordinal scale, which is then appropriate to be included in ordinary regression techniques. Cunha et al. (2021) provide good guidance about measuring cognitive ability for economic research.

Other than the two measures mentioned above, several variables are also constructed from various modules of IFLS5 to be included as controls for analysis in this study. They consist of a set of child's characteristics which are age, gender, years of schooling, and also height-for-age standardized score according to WHO, as well as a set of household and parents' characteristics namely the number of household member, log of per capita expenditure, mother and father's years of schooling, an indicator of whether other household members other than the child has mobile phone, and also the mean value of Raven and arithmetic standardized score of household members excluding the child.

Besides using data from IFLS5, this study also utilizes data from Indonesian Village Potential Statistics (PODES). PODES is a census of all villages in Indonesia and records several aspects such as village administration, demography, environment, disaster, education, health, culture, etc. In PODES 2014, the strength of the mobile phone signal is recorded in 3 categories: no signal at all, weak signal, and strong signal. To instrument the ownership and usage of mobile phones by the children, a variable which quantifies the aggregate mobile phone signal strength is constructed at the sub-district (*kecamatan*) level, and then linked to the IFLS dataset. The aggregation is taken because the lowest administration level of the survey area in IFLS is at the sub-district level. Several methods of aggregation are tried and compared to get the best first-stage regression result, which will be explained in the subsequent section.

The basic causal relationship between mobile phone usage and cognitive measures in a cross-sectional setting can be modeled as:

$$Cognitive_i = \beta\ Phone_i + X_i'.\gamma + Y_i'.\delta + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where i represents an individual child, X is a set of observable child and other level characteristics, Y is a set of confounding factors correlated with both mobile phone usage and cognitive measures, and ε is an idiosyncratic error term. Coefficient β is the parameter of interest of this study, which reflects the causal effect. However, estimating Equation 1 without including a full set of all confounding factors Y would leave us with a biased estimation of β. Several studies on the same topic have identified possible confounding factors such as motivation (Baert et al., 2020). In the context of mobile phone ownership, the confounding factors can also come from socio-economic characteristics such as household income, as well as parents' characteristics and parenting methods (Dempsey et al., 2020).

To tackle this possible bias, this study employs the instrumental variable (IV) technique to eliminate the endogeneity issue in estimating β. Two requirements for a variable to be used as an instrument are instrument exogeneity and instrument relevance. The instrument exogeneity assumption requires that the instrument does not affect the outcome directly or through omitted variables (which is usually referred to as exclusion restriction), and there is no reverse effect of the outcome on the instrument. The instrument relevance assumption demands that the instrument is highly correlated with the main regressor.

This study investigates mobile phone ownership and usage by children with the aggregate measure of mobile phone signal strength at the sub-district level in which the children reside. The first stage equation for the IV estimation is:

$$Phone_{ij} = \eta\ Signal_j + X_i'.\theta + \upsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where $Signal$ is the aggregate measure of signal strength in sub-district j.

Next, this study examines whether signal strength serves as a good instrument for this analysis. First, signal strength is certainly correlated with children's mobile phone ownership, as in areas with a lack of signal, there is no necessity to have a mobile phone. The stronger the signal, the more likely the people, including the children to have and use mobile phones. To what extent they are correlated is explained further in the results section. Second, signal strength arguably affects children's cognitive ability only through mobile phone ownership or usage, hence satisfying the exclusion restriction. There is indeed a possibility that mobile signal strength affects the economic development of the area, and then affects children through the increase in socio-economic characteristics of the family. To account for this, household characteristics are controlled in the regression to minimize the causal channel through omitted variables.

RESULTS AND DISCUSSION

Table 1 presents the variables included in this analysis. The first two variables are the outcome of interest, namely fluid intelligence as measured by the Raven test and crystallized intelligence as measured by the arithmetic test. Both measures are in standardized scores constructed using the distribution of respondents across all ages, not exclusively to children. The average fluid intelligence score is slightly above the all-ages average, while the average crystallized intelligence score is slightly below the all-ages average. This is probably because arithmetic skill is a specific skill which mainly acquired from school, and since the skills of several arithmetic test items are not yet taught in the early grades of primary school, the younger children were more likely to be unable to solve them.

Table 1.
Summary Statistics

	N	Mean	Std.Dev.	Min.	Max.
Raven score (std.)	7716	0.02	0.92	-2.70	1.73
Arithmetic score (std.)	7716	-0.01	0.96	-2.41	1.71
Has mobile phone	7887	0.34	0.47	0.00	1.00
Female	7887	0.48	0.50	0.00	1.00
Years of schooling	7887	3.89	2.35	0.00	11.00
Age in years	7739	10.91	2.30	1.08	16.75
Standardized height-for-age	7722	-1.25	1.08	-4.98	3.43
Other HH member has mobile phone	7663	0.92	0.27	0.00	1.00
Father's years of schooling	7466	9.19	4.10	0.00	22.00
Mother's years of schooling	7701	8.86	3.99	0.00	19.00
Household size	7887	4.85	1.70	1.00	16.00
Log(PCE)	7512	13.61	0.64	11.19	16.47
Mean of other HH member’s Raven	7680	0.02	0.73	-2.70	1.73
Mean of other HH member’s arithmetic	7617	-0.03	0.74	-2.85	2.82

Source: Author’s calculation, 2025

Regarding the main regressor, which is the mobile phone ownership, 34 percent of all sample children were reported to own a mobile phone. This figure is quite high considering that the sample children are below 15 and the survey was administered in 2014-2015. Apart from asking about mobile phone ownership, IFLS5 also asked about the use of the mobile phone. In Table 2, we can see that the top three mobile phone uses are for private conversation, text message, and entertainment or multimedia. As a note, the mobile phone type owned by the majority of people in Indonesia at that time was still basic or feature phone, while the smartphone was in its inception of widespread adoption. Another significant portion of the children (almost half of the mobile phone owners) also use their mobile phones for accessing social media. Mobile phone uses other than those mentioned are minor.

Table 2.
Mobile Phone Utilization

Types of Mobile Phone Usage	Percent of Mobile Phone Owners	Percent of All Sample Children
Private conversation	82.0	28.1
Business conversation	5.2	1.8
Text message	84.4	28.9
Email	9.0	3.1
Social media	45.1	15.5
Mobile banking	0.3	0.1
Types of Mobile Phone Usage	**Percent of Mobile Phone Owners**	**Percent of All Sample Children**
Transferring phone credit	3.9	1.3
Entertainment/ multimedia	78.1	26.8

Source: Author’s calculation, 2025

Besides outcome variables and the main regressor, summary statistics are also displayed for control variables in Table 1. The first set of covariates are child characteristics, namely gender, years of schooling, age, and standardized height-for-age (HAZ). The second set of covariates are child’s household and parent characteristics, namely a dummy of whether other household members own any mobile phones, father’s and mother’s years of schooling, the number of household members, monthly per capita expenditure in natural log, as well as the average of Raven and arithmetic standardized scores of other household members except the child. The last two variables are included to control for any genetic or nurturing effect on the cognitive abilities.

Table 3.
Baseline Regression Result

	(1) Raven score	(2) Raven score	(3) Raven score	(4) Arithmetic score	(5) Arithmetic score	(6) Arithmetic score
Has mobile phone	0.505***	0.189***	0.121***	0.254***	0.177***	0.105***
	(0.021)	(0.024)	(0.025)	(0.023)	(0.027)	(0.028)
Age in years		-0.031**	0.022		-0.044***	-0.015
		(0.013)	(0.014)		(0.014)	(0.015)
Height-for-age (z-score)		0.066***	0.024**		0.038***	0.010
		(0.009)	(0.010)		(0.010)	(0.011)
Female		-0.089***	-0.057***		0.075***	0.093***
		(0.020)	(0.020)		(0.022)	(0.023)
Years of schooling		0.151***	0.112***		0.064***	0.050***
		(0.013)	(0.013)		(0.014)	(0.015)
Household size			-0.016***			-0.009
			(0.006)			(0.007)
Log(PCE)			-0.034*			-0.010
			(0.018)			(0.021)
Other HHM has mobile phone			0.064			0.080*
			(0.040)			(0.045)
Father's years of schooling			0.005			0.001
			(0.003)			(0.004)
Mother's years of schooling			0.008**			0.010***
			(0.003)			(0.004)
Mean of other HHM Raven			0.408***			
			(0.016)			
Mean of other HHM arithmetic						0.348***
						(0.016)
Constant	-0.153***	-0.171*	-0.277	-0.097***	0.179*	-0.086
	(0.013)	(0.099)	(0.271)	(0.013)	(0.105)	(0.307)
Observations	7716	7651	6652	7716	7651	6610
R-squared	0.068	0.149	0.261	0.016	0.024	0.106

Notes: Robust standard errors in parentheses, ***p<0,01 ** p<0,05 * p<0,1
Source: Author's calculation, 2025

Before performing the IV estimation, the baseline OLS regression results are examined. The simplest correlation between mobile phone ownership and cognitive outcomes without controlling for other factors can be seen in columns 1 and 4 of Table 3. Children who own mobile phones have both a higher average Raven and arithmetic score than those who do not. The difference in Raven score is slightly more than 0,5 standard deviation (SD), which is remarkably high. Meanwhile, the difference in the arithmetic score is half of it.

By adding controls, the estimated coefficients of interest are consistently decreasing. Adding child characteristics-related variables significantly drops the mobile phone ownership coefficients to below 0.2 SD in both measures of cognitive function. Adding household and parental characteristics decreases the coefficients further, though not dramatically. The decrease in coefficient values along with the addition of controls is a sign that there exists a positive bias in our coefficient of interest. This is most probably due to selection. The ownership of mobile phones among children is obviously not random. Those from households with more purchasing power, more education, and more technology literacy are more likely to have mobile phones and also more likely to score higher in both cognitive measures.

In addition to mobile phone ownership, the correlations between specific use of mobile phones and cognitive outcomes are also examined. In Table 4, it can be seen that after controlling for children and household characteristics, statistically significant correlations also exist between all types of mobile phone utilization and cognitive outcomes. It should be noted that the base category for these dummies is not using mobile phones for the corresponding activities or not having a mobile phone at all.

Table 4.
Regression Coefficients Between the Specific Use of Mobile Phones and Cognitive Measures

Types of Mobile Phone Usage	Raven score	Arithmetic score
Private conversation	0.075***	0.081***
	(0.026)	(0.029)
Text message	0.099***	0.091***
	(0.026)	(0.030)
Social media	0.053*	0.065*
	(0.031)	(0.036)
Entertainment/ multimedia	0.118***	0.081***
	(0.025)	(0.029)

Notes: Robust standard errors in parentheses. ***p<0,01, ** p<0,05, * p<0,1.
Source: Author's calculation, 2025

To further control the confounding factors at the household level, a set of regressions is also estimated, including household fixed effects. In Table 5, the results show that after taking into account the heterogeneity at the household level, besides the marked reduction in coefficient magnitudes, there is also no statistically significant relationship between mobile phone ownership or use and cognitive measures. This result is arguably close to the actual causal effect since all of the household-level and higher-level confounders have been ruled out (except for the case in which the child had ever moved from other households), and also at least some of the parental confounders. The main confounders that still persist are children's characteristics, particularly psychological traits. Several of these, which are mentioned in previous studies, are motivation, effectiveness in regulating focus and attention, and self-control (Baert et al., 2020). These traits are likely to correlate negatively with mobile phone ownership but positively with cognitive outcomes, hence creating a negative bias in our coefficients of interest. However, the null effects found in these regressions should be interpreted as the absence of detectable effects rather than as definitive evidence ruling out potential negative effects of mobile phone use on cognitive outcomes, as the estimation strategy may still be subject to unobserved heterogeneity. To provide additional evidence on the causal relationship, an instrumental variable approach is employed.

One assumption on which the IV technique relies is instrument relevance. To check this assumption, the F-statistic of the instruments in the first stage regression should be examined. Any instrument with an F-statistic less than 10 should be considered a weak instrument and not be used (Wooldridge, 2025). Table 6 presents the F-statistics of the aggregate signal strength measure included in the first-stage regressions of several main regressors being instrumented. Signal strength seems to be a sufficiently strong instrument for mobile phone ownership and mobile phone utilization in multimedia or entertainment purposes, while it is a weak instrument for the other main regressors. Consequently, these two main regressors are instrumented in the second-stage regression.

Table 5.
Main Regressor Coefficients from Regression Results with Household Fixed Effect

Regressor	Raven score	Arithmetic score
Has mobile phone	0.015	0.007
	(0.029)	(0.033)
M. phone for private conversation	-0.007	-0.003
	(0.027)	(0.032)
M. phone for text message	-0.011	0.014
	(0.028)	(0.033)
M. phone for social media	-0.003	0.005
	(0.030)	(0.033)
M. phone for entertainment/ multimedia	0.025	0.006
	(0.030)	(0.029)

Notes: Robust standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1.
Source: Author's calculation, 2025

Table 6.
First Stage F-statistic of The Instrument

Main regressor	Outcome: Raven score	Outcome: Arithmetic score
Has mobile phone	16.00	15.05
Private conversation	7.68	7.16
Text message	7.72	7.58
Social media	9.61	8.91
Entertainment/ multimedia	14.86	14.20

Source: Author's calculation, 2025

The results of the instrumental variable regressions are reported in Table 7. The estimated coefficients for mobile phone ownership and mobile phone use for entertainment purposes are positive for Raven scores and negative for arithmetic scores. However, these estimates are accompanied by relatively large standard errors, indicating limited precision. Standard errors are clustered at the sub-district level to account for within–sub-district correlation arising from variation in the instrument. As a result, none of the estimated coefficients are statistically significant, suggesting that no causal effects can be detected given the available data, instrument strength, and statistical power.

The coefficients exhibit differing signs across the two cognitive outcomes. This pattern is discussed cautiously and for conceptual consistency with the theoretical framework rather than as empirical evidence of differential effects. Raven scores, which proxy for fluid intelligence, primarily capture abstract reasoning and pattern recognition. Engagement with mobile phones and digital devices often involves visually intensive and pattern-based tasks, such as playing games, which could plausibly relate to this dimension of cognition. In contrast, arithmetic ability, used here as a proxy for crystallized intelligence, reflects domain-specific skills that depend heavily on formal instruction and cumulative learning. From a theoretical perspective, mechanisms such as distraction or multitasking may therefore have different implications across these cognitive dimensions. Given the limited precision of the IV estimates, this discussion should be interpreted as speculative rather than conclusive.

Table 7.
Instrumental Variable Regression Result

	(1) Raven score	(2) Raven score	(3) Arithmetic score	(4) Arithmetic score
Has mobile phone	0.562		-0.234	
	(0.761)		(0.919)	

Continue				
Multimedia/entertainment on mobile phone		0.614 (0.848)		-0.253 (0.972)
Controls	Yes	Yes	Yes	Yes
Observations	6652	6652	6610	6610
R-squared	0.226	0.217	0.087	0.087

Notes: Standard errors clustered at sub-distrcit level in parentheses. ***p<0.01, ** p<0.05, * p<0.1.
Source: Author's calculation (2025)

CONCLUSIONS AND RECOMMENDATIONS

This study empirically examines whether mobile phone ownership or usage among school-age children affects cognitive ability, particularly fluid and crystallized intelligence, using survey data from Indonesia. Baseline regressions show positive correlations between mobile phone ownership or use and cognitive measures. However, these associations disappear once household fixed effects are included, indicating positive selection bias. Instrumental variable estimates likewise provide no evidence of detectable effects. Beyond the empirical findings, this study contributes to the literature on digital technology and child development by emphasizing the distinction between access and impact. The absence of detectable effects suggests that potential cognitive consequences of mobile phone use may be indirect, context-dependent, or mediated by factors such as usage patterns, content, and supervision. These results also indicate that standard measures of cognitive ability, including fluid and crystallized intelligence, may not fully capture all dimensions through which digital technologies influence children's development.

From a policy and parental perspective, these findings do not imply that mobile phone use is inconsequential for children's development. Rather, they suggest that ownership alone may be an insufficient indicator of cognitive impact. Policy discussions and parental guidance may benefit from focusing more on usage patterns, content quality, supervision, and the integration of mobile phones into educational activities, rather than merely on access or ownership. At the same time, the limitations of the instrumental variable approach used in this study highlight the need for future research employing stronger sources of exogenous variation, richer measures of cognitive and non-cognitive outcomes, and longitudinal designs.

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