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The Impact of Household Digital Resources Investment on Student Performance: An Empirical Study Based on CEPS2013-2014 Data

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Abstract

The popularity of home digital resources (e.g., computers, Internet) in education has sparked debates about their impact on student achievement. Family socioeconomic status, parental education/occupation, and income indirectly affect performance by influencing resource access (e.g., tutoring, digital devices). This study uses generalized ordered Logit, ordered Logit, and ordered Probit models to analyze 2013-2014 CEPS baseline data of 15,925 students, examining how family digital resources affect grades. Controls include household registration, nationality, study pressure, and parental education/occupation. Interaction terms, square terms, and marginal effect analysis test nonlinearities and population differences, exploring mechanisms and moderators to inform resource allocation and policy. Literature shows: Cabero-Almenara linked stronger digital competence to better performance, shaped by resource use, preparation, and parental education; Hammer found parents influence students' digital self-efficacy, with smartphones mediating learning tech use; Rohatgi noted basic ICT self-efficacy boosts literacy across genders; Zhong's PISA study highlighted school ICT access, spending, home access, SES, and gender; Wellman found internet supplements communication but heavy use reduces community commitment. Digital competence, parental support, self-efficacy, and equitable access mediate internet's academic impact.

Keywords

Digital competence; Gital media; Parental education; Home ICT access.

1. Introduction

1.1. The Research Background and Problem Identification

With the advancement of information technology and digital education, family investment in digital resources-including networks, intelligent equipment, online learning platforms, and educational APPs-has grown annually, becoming a crucial aid for students' learning. However, disparities in family economic conditions and parental education lead to uneven digital investment, which may exacerbate educational inequality. The COVID-19 epidemic's online education phase highlighted this issue: insufficient home digital equipment revealed stark educational gaps, yet the long-term impact and underlying mechanisms of such factors on academic performance remain understudied.

China Internet Network Information Center (CNNIC) data shows that by 2023, China had over 1 billion Internet users, with the 10-19 age group accounting for nearly 20% [1]. Families have become key spaces for students to access information technology, but gaps in household digital investment may cause unequal access to high-quality digital educational resources, affecting academic outcomes. While school informatization has advanced (multimedia classroom

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penetration exceeds 90%), systematic empirical analysis of how the family digital environment-especially its investment-influences middle school students' grades is lacking.

Theoretically, most studies focus on school informatization or macro-policies, ignoring family-level digital investment and its potential linear, nonlinear, or threshold effects (e.g., excessive investment reducing efficiency). Educational production function theory (Hanushek,1992) emphasizes family input as key to educational output; academic achievement (a core quality indicator) may be shaped by digital resources via diversified learning and enhanced autonomy, but specific mechanisms are underexplored.

Since 2010, policies like The Outline of China's National Plan for Medium and Long-Term Education Reform and Development (2010-2020) have stressed IT's role in advancing education equity and quality [2]. This study uses ordered Probit regression, group t-tests, Pearson correlation analysis, and marginal effect analysis to examine household digital investment's impact on scores, controlling for family SES and parental education. It aims to provide empirical evidence for rational resource allocation, school support policies, and improved educational equity.

1.2. Objectives of the Study

In the Educational Informatization 2.0 era, family digital resource investment influences middle school students' education. Using National Sex Education Survey data, this study explores its impact on students' achievement: clarifies the current status of such investment and overall achievement in China, verifies its positive/negative effects, and examines if family background (parental education, economic status, etc.) moderates this relationship. It aims to provide empirical support for rational family resource allocation, school digital teaching optimization, and government educational equity policies, while offering suggestions to improve achievement and promote equity.

1.3. Research Significance

This study focuses on family digital resource investment's impact on middle school students' achievement, helping verify relevant theories' explanatory power for student achievement differences in the digital age. Previous studies focused on information technology's impact on students' cognitive development, but research on the relationship between family digital resource investment and students' achievement-especially national empirical research-is insufficient.

To fully understand this relationship, this study uses national education tracking survey data to conduct quantitative research on the links between family digital resource investment, influencing family background factors, and middle school students' achievement. It enriches research on adolescent academic development and educational equity, and provides empirical support for promoting educational equity.

2. Literature Review

2.1. Fires Research on Student Achievement

Factors affecting student achievement are a core educational research topic, with existing studies focusing on family background, school type, and extracurricular tutoring. Family Background: Studies show family SES correlates positively with achievement-higher parental education and better economic conditions boost performance (PISA, Shanghai data). Family cultural capital indirectly affects performance by influencing educational inputs (tutoring, digital resources, parental IT Literacy) [2, 3]. School Types: Urban/key schools, with richer resources, outperform rural/non-key ones (CEPS data). School informatization and achievement show an "inverted U-shape": moderate use helps, but over-reliance harms

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vulnerable groups; It also affects students 'performance indirectly by affecting self-efficacy [4]. Extracurricular Tutoring: Its effects vary by subject and family background-math tutoring helps, language tutoring may crowd out other learning; high-SES students have more access, but equal opportunities narrow gaps [5, 6].

2.2. Information Technology and Student Achievement Correlation Research

Information technology permeates education, with its application effects depending on use mode, scenario, and support measures, requiring dialectical analysis from a historical materialism perspective [6-8]. Positive Effects: Teaching Tools: Multimedia (Flash, Geometer) dynamically presents math concepts, boosting interest and understanding [7, 8]. Resource Sharing: MOOCs and online schools (e.g., Chengdu No.7 Middle School Dongfang Wendao) deliver quality resources to vulnerable areas, narrowing gaps [8-10]. Personalized Learning: Intelligent analytics tailor paths for students, improving efficiency [9]. Challenges: Use Mode: Academic internet use raises grades by 5-7%, while entertainment use lowers them by 6% (PISA Shanghai) [10, 11].

Excessive Informatization: Disrupts concentration, especially for rural students (CEPS) [11, 12]. Teacher Capacity: Inadequate IT skills lead to idle/inefficient equipment [12].

2.3. Digital Divide Related Research

The digital divide has shifted from "access divide" to "use divide," exacerbating educational inequality. Access Gap: Urban-rural digital device (computer, network) coverage differs sharply; rural families lack resources, limiting after-school learning and policies like "Full coverage of digital resources at teaching sites" improve access but lack sustainability [13-15]. Use Gap: High-SES families guide children to use the Internet for learning, while low-SES families favor entertainment [16, 17]; urban students gain better digital literacy from early IT exposure, rural students lack guidance[18-20].Responses: Governments should provide free online courses and digital literacy training for vulnerable groups; schools guide proper Internet use via "online learning groups," families supervise use to ≤30 minutes daily (PISA recommendations) [21]. In short, IT’s impact on equity depends on resource allocation and use. Future research should explore balancing its "double-edged sword" effect, home-school collaboration paths, and emerging tech’s (AI, VR) differential impacts [22, 23].

3. Research Design

3.1. Hypotheses and Data Sources

3.1.1. Research Hypotheses

Hypothesis 1: Family digital resource investment has a positive impact on middle school students’ academic performance-students with such investment have higher grades.

Hypothesis 2: Family digital resource investment has a negative impact-students with such investment have lower grades.

Hypothesis 3: Family digital resource investment has no impact-changes in investment do not affect students’ grades.

3.1.2. Data Sources

The data comes from the China Education Panel Survey (CEPS), a large-scale follow-up survey by the China Research and Data Center of Renmin University of China. It uses a multi-stage DPS sampling method, surveying about 20,000 junior high school students and related personnel from 112 schools in 28 county-level units, with a 30-year tracking period. This study uses 2013-2014 baseline survey data, obtaining 15,925 valid observations after data cleaning and missing value processing.

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3.2. The Measurement of Variables

3.2.1. Dependent Variable

The dependent variable is academic performance level, measured by core grades (grade_score). Grades are crucial for students' self-improvement, career planning, and serve as indicators for student selection, teacher evaluation, and educational resource allocation.

3.2.2. Independent Variable

The household-level independent variable is "whether there is a computer and Internet," measuring household IT utilization. Having a computer and Internet helps students access high-quality resources (e.g., MOOCs) and use multimedia tools, but entertainment use can reduce grades. The original 0-2 variable (0=none, 1=computer without network, 2=computer with network) is reclassified: 0=none or computer without network, 1=computer with network.

3.2.3. Controlling Variables

Given that academic performance was influenced by many factors, the following variables were controlled for: years of parent education (converting 1-9 categories into years of education), parent occupation (combined into 4 categories), family economic conditions (5-level scale into a dualistic variable), hukou (combined into rural and urban hukou), nationality (Han and non-Han), learning pressure (reverse coding the 4-level scale), and students and parents 'educational expectations (converting 1-10 categories into years of education). The data after processing were described in Table 1 and 2.

Table 1. Descriptive Statistics of Non - continuous Variables

Categorical Variables	Categories	Proportion	Sample Size
Gender	Male	50.25%	8003
	Female	49.75%	7922
Academic Performance	Poor	9.27%	1476
	Below Average	20.30%	3233
	Average	28.98%	4615
	Above Average	32.57%	5187
	Very Good	8.85%	1414
	Excellent	44.21%	7041
Only Child	Yes	55.79%	8884
	No	44.21%	7041
Household Registration	Rural Household Registration	53.92%	8669
	Urban Household Registration	46.08%	7322
Ethnic Group	Han	91.76%	14613
	Non - Han	8.24%	1312
Learning Pressure	None	10.14%	1615
	Moderate	17.95%	2858
	Relatively High	47.36%	7542
	Very High	24.55%	3910
Family Economic Condition	Good	12.26%	1952
	Not Good	87.74%	13973
Whether There is Computer Network at Home	No	38.52%	6134
	Yes	61.48%	9791

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Table 2. Descriptive Statistics of Continuous Variables

Continuous Variables	Sample Size	Mean	Standard Deviation	Minimum Value	Maximum Value
Students' Educational Expectation (years)	15925	16.08119	4.417118	0	22
Parents' Educational Expectation (years)	15925	15.57714	4.168084	0	22
Mother's Years of Education	15925	9.615259	3.549323	0	19
Father's Years of Education	15925	10.38807	3.145869	0	19
Father's Occupational Status	15925	2.031334	0.7875	1	4
Mother's Occupational Status	15925	1.89281	0.821023	1	4

3.3. Study Design

3.3.1. Overview of Research Framework and Methodology

According to the research needs of the correlation between digital resources and academic performance, comb the analysis logic and construct the research framework, focus on exploring the influence and mechanism of digital resources on academic performance. The study first explored the relationship between variables through descriptive analysis and correlation analysis, then analyzed the main effect with regression model, combined with marginal effect analysis to accurately measure the impact degree, and finally ensured the reliability of the conclusion through robustness test, as follows:

3.3.2. Descriptive Statistics and Correlation Analysis

(1) Descriptive statistics

Stata16 software was used to process and analyze the data in order to grasp the characteristics of the data as a whole, initially verify the research hypothesis and lay the foundation for subsequent in-depth analysis. Descriptive statistics can be used to understand the distribution of household digital resource use and student achievement, screen outliers, and initially discover the difference between resource use and achievement through group comparison. The preliminary conclusion of this study is that students in families using digital resources have significantly higher mean scores, which lays the foundation for further steps and points out the general direction.

(2) Correlation analysis

Gamma correlation analysis: applies to two ordered categorical variables, focusing on the consistency of variable rank changes, and measures the strength and direction of the association by calculating gamma coefficients. The closer the coefficient is to ± 1, the more significant the association is.

3.3.3. Regression Model Analysis

(1) Necessary preparations before reunification

Oparallel test, i.e. parallel line test, is mainly applied to ordered regression models such as ordered Logit model and ordered Probit model, and is a key test method to judge whether the "proportional dominance hypothesis" is satisfied. This hypothesis assumes that the independent variable's influence on the dependent variable is constant at different dependent variable levels, i.e., the regression coefficients are the same for each category, i.e., the regression lines are parallel. The corresponding p-value will be obtained through aparallel test. When the p-value is greater than 0.05, it indicates that the "proportional dominance hypothesis" is satisfied, and the ordered Logit model can be used for analysis; if the p-value is less than or equal to 0.05, it indicates that the hypothesis is not satisfied, which means that the influence of independent variables on different levels of dependent variables is not constant. In this case,

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other models more suitable for data characteristics such as generalized ordered Logit model need to be used.

(2) Regression model

Ordered Logit model: A regression model used to deal with dependent variables that are ordered categorical variables. Suppose there is a potential continuous variable, divide it into several ordered categories by some thresholds, construct a model based on Logit function, measure the influence of independent variables on the transition probability between different categories of dependent variables by estimating regression coefficients, and assume that the influence of independent variables on dependent variables is the same among various categories, i.e., satisfy the "proportional dominance hypothesis", the formula is:

$$y^* = X_i\beta + \epsilon_i \tag{1}$$

Y* Latent variable A continuous variable that is unobservable and represents the underlying trend of the explained variable.

Xi is an argument vector including constant terms (in this study, Xi includes variables such as digital_resource, male, stonly, etc.), and β is the corresponding coefficient vector.

ϵi is a random perturbation term and obeys a logical distribution.

Ordered Probit model: Ordered Logit model and Ordered Logit model are both statistical methods for dealing with ordered categorical dependent variables. The core difference lies in the latent distribution assumption. The former assumes that the latent variables obey normal distribution, while the latter assumes logical distribution. Both of them need to satisfy the "proportional dominance hypothesis", and both of them explain the influence direction and intensity of independent variables on the change of dependent variable category through maximum likelihood estimation parameters. The formula is as follows:

$$y_i^* = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \epsilon_i \tag{2}$$

In the formula:

yi* is the latent variable corresponding to the ith observed value, which reflects the true level of the dependent variable, but cannot be directly observed;

β0 is the intercept term;

βj (j= 1, 2, ..., k\) is the coefficient corresponding to the independent variable xji, representing the influence degree of the independent variable on the latent variable yi*;

Xki is the kth argument of the ith observation value. In the code, the arguments include digital_resource, stonly, hukou, etc.;

ϵi is a random perturbation term, usually assumed to obey a standard normal distribution N(0,1)

Generalized Ordered Logit Model (GOLM): An extension of the Ordered Logit Model, mainly used to relax the constraints of the Proportional Dominance Hypothesis. By allowing independent variables to have different regression coefficients at different class boundary points and introducing class-specific coefficient matrices, the model can more flexibly describe the asymmetric effects of independent variables on the grade transformation of dependent variables, which is suitable for the scenarios where dependent variables are ordered and proportional dominance hypothesis does not hold. The formula is:

$$\log\left(\frac{P(Y \le j|X)}{P(Y > j|X)}\right) = \alpha_j + \beta X \ (j = 1,2, \dots, J-1) \tag{3}$$

In the formula:

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J is the number of classes of Y (here J=5) αj is the threshold parameter (one for each class boundary) that determines the position of the class boundary. Different J's correspond to different intercepts, reflecting the differences in the boundaries of different categories.

βj is the coefficient vector of the argument X corresponding to the Jth class boundary (assuming the same for all class boundaries). Different from the traditional ordered logistic regression, in the generalized ordered Logit model, the independent variable coefficient vector βj can be different for different class boundaries J, which allows the independent variable to have different effects on different class boundaries, thus relaxing the parallelism assumption.

Parallelism hypothesis: β is constant on all class boundaries J.

3.3.4. Marginal Effect Analysis

Overview of research framework and methodology: according to the research needs of the correlation between digital resources and academic performance, comb the analysis logic and construct the research framework, focus on exploring the influence and mechanism of digital resources on academic performance. The study first explored the relationship between variables through descriptive analysis and correlation analysis, then analyzed the main effect with regression model, combined with marginal effect analysis to accurately measure the impact degree, and finally ensured the reliability of the conclusion through robustness test, as follows:

$$\frac{\partial \Pr(y=j)}{\partial digital\_\mathrm{resource}} = \emptyset(\alpha_j - x\beta)\cdot\beta \tag{4}$$

In the formula:

Pr(y=j): Probability of student grade y being category j.

digital_resource: Measures family digital resource investment/use.

β: Coefficient vector, shows digital_resource's (and x's) influence direction/intensity on potential y*.

αj: Threshold parameter, maps continuous y* to discrete y.

x: Independent variables (including controls like family income) for confounding control.

Φ: Standard normal PDF, adjusts to determine independent variables' marginal effect on Pr(y=j).

3.3.5. Robustness Test

Robustness test is a necessary link to consolidate the reliability of conclusions, regardless of the results of basic regression, it should be carried out. Because of the limitation of data, it is not convenient to change the core independent variable, so we adopt the method of replacing the model, use the ordinary least squares (OLS) regression, compare the results with the results of ordered model (ordered Logit, ordered Probit, etc.), verify the consistency of the influence of digital resources on academic performance from different model perspectives, check the influence of model setting and other factors on the conclusion, ensure the relationship between digital resources and academic performance and the conclusion are true and reliable, and lay a solid foundation for subsequent analysis.

4. Research Finding

4.1. Descriptive Analysis of Variables

The study includes 15,925 samples: 50.25% boys, 49.75% girls; 44.21% only children, 55.79% non-only children; 53.92% rural households, 46.08% urban; 91.76% Han nationality; 47.36% with "larger" study pressure.

Regarding core variables: 61.48% of families have computers and Internet, 38.52% do not. Students with digital resources have an average score (3.17) slightly higher than those without

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(3.03), but Cohen's d≈0.13 (weak positive association). The correlation between academic performance and household IT equipment needs further regression analysis, potentially involving the "use gap" and "skill difference" in the digital divide.

Control variables: Parental and student educational expectations average 16.08 and 15.58 (both undergraduate and above); fathers have an average of 10.39 years of education (high school level), higher than mothers' 9.62 years (junior to senior high); fathers' average occupational status (2.03) is higher than mothers' (1.89); 87.74% perceive family economic conditions as "bad," 12.26% as "good."

4.2. Descriptive Statistics and Correlation Analysis

Table 3. Gamma Correlation Analysis Results for Core Variables

Variable	Coefficient (Coef.)	Standard Error (SE)	z - value	p - value	95% Confidence Interval
Fixed Effects					
digital_resource	0.034	0.004	8.46	<0.001	[0.026, 0.041]
Intercept (_cons)	1.341	0.005	259.61	<0.001	[1.331, 1.351]
Distribution Parameter					
α (Dispersion Parameter)	0.244	0.003	-	-	[0.238, 0.249]
κ (Shape Parameter)	1.831	0.033	54.86	<0.001	[1.766, 1.897]
Model Fitting					
Log - Likelihood Value	-6911.71				
Likelihood Ratio Test (x^2)	70.37			<0.001	

As shown in Table 3, gamma correlation analysis with 15,925 observations showed overall significance via likelihood ratio test (LRchi2 (1)=70.37, p=0.000), indicating at least one independent variable significantly affects the dependent variable. Loglikelihood improved from -6946.8987 (constant model) to -6911.7139 (full model), showing better fit with added variables. The digital_resource_cons coefficient (0.0336595, p=0.000) means each 1-unit increase in household digital resource use raises the logarithmic expectation of student performance by 0.0337 units, with 95% confidence interval [0.0259, 0.0415] excluding 0. The constant term (1.340689, p=0.000) was significant. Distribution parameters: sigma=0.2436 (dispersion) and kappa=1.8311 (shape). Kappa>1 indicates right-biased, thick-tailed distribution. Results confirm family digital resource use positively correlates with students' scores, and the right-leaning data aligns with common score distributions, supporting subsequent regression.

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4.3. Regression Model Analysis

Table 4. Results of generalized ordered logit regression

Academic Performance Level	Variable Name	Odds Ratio	z - value	P - value	95% Confidence Interval
Common Control Variables	Gender (Male = 1)	1.509295	8.08	0	[1.292593, 1.863478]
	Student's Educational Expectation (Years)	0.750327	-11.65	0	[0.679522, 0.830264]
	Mother's Years of Education (Years)	0.979383	-2.09	0.037	[0.962728, 0.996359]
	Learning Pressure	2.093983	26.09	0	[1.853577, 2.367244]
Not Good (Relative to Higher Levels)	Family Digital Resource Input	0.948729	-0.76	0.445	[0.828928, 1.085844]
Below Average (Relative to Higher Levels)		0.945391	-1.23	0.218	[0.846379, 1.053687]
Medium (Relative to Above - Medium)		1.013496	0.32	0.749	[0.935711, 1.100264]
Above - Medium (Highest Level)		1.037415	0.52	0.602	[0.907994, 1.189784]

As shown in Table 4, the generalized ordered Logit model was overall significant (Waldchi2 test, Prob>chi2=0.0000), meaning independent variables (core digital_resource, controls like male) jointly explained grade_score. But its low pseudo-determination coefficient (PseudoR2=0.1317) limited explanatory power. digital_resource's OddsRatio for grades ("bad", "middle-lower", "middle-upper") was insignificant (P>0.05), with no confirmed correlation. Controls differed: males had higher poor-grade odds; longer child/maternal education reduced them. Robustness tests, model adjustments, and deeper control variable path analysis are needed to refine conclusions.

4.4. Marginal Effect Analysis

Table 5. Marginal Effect Analysis Results

Academic Performance Level	Marginal Effect (dy/dx)	Standard Error	z - value	p - value	95% Confidence Interval
Not Good (Level 1)	-0.000009	0.00209	-0.04	0.966	[-0.0042, 0.0040]
Below Average (Level 2)	-0.00018	0.00426	-0.04	0.966	[-0.0085, 0.0082]
Medium (Level 3)	-0.00005	0.0012	-0.04	0.966	[-0.0024, 0.0023]
Above Average (Level 4)	0.00024	0.00549	0.04	0.966	[-0.0105, 0.0110]
Very Good (Level 5)	0.00009	0.00206	0.04	0.966	

Note: Marginal effects represent the increase or decrease in the probability of being at a grade with numerical resources (=1) compared to no resources (=0) (mean marginal effects). All variables were set as at means. Control variables included household registration, study pressure, and parental education. Significant markers: ***p<0.01, **p<0.05, *p<0.1 (none of the results were significant).

As shown in Table 5, his paper analyzed Ordered Probit Model marginal effects to assess household digital resource input's impact on academic grades using 15,925 samples. Controlling for household registration, parental education, etc., digital resource ownership showed insignificant marginal effects (p=0.966): minimal changes in "poor" (-0.00896pp) and

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"good" (+0.00886pp) grade probabilities, with confidence intervals including zero. Visualization confirmed this aligns with model coefficients (β=0.0008). Findings suggest device penetration alone isn't key-synergy with digital literacy, parental supervision, etc., is needed, offering insights for policy and future research.

4.5. Robustness Test

Using 15,925 samples, this study examined how family digital resource input and other controls affect students' ordered grades. The likelihood ratio test showed all independent variables had a highly significant combined effect ($LR\chi^2(12)=5736.44$, $p<0.001$), with pseudo-$R^2=0.1217$ (explaining 12.17% of grade variation). The core variable digital_resource had an insignificant coefficient (0.0008, z=0.04, p=0.966; 95% CI [-0.0377, 0.0394]), indicating no significant impact on achievement after controlling covariates-verified by robust standard errors.

Significant predictors: Learning stress (β=0.586, z=53.67, p<0.001) positively correlated with grades; economic conditions (β=-0.099, z=-3.66, p<0.001), urban household registration (β=-0.044, z=-2.23, p=0.026), and ethnic minority status (β=-0.053, z=-2.63, p=0.009) correlated with lower grades. Parental education showed intergenerational effects (mother: β=0.024; father: β=0.025, both p<0.001). Significant cut-point parameters (cut1-cut4) supported ordered classification rationality. Findings suggest equipment popularization alone is insufficient-guidance and family support are needed for better educational outcomes, as shown in Table 6.

Table 6. Results of Ordered Probit All-Variable Model

Variable	Coefficient (Coef.)	z - value	P - value
Digital Resources (Available = 1)	0.0008	0.04	0.966
Household Registration (Urban = 1)	-0.044**	-2.23	0.026
Ethnicity (Han = 1)	-0.053**	-2.63	0.009
Learning Pressure	0.586***	53.67	0
Student's Educational Expectation	0.056***	23.04	0
Economic Conditions (Good = 1)	-0.099***	-3.66	0

5. Result and Discussion

5.1. Research Conclusions

Using 2013-2014 CEPS baseline data, this study employs descriptive statistics, correlation analysis, ordered Probit regression, and marginal effect analysis to explore the impact of family digital resource investment on middle school students' performance.

5.1.1. The Correlation Characteristics Between Family Digital Resources Input and Middle School Students 'Achievement

Descriptive statistics: 61.48% of households have computers and networks. Students with digital resources have a slightly higher average score, but Cohen's d≈0.13 (weak positive association). Correlation analysis: The Gamma coefficient of digital resources and grades is 0.0975 (weak positive correlation), not passing the significance test-no obvious linear correlation exists. Regression and marginal effect: The Generalized Ordered Logit model shows the odds ratio of digital resources in each grade is not significant (P>0.05). Marginal effect analysis reveals having digital resources increases the probability of being a "top student" by only 0.00886 percentage points (not statistically significant).

5.1.2. Effects of Key Control Variables

Educational expectation: Students' (rho=0.4243) and parents' (rho=0.3871) educational expectations are moderately correlated with achievement. The odds ratio of achievement improvement decreases with higher expectations (OR=0.7503).

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Study stress: Study stress and achievement have a strong positive correlation (Gamma=0.6295). Each stress level increase raises the achievement improvement odds ratio by 2.094. Family background: Parental education has a weak positive correlation with achievement (mother: rho=0.1607; father: rho=0.1684), with significant regression coefficients (mother: OR=0.9793, P=0.037). Parents' occupational status has a weak correlation (rho<0.1). Group differences: Male students are more likely to have poor performance (OR=1.509); urban students perform slightly better; economic conditions are negatively correlated with achievement (Gamma=-0.1583).

5.2. Discussion and Analysis

5.2.1. Consistency Between Theoretical Explanations and Research Findings

Educational production function theory: This study finds family digital resources do not significantly improve performance, differing from Hanushek's (1992) view. This may be because digital resources' output depends on "use quality" rather than "possession quantity," and existing models ignore usage scenarios-consistent with PISA Shanghai data that academic Internet use boosts grades.

Digital divide theory: The study confirms the shift from "access divide" to "use divide." Low-SES families lack scientific guidance for digital device use, aligning with Gavria & Raphael's (2001) view that technology use ability differences worsen inequality, requiring policy shifts to "use empowerment."

Nonlinear relationship: No nonlinear effects of digital resources are found, but Gong Botao (2019) notes an "inverted U-shaped" relationship between school informatization and achievement. Family scenarios may have similar threshold effects, but this study cannot verify due to sample limitations.

5.2.2. Realistic Enlightenment and Policy Implications

Family digital resource allocation: Families may mistakenly believe "device ownership equals educational gain." Non-technical factors (e.g., study stress, educational expectations) have more significant effects. Parents should focus on "resource use management" (e.g., setting Internet rules).

Urban-rural educational resource synergy: Urban families invest in diverse education, while rural families' digital resources are underutilized. Policies should promote "urban-rural digital education communities" (e.g., "famous school online classrooms").

Education informatization policy adjustment: Supporting Lei Wanpeng's (2018) "three misunderstandings of education informatization policy," the government should shift from "hardware coverage" to "software empowerment" (e.g., digital literacy training, developing rural-friendly educational APPs).

5.2.3. Limitations of the Study and Future Prospects

Variable measurement: Only "whether there is a computer and Internet" measures digital resource investment, ignoring device type, use frequency, and content preference. Future studies can use log data to refine measurements.

Sample and time constraints: Data is from 2013-2014, lacking follow-up on later IT developments, and focuses on junior high students. Future research can use tracking data for dynamic effect analysis.

Mechanism analysis: The study does not explore mediating pathways (e.g., learning autonomy). Future studies can introduce learning behavior scales to test mechanisms like cognitive overload.

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5.3. Countermeasures and Suggestions

5.3.1. Family Level: From "Equipment Ownership" To "Scientific Management"

Establish digital resource use norms: Parents should create "learning Internet schedules," limit daily entertainment use to 30 minutes, and guide children to use educational platforms (e.g., National Primary and Secondary School Smart Education Platform) through "parent-child learning."

Digital literacy and supervision: Low-education parents can learn supervision skills via community training (e.g., "digital parenting classes"), use parental controls, and monitor online learning to avoid the "device use = effective learning" bias.

5.3.2. School Level: Strengthen The Synergy Effect of "Technology-Teaching"

Differentiated digital resource support: For rural students' low home equipment efficiency, schools can offer "digital after-school services" (e.g., teacher guidance for online homework) and develop offline learning packages.

Improve teachers' digital teaching ability: Strengthen IT training, especially for rural teachers' "technology-subject" integration skills (e.g., "micro-class workshops"), and establish "family digital learning support hotlines.

5.3.3. Government Level: Optimize Policy Orientation and Resource Allocation

Build a "digital education equity ecosystem": Increase rural family "soft investment" (e.g., free educational APP memberships, "digital literacy into families"), and promote resource sharing via "urban-rural school pairing."

Improve education informatization evaluation: Replace simple equipment coverage assessments with "family digital resource use efficiency" indicators (e.g., "family digital learning participation"), guiding policies to "effect orientation." This study verifies the complex relationship between family digital resource investment and middle school students' achievement, highlighting that "use quality" rather than "device ownership" is key to technology empowering education. Future research should refine variable measurement, track long-term effects, and analyze mechanisms to support education informatization 2.0-era equity and quality improvement.

6. Conclusion

This study explores the impact of family digital resource investment on middle school students' academic performance using baseline data from the 2013-2014 China Education Panel Survey (CEPS). Key findings reveal that family digital resource ownership (e.g., computers and internet access) has an extremely weak and statistically insignificant positive effect on students' academic performance. In contrast, non-technical factors such as learning pressure, educational expectations, parental education level, and gender have more significant impacts on academic outcomes. Future research could refine measurements of digital resource variables by incorporating usage frequency and content preferences. Additionally, longitudinal tracking data should be adopted to analyze the dynamic effects of digital resources across different academic stages. Further exploration is also needed into mediating mechanisms like learning autonomy to clarify why digital resource ownership does not translate to improved academic performance.

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