Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Digital Education and Income Inequality: Evidence from a Heterogeneous-Agent DSGE Model

zheyan zheng

1272238565@qq.com

Ningbo University

xinmiao zhou

Ningbo University

kai zhang

Ningbo University

Fujun Lai

Yunnan University of Finance And Economics

Research Article

Keywords: digital education, income inequality, heterogeneous households, digital literacy, human capital

Posted Date: November 13th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11363024/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Digital Education and Income Inequality:

Evidence from a Heterogeneous-Agent DSGE Model

Zheyan Zheng Xinmiao Zhou Kai Zhang Fujun Lai*

Abstract: Digital education technologies expand educational access, but their distributional effects are not necessarily inclusive. Differences in educational service choices, digital literacy, and human capital conversion capacity across income groups may generate uneven outcomes. To investigate, we construct a dynamic stochastic general equilibrium (DSGE) model with three heterogeneous household types (high-, middle-, and low-income), incorporating school education, online education, and offline tutoring. We examine how online education productivity shocks, educational service substitution elasticity, and digital literacy accumulation affect human capital and income inequality, supplemented by PISA 2022 microdata evidence. Findings: First, although higher online education productivity reduces costs, it may crowd out traditional investment. This damages low-income households' digital literacy and human capital, widening income inequality. Second, a decline in human capital conversion efficiency narrows the income gap short-term, then widens it, but this narrowing does not imply absolute improvement for low-income households. Third, while reducing substitution elasticity or raising digital literacy accumulation efficiency helps low-income households, neither alone narrows the relative income gap; combining both improves human capital accumulation outcomes. PISA 2022 evidence confirms the income heterogeneity in digital learning outcomes. These findings suggest that digital education's inclusiveness depends on both the substitution structure of educational services and households' ability to convert digital learning into human capital.

Keywords: digital education; income inequality; heterogeneous households; digital literacy; human capital

1. Introduction

With the widespread application of digital technologies in education, digital education forms such as online courses and intelligent teaching platforms have gradually become important complements to traditional education. Digital education breaks through the constraints of time and space, reduces the cost of accessing certain educational resources, and offers new possibilities for improving the distribution of

educational opportunities. However, improved accessibility of educational resources does not necessarily translate into equality of educational outcomes. Households at different income levels differ in their ability to spend on education, their choice of educational services, their digital literacy, and their ability to convert learning outcomes. Even when faced with the same digital technology progress, they may obtain different benefits. Therefore, whether digital education alleviates or exacerbates income inequality is not a simple technical question, but a complex economic issue involving the allocation of educational resources, household heterogeneity, and human capital accumulation.

From a theoretical perspective, advances in digital education technology may affect income distribution through at least two channels. On the one hand, higher productivity in online education reduces the cost of educational services, expands the coverage of high-quality educational resources, and provides more learning opportunities for households previously constrained by economic conditions. On the other hand, the development of digital education may also change the relative costs and substitution relationships among different educational services, prompting households to reallocate educational investments across school education, online education, and offline tutoring. If households at different income levels differ in their educational choices and in their ability to convert learning inputs into human capital, the reallocation of educational resources may generate uneven accumulation effects. In particular, when low-income households rely more heavily on traditional school education while their digital learning capabilities are relatively insufficient, the decline in online education costs may not compensate for the losses caused by reduced traditional educational investment. As a result, digital education technology progress may, while improving access to educational resources, produce outcomes that are inconsistent with the goal of improving income distribution.

Existing research provides an important foundation for understanding the economic impact of digital education, yet there is still room for further development. On the one hand, research on digital technology and educational equity has primarily focused on the accessibility of educational resources, learning performance, and group differences, while the dynamic mechanisms through which digital education affects income inequality via household educational choices and human capital accumulation still require deeper analysis. On the other hand, while studies of household heterogeneity in macroeconomic models emphasize differences in income, wealth, and consumption decisions, they have paid relatively limited attention to the substitution relationships among educational services such as school education, online education, and offline tutoring, as well as the role of digital literacy between educational investment and

human capital formation. Therefore, it is necessary to incorporate educational service choice, digital literacy accumulation, and human capital formation into a unified dynamic analytical framework, in order to explain why digital education technology progress may produce different distributional outcomes and which policy conditions can improve the accumulation situation of low-income households.

Against this background, this paper constructs a dynamic stochastic general equilibrium (DSGE) model with three types of heterogeneous households—high-, middle-, and low-income—incorporating school education, online education, and offline tutoring into a unified framework, and characterizes the dynamic relationship between digital literacy accumulation and human capital formation. On this basis, the paper focuses on three questions. First, how does an increase in online education productivity affect the digital literacy, human capital, and income gaps of households at different income levels through changes in educational service prices and the reallocation of household educational investment? Second, when human capital conversion efficiency changes, how do the adjustment processes of different income households affect the dynamic evolution of the income gap? Third, can adjusting the elasticity of substitution across educational services and raising the digital literacy accumulation efficiency of low-income households improve their human capital accumulation and alleviate the pressure of widening income inequality? In addition, this paper uses PISA 2022 microdata to examine the association between digital learning activities and student academic achievement and its income heterogeneity, providing supplementary micro-level evidence for the household differences emphasized by the model.

This paper contributes to the literature in three ways. First, it incorporates the substitution relationship among educational services into the dynamic general equilibrium analysis of heterogeneous households, revealing the resource allocation mechanism through which digital education technology progress affects income distribution. Second, it links digital literacy accumulation with human capital formation, emphasizing that the economic effect of educational investment depends not only on the cost of resource access but also on households' ability to convert digital learning into effective human capital. Third, it compares the effects of adjusting the substitution structure of educational services and raising the digital literacy accumulation efficiency of low-income households through policy simulations, and combines PISA microdata to examine the income heterogeneity of the relationship between digital learning activities and academic achievement, providing theoretical analysis and empirical reference for understanding the distributional effects of digital education and related policy design.

2. Literature Review

2.1 Education, Human Capital, and Income Inequality

Education is an important channel through which family background affects long-term individual income. Becker and Tomes (1976, 1979), starting from household human capital investment and credit constraints, point out that differences in household resource endowments affect children's educational investment and may further translate into human capital and income gaps. Becker and Tomes (1986) further discuss the relationship between returns to human capital, family economic conditions, and intergenerational mobility. These studies show that education is not only an important investment for improving individual ability, but also a key link connecting family resource endowments, human capital formation, and income distribution.

Regarding the dynamic formation of human capital, Cunha and Heckman (2007, 2008) emphasize that ability formation has the characteristic of dynamic accumulation, with dynamic complementarity between investments at different stages, and the ability base formed in early stages affects the marginal return of subsequent investments. This means that differences in initial household endowments may affect individual long-term development through continuous human capital accumulation. Chetty et al. (2014) find that childhood neighborhood environment has a long-term relationship with adult income; Chetty et al. (2022) further examine the relationship between social environment and upward mobility from the perspective of economic connectedness. Domestic studies also find that digital infrastructure can improve upward intergenerational income mobility among rural residents (Fang et al., 2023).

Overall, existing research reveals the intrinsic link between education and income inequality from the perspectives of household resource constraints, educational investment, and dynamic ability accumulation. However, the economic consequences of educational investment depend not only on the scale of investment, but may also be affected by the way educational resources are supplied and the allocation relationship among different forms of education. With the development of digital education forms such as online education, the educational service choices faced by households have changed, and their impact on traditional educational investment, human capital accumulation, and long-term income deserves further study.

2.2 Technical Change, Digital Education, and Income Distribution

The impact of technological progress on income distribution exhibits significant heterogeneity. Acemoglu (2002) proposes the theory of skill-biased technical change, pointing out that technological progress can change the relative demand for workers of different skills, thereby affecting the wage structure. Acemoglu and Autor (2011) further incorporate technological progress, task allocation, and human capital into a unified analytical framework. Autor et al. (2003) find that computer capital can substitute for some routine tasks while complementing non-routine cognitive tasks. Autor et al. (2008) and Goldin and Katz (2008), starting from the relationship between technology demand and education supply, analyze changes in the skill premium and wage inequality. Autor (2015) further points out that automation may simultaneously produce labor substitution, task creation, and human-machine complementarity effects, indicating that the distributional outcome of technological progress depends on the degree of matching between technological characteristics and the abilities of different groups. In recent years, domestic research has also begun to pay attention to the differentiated impact of artificial intelligence technology on employment and income distribution (Chen et al., 2024; Liu and Yuan, 2026).

The above studies mainly focus on how technological progress changes the task structure, skill demand, and labor income in the production process, whereas digital education technology directly acts on the supply of educational resources and household learning activities. Digital education forms such as online courses can reduce the cost of accessing certain educational resources and expand households' educational choices, but their actual effects are still influenced by factors such as learning investment, usage ability, and family background. The study by Bettinger et al. (2017) on the effectiveness of online education, and the study by Bettinger et al. (2022) on the digital divide, provide relevant evidence for understanding the actual effects of digital education. Studies during the pandemic also find that online learning may cause learning losses, and that students from different socioeconomic backgrounds are affected differently (Jackman et al., 2020; Kuhfeld et al., 2020).

It follows that the popularization of digital education technology does not mean that its benefits can be equally distributed across households. However, unlike general technological progress, which primarily changes skill demand in the labor market, digital education technology may also affect households' allocation of investment among school education, online education, and offline tutoring by changing the relative costs of educational services. Different households differ in their dependence on educational

services and their learning abilities; therefore, higher online education productivity may generate different household educational investment responses, further affecting human capital formation and income distribution. How to connect this resource allocation process with long-term income inequality is a question that still requires in-depth exploration in existing research.

2.3 Digital Literacy and Educational Service Supply Structure

The availability of digital education resources is not equivalent to effective learning ability. Whether digital technology can improve educational outcomes also depends on whether individuals can effectively use digital tools, screen information, and convert learning activities into actual capabilities. Hargittai (2007) points out that the digital divide is no longer merely a difference in technology access, but also involves usage skills and the ability to derive actual benefits from digital technology. van Deursen et al. (2011) emphasize that digital skills have levels, and different types of skills need to be formed through continuous learning and practice; van Deursen and van Dijck (2019) further discuss digital skills from the dimensions of operation, information, communication, and problem solving. These studies indicate that digital literacy not only affects individuals' ability to use digital resources, but may also affect the actual returns on digital education investment.

At the same time, the development of digital education may also change the way households allocate educational services. Online courses, school education, and offline tutoring are not necessarily independent of each other, and changes in their relative prices and learning effects may affect household educational choices. Schwerdt and Wößmann (2017) examine the effectiveness of private tutoring, and Hulleman et al. (2010) study the relationship between out-of-school learning investment and academic performance, suggesting that the effectiveness of educational investment may vary with group characteristics and investment methods. The adjustment of the supply of subject-based after-school tutoring by China's "Double Reduction" policy also reflects the connection between changes in the education supply structure and the allocation of household educational investment.

Taken together, the distributional effects of digital education may depend on two interrelated aspects: first, the substitution relationship among educational services, that is, how households adjust their investment in different educational services after changes in online education costs or productivity; second, the accumulation of digital literacy and its impact on effective learning, that is, whether households can

convert digital education resources into actual human capital returns. When households at different income levels differ in their choice of educational services and in digital literacy accumulation, the same digital education technology progress may produce different educational investment responses and human capital outcomes. Therefore, it is necessary to combine the allocation of educational services with digital literacy accumulation to examine the heterogeneous distributional effects of digital education technology progress.

2.4 Heterogeneous-Agent DSGE Models and Education

Educational investment and human capital formation have the characteristic of intertemporal decision-making, and generate general equilibrium effects through channels such as labor income and household resource allocation. Dynamic stochastic general equilibrium (DSGE) models can incorporate household decisions, market prices, and macroeconomic outcomes into a unified framework, providing a theoretical tool for analyzing education policy and its distributional effects. Leeper et al. (2017) incorporate private educational investment into the DSGE framework and analyze the relationship between public education quality and private education expenditure, providing an important foundation for studying the macroeconomic impact of educational investment.

At the same time, household heterogeneity is an important prerequisite for understanding differences in income distribution. Ichino (2011) introduces heterogeneous agents into DSGE analysis, and Han, Lu and Wright (2016) discuss the impact of agent heterogeneity on macroeconomic dynamics. These studies suggest that differences across households in initial resource endowments and decision-making behavior may alter the transmission process of policy shocks. Therefore, when studying the income distribution effects of digital education, examining only the average response of a representative household is insufficient to fully reflect differences in educational choices, human capital accumulation, and income changes across income groups.

Existing research provides a methodological foundation for incorporating educational investment and household heterogeneity into a dynamic general equilibrium framework, but the digital education context also involves specific mechanisms such as changes in the relative costs of educational services, reallocation of household educational investment, and dynamic accumulation of digital literacy. Higher online education productivity may not only affect the price of online education, but also change household demand for other educational services; differences in digital literacy accumulation across households may

further affect the conversion of educational investment into human capital, and feed back into household income distribution through labor income. Therefore, it is necessary to construct a DSGE model that simultaneously characterizes heterogeneous households, educational service choice, digital literacy accumulation, and human capital formation, in order to analyze the dynamic transmission mechanism and distributional consequences of digital education technology shocks.

2.5 Discussion of the Literature

In summary, existing research provides an important foundation for understanding education and income inequality from the perspectives of household educational investment, dynamic human capital accumulation, the distributional effects of technological progress, digital literacy, and educational service supply. However, three research gaps remain. First, while the link between educational investment and income distribution is well established, fewer studies examine how digital education technology reshapes the allocation of investment across different educational services and thereby affects human capital accumulation differently across income groups. Second, although digital literacy research emphasizes the importance of digital technology usage ability, the dynamic interplay between literacy accumulation and household educational choices in shaping human capital formation warrants further analysis in a general equilibrium framework. Third, learning outcomes from digital education may vary by family background, but partial evidence on learning results cannot fully capture the dynamic relationships among educational service prices, household investment, human capital, and income distribution.

To address these gaps, this paper constructs a DSGE model with three types of heterogeneous households—high-, middle-, and low-income—and three types of education—school education, online education, and offline tutoring. The model incorporates the substitution relationship among educational services and the dynamic accumulation of digital literacy into a unified analytical framework, and examines the impact of online education productivity shocks on educational investment, human capital accumulation, and income inequality across households at different income levels. On this basis, the paper analyzes the effects of policy interventions—adjusting the elasticity of substitution across educational services and raising the digital literacy accumulation efficiency of low-income households—through simulation exercises, and uses PISA 2022 microdata to provide supplementary micro-level evidence on the income heterogeneity of the association between digital learning activities and academic achievement.

3. Model Construction of Digital Education and Income Inequality

3.1 Overview of the Model

To investigate the impact of digital education on human capital accumulation and income inequality across income groups, this paper constructs a dynamic stochastic general equilibrium (DSGE) model that includes heterogeneous households, an education service supply sector, a government sector, and a final goods sector. The model incorporates household income heterogeneity, digital literacy accumulation, and multiple types of educational investment into a unified analytical framework, focusing on characterizing the mechanism through which digital education affects the distribution of labor income by changing the efficiency of household educational investment and the process of human capital accumulation.

Households in the model are divided into three types: high-income, middle-income, and low-income, denoted as $iinH, M, L$. The population share of each type is λ_i, satisfying $\Sigma_i \lambda_i = 1$. Different types of households differ in initial human capital, family background, education preferences, and digital literacy. Under budget and time constraints, households choose consumption, labor supply, educational service purchases, and the allocation of study time, and accumulate digital literacy and human capital through educational investment.

The education service supply sector consists of three parts: public education, online education, and offline tutoring. Public education supply follows an exogenous process, and its price adjusts according to the relative relationship between demand and supply. Online education and offline tutoring are each provided by corresponding production technologies and priced under competitive market conditions. The government participates in resource allocation through labor income taxes, consumption taxes, and transfer payments to low-income households, and bears public education expenditure. The final goods sector produces final goods for household consumption. The labor market and product markets clear through the interaction of household decisions and firm production.

The model is built along four dimensions: the household sector, the education service supply sector,

the government sector, and market clearing conditions, to analyze the impact of digital education on human capital accumulation and income inequality across different income groups.

3.2 Household Sector

3.2.1 Household Utility Function

There are three types of households in the economy: high-income, middle-income, and low-income. The household type is denoted as $iinH, M, L$, and the population share of each type is λ_i, satisfying:

$$\lambda_H + \lambda_M + \lambda_L = 1 \tag{1}$$

Different types of households differ in income level, initial human capital, family background, and educational preferences. Household utility is jointly determined by consumption, education level, and leisure. Considering the substitution relationship between household labor supply and study time, the utility function of household i in period t is specified as:

$$U_t{}^i = lnC_t{}^i + \theta_i lnE_t{}^i - \chi_i \frac{(L_t{}^i)^{1+\varphi}}{1+\varphi} \tag{2}$$

where $C_t{}^i$ denotes household consumption, $E_t{}^i$ denotes composite educational investment, and $L_t{}^i$ denotes labor time; θ_i is the education preference parameter, χ_i is the utility weight of labor supply, and φ is the inverse elasticity of labor supply parameter.

This specification reflects the trade-off households face in allocating resources among consumption, education, and labor. Increasing educational investment helps improve the level of education, but purchasing educational services requires expenditure, and learning activities also take up time that could be used for work. Therefore, differences across households in income constraints, educational preferences, and digital literacy will affect their educational investment choices and subsequent human capital accumulation.

Households maximize expected lifetime utility by choosing consumption, labor time, the quantity of each type of educational service purchased, and the corresponding study time:

$$max_{\{C_t{}^i, L_t{}^i, G_t{}^i, O_t{}^i, S_t{}^i, s_{G,t}{}^i, s_{O,t}{}^i, s_{S,t}{}^i\}} E_0 \sum_{t=0}^{\infty} \beta^t U_t{}^i \tag{3}$$

where $\beta in(0,1)$ is the discount factor. Household decisions are constrained by budget constraints,

time constraints, and the dynamic evolution equations of digital literacy and human capital. The first-order conditions of the household optimization problem are provided in the appendix.

3.2.2 Composite Educational Investment

To distinguish the roles of different educational channels, household educational investment is divided into three categories: public education, online education, and offline tutoring, with ${G_t}^i$, ${O_t}^i$, and ${S_t}^i$ denoting the purchase quantities of the corresponding educational services, respectively.

Considering that the three types of educational services differ in teaching methods, resource allocation, and learning effects, a constant elasticity of substitution (CES) function is used to characterize composite educational investment:

$$ {E_t}^i = [\alpha_i ({G_{t,eff}}^i)^{\frac{\sigma-1}{\sigma}} + \beta_i ({O_{t,eff}}^i)^{\frac{\sigma-1}{\sigma}} + \gamma_i ({S_{t,eff}}^i)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \quad (4) $$

where ${G_{t,eff}}^i$, ${O_{t,eff}}^i$, and ${S_{t,eff}}^i$ denote the effective investment in public education, online education, and offline tutoring, respectively; α_i, β_i, and γ_i are the corresponding weight parameters, satisfying:

$$ \alpha_i + \beta_i + \gamma_i = 1 \quad (5) $$

The parameter σ represents the elasticity of substitution across different educational channels. The CES specification allows us to characterize households' combined choice of various educational services while preserving the differences across educational channels.

3.2.3 Digital Literacy and Effective Educational Investment

The impact of digital education depends not only on the quantity of educational services purchased by households, but also on households' ability to use digital technology to access and absorb educational resources. To this end, digital literacy (also referred to as digital capability in the model) is introduced into the effective educational investment function, so that digital literacy can affect the actual educational effectiveness of different educational channels.

The effective investment in public education is:

$$ {G_{t,eff}}^i = \psi_G ({D_t}^i)^{\eta_{G,i}} ({G_t}^i)^{\mu_G} ({s_{G,t}}^i)^{1-\mu_G} \quad (6) $$

The effective investment in online education is:

$$O_{t,eff}{}^{i} = \psi_O (D_t{}^{i})^{\eta_{O,i}} (O_t{}^{i})^{\mu_O} (s_{O,t}{}^{i})^{1-\mu_O} \quad (7)$$

The effective investment in offline tutoring is:

$$S_{t,eff}{}^{i} = \psi_S (D_t{}^{i})^{\eta_{S,i}} (S_t{}^{i})^{\mu_S} (s_{S,t}{}^{i})^{1-\mu_S} \quad (8)$$

where $D_t{}^{i}$ denotes household digital literacy, and $s_{G,t}{}^{i}$, $s_{O,t}{}^{i}$, and $s_{S,t}{}^{i}$ denote the study time households allocate to public education, online education, and offline tutoring, respectively; ψ_G, ψ_O, and ψ_S are efficiency parameters; $\eta_{G,i}$, $\eta_{O,i}$, and $\eta_{S,i}$ represent the degree of influence of digital literacy on the effective investment of different educational channels, respectively; μ_G, μ_O, and μ_S are contribution parameters for the quantity of educational services purchased, all satisfying $0 < \mu_j < 1$.

The above specification indicates that the effective investment in educational services is jointly determined by the quantity of educational services purchased, study time, and household digital literacy. Even if households purchase the same quantity of educational services, the effective educational investment they ultimately form may differ due to differences in study time and digital literacy. By allowing the degree of influence of digital literacy to vary with household type and educational channel, the model can characterize the differentiated benefits that different income groups obtain from digital education.

3.2.4 Household Time Constraint

Households allocate their disposable time to labor and three types of educational activities. Normalizing total household disposable time to 1, the household time constraint is:

$$L_t{}^{i} + s_{G,t}{}^{i} + s_{O,t}{}^{i} + s_{S,t}{}^{i} = 1 \quad (9)$$

where $L_t{}^{i}$ is labor time, and the other three terms are the study time households spend on public education, online education, and offline tutoring, respectively. This constraint reflects the time allocation relationship between household labor supply and learning activities.

3.2.5 Household Budget Constraint

Households earn income through labor, and use income for consumption, purchasing educational services, and receiving government transfer payments. The budget constraint of household i in period t is:

$$(1+\tau_c){C_t}^i + {P_{G,t}}^i {G_t}^i + P_{O,t}{O_t}^i + P_{S,t}{S_t}^i = (1-\tau_{l,t}) w_t {H_t}^i {L_t}^i + {Tr_t}^i \quad (10)$$

where τ_c is the consumption tax rate, $\tau_{l,t}$ is the labor income tax rate, w_t is the wage per unit of effective labor, ${H_t}^i$ is household human capital, and ${Tr_t}^i$ is the transfer payment provided by the government to households. ${P_{G,t}}^i$, $P_{O,t}$, and $P_{S,t}$ are the prices of public education, online education, and offline tutoring, respectively.

Considering that government transfer payments are mainly used to support low-income households:

$${Tr_t}^H = {Tr_t}^M = 0, {Tr_t}^L \geq 0 \quad (11)$$

In the model, households need to pay corresponding fees for public education services, and the price is determined by the pricing rule of the public education supply sector. Households trade off consumption and different types of education expenditure under budget constraints, thereby forming differentiated educational investment choices.

3.2.6 Digital Literacy Accumulation

Household digital literacy changes over time. This paper treats digital literacy as a state variable that can be accumulated through educational activities, and its dynamic evolution equation is specified as:

$${D_{t+1}}^i = (1-\delta_{D,i}){D_t}^i + \nu_G {s_{G,t}}^i + \nu_{O,i} {s_{O,t}}^i + \nu_S {s_{S,t}}^i \quad (12)$$

where $\delta_{D,i}$ is the digital literacy depreciation rate, and ν_G, $\nu_{O,i}$, and ν_S represent the degree of contribution of the three types of educational activities to digital literacy accumulation, respectively.

This specification implies that households' existing digital literacy is subject to depreciation but can also be supplemented through participation in educational activities. Among them, online education study time directly participates in the digital literacy accumulation process, thereby linking household educational choices with changes in digital literacy. Combined with the effective educational investment function described above, the dynamic change in digital literacy further affects households' efficiency in using educational resources in subsequent periods.

3.2.7 Human Capital Accumulation

Household human capital is an important determinant of labor income. To characterize the relationship between educational investment, family background, and human capital accumulation, the

dynamic evolution equation of household human capital is specified as:

$$H_{t+1}{}^{i} = (1-\delta_H)H_t{}^{i} + A(X^i)^{\nu}(E_t{}^{i})^{\gamma} + B(X^i)^{\kappa} \quad (13)$$

where $H_t{}^{i}$ is household human capital, δ_H is the human capital depreciation rate, X_i denotes family background, and A, B, ν, γ, and κ are relevant parameters.

The first term on the right-hand side of the equation represents the stock of existing human capital after depreciation; the second term represents the contribution of composite educational investment to human capital accumulation, and allows family background to affect the conversion of educational investment into human capital; the third term represents the direct effect of family background on human capital accumulation.

Through this specification, educational investment can not only affect households' current educational level, but also change future labor income through human capital accumulation. Because different households differ in family background, educational investment, and digital literacy, the impact of digital education on human capital may exhibit different group characteristics.

3.2.8 Household Labor Income

Household labor income is jointly determined by wages, human capital, and labor time:

$$Y_t{}^{i} = w_t H_t{}^{i} L_t{}^{i} \quad (14)$$

where $Y_t{}^{i}$ denotes household pre-tax labor income. After deducting the labor income tax, the labor income available for household consumption and education expenditure is $(1-\tau_{l,t})Y_t{}^{i}$.

Thus, household labor income is affected both by the wage level and labor time, and by the state of household human capital accumulation. Digital education may further alter the labor income and relative gaps of different income groups by affecting households' effective educational investment and human capital accumulation.

3.3 Education Service Supply Sector

The supply of educational services is divided into three sectors: public education, online education, and offline tutoring. Different sectors have different supply methods and price formation mechanisms, reflecting differences in resource allocation and technological conditions across educational channels.

3.3.1 Public Education

Public education supply is determined by an exogenous process:

$$G_{s,t} = \overline{G_s} exp(g_t) \tag{15}$$

where $\bar{G}$ is the steady-state level of public education supply, and $\hat{g}_t$ represents the fluctuation of public education supply relative to the steady state. Its dynamic process is specified as:

$$g_t = \rho_g g_{t-1} + \varepsilon_{g,t} \tag{16}$$

where ρ_g is the autoregressive coefficient and $varepsilon_{g,t}$ is the public education supply shock.

Total household demand for public education is:

$$G_{d,t} = \sum_{i \in \{H,M,L\}} \lambda_i {G_t}^i \tag{17}$$

The price of public education adjusts according to the relative relationship between total demand and exogenous supply, specified as:

$${P_{G,t}}^i = \overline{P_G}(1 + \delta_i)(\frac{G_{d,t}}{G_{s,t}})^{\xi} \tag{18}$$

where $\bar{P}_G$ is the baseline level of the public education price, δ_i is the price adjustment parameter corresponding to different types of households, and ξ is the sensitivity of price to changes in the supply-demand ratio.

The above specification causes the public education price to be simultaneously affected by public education demand, supply changes, and household type differences. It should be noted that public education supply follows an exogenous process and reflects the supply-demand relationship through a price adjustment rule, rather than imposing a separate market clearing condition.

3.3.2 Online Education

The online education sector provides educational services using digital platforms. Let the total supply of online education services be:

$$O_t = {A_{O,t}}^{eff} N_{O,t} \tag{19}$$

where $N_{O,t}$ is the labor input used by the online education sector, and ${A_{O,t}}^{eff}$ is the effective productivity after accounting for platform scale effects, specified as:

$$A_{O,t}{}^{eff} = A_{O,t} N_{t-1}{}^{\rho} \tag{20}$$

where $A_{O,t}$ is the basic productivity of online education, N_{t-1} is the platform user scale in the previous period, and ρ is the platform scale effect parameter. This specification reflects that the scale of platform users may affect the effective productivity of online education through network effects.

The platform user scale evolves according to the following equation:

$$N_t = (1 - \delta_N) N_{t-1} + \sum_{i \in \{H,M,L\}} \lambda_i O_t{}^{i} \tag{21}$$

where δ_N is the user scale attrition rate, and $\Sigma_i \lambda_i O_t{}^{i}$ represents the weighted total of online education service demand from all types of households in the current period.

The basic productivity of online education follows a log-AR(1) process:

$$lnA_{O,t} = (1 - \rho_O) ln\overline{A_O} + \rho_O lnA_{O,t-1} + \varepsilon_{O,t} \tag{22}$$

where $\bar{A}_O$ is the steady-state productivity, ρ_O is the autoregressive coefficient, and $varepsilon_{O,t}$ is the online education productivity shock.

Assuming the online education sector operates in a competitive market, its profit function is:

$$\Pi_{O,t} = P_{O,t} A_{O,t}{}^{eff} N_{O,t} - w_t N_{O,t} \tag{23}$$

Under perfect competition, firms choose labor input according to the profit maximization principle. From the first-order condition, the online education price is obtained as:

$$P_{O,t} = \frac{w_t}{A_{O,t}{}^{eff}} \tag{24}$$

Thus, the online education price depends on the wage level and the effective productivity of online education. Platform scale effects and productivity changes can affect the online education price through effective productivity, and further affect the online education investment choices of different types of households.

3.3.3 Offline Tutoring

The offline tutoring sector provides educational services using labor input, and its total supply function is specified as:

$$S_t = A_{S,t} N_{S,t} \tag{25}$$

where S_t is the total supply of offline tutoring services, $N_{S,t}$ is the sector's labor input, and $A_{S,t}$ is the productivity of offline tutoring.

Offline tutoring productivity follows a log-AR(1) process:

$$lnA_{S,t} = (1-\rho_S)ln\overline{A_S} + \rho_S lnA_{S,t-1} + \varepsilon_{S,t} \tag{26}$$

where $\bar{A}_S$ is the steady-state productivity, ρ_S is the autoregressive coefficient, and $varepsilon_{S,t}$ is the offline tutoring productivity shock.

Assuming the offline tutoring sector is in a perfectly competitive market, its profit maximization condition is:

$$P_{S,t}A_{S,t} = w_t \tag{27}$$

From this, the price of offline tutoring services is obtained as:

$$P_{S,t} = \frac{w_t}{A_{S,t}} \tag{28}$$

Combined with the online education price equation, the relative price of the two types of educational services can be obtained:

$$\frac{P_{O,t}}{P_{S,t}} = \frac{A_{S,t}}{A_{O,t}{N_{t-1}}^{\rho}} \tag{29}$$

This equation indicates that, given other conditions, the relative price of the two types of educational services depends on their productivity and the scale effect of the online education platform. Price changes in online education and offline tutoring will affect households' resource allocation across different educational channels.

3.4 Government Sector

The government raises fiscal revenue by levying labor income taxes and consumption taxes, and bears public education expenditure and transfer payments to low-income households. This paper links taxes, education fees, and transfer payments through the government budget constraint to characterize the impact of government fiscal policy on household resource allocation.

3.4.1 Government Expenditure and Revenue

Let government public education expenditure be:

$$G_t{}^{gov} = \overline{P_G} G_{s,t} \tag{30}$$

where $G_t{}^{gov}$ denotes government public education expenditure, and $G_{s,t}$ is the quantity of public education supply.

Considering that households need to pay fees for public education services, and assuming that the relevant education fees are collected by the government, the government's public education fee revenue is:

$$R_t{}^{G} = \sum_{i\in\{H,M,L\}} \lambda_i P_{G,t}{}^{i} G_t{}^{i} \tag{31}$$

The weighted total consumption of all types of households is:

$$C_t = \sum_{i\in\{H,M,L\}} \lambda_i C_t{}^{i} \tag{32}$$

The weighted pre-tax labor income in the economy is:

$$Y_t{}^{lab} = w_t \sum_{i\in\{H,M,L\}} \lambda_i H_t{}^{i} L_t{}^{i} \tag{33}$$

3.4.2 Government Transfer Payment Rules

To reflect the government's income support for low-income households, this paper specifies that transfer payments are related to the human capital gap between high- and low-income households:

$$Tr_t{}^{L} = max\{0, \rho_{Tr} Tr_{t-1}{}^{L} + \varphi[\frac{H_t{}^{H} - H_t{}^{L}}{H_t{}^{L}} - gap_{target}]\} \tag{34}$$

where $Tr_t{}^{L}$ is the transfer payment provided by the government to low-income households, ρ_{Tr} is the persistence parameter of transfer payments, $varphi$ is the response coefficient of transfer payments to changes in the human capital gap, and gap^{target} is the target gap parameter.

This rule causes transfer payments to adjust with changes in the relative human capital gap between high- and low-income households. When the gap is above the target level, transfer payments tend to increase; at the same time, a non-negativity constraint ensures that transfer payments do not fall below zero.

3.4.3 Government Budget Constraint

Government revenue consists of labor income tax, consumption tax, and public education fees, while

expenditures include public education expenditure and transfer payments to low-income households. The government budget constraint is:

$$\tau_{l,t} Y_t^{lab} + \tau_c C_t + R_t^{G} = G_t^{gov} + Tr_t^{L} \tag{35}$$

where the consumption tax rate τ_c is taken as a given parameter, and the labor income tax rate $\tau_{l,t}$ adjusts endogenously according to the government budget constraint. This fiscal arrangement incorporates public education expenditure, household education fees, consumption tax revenue, and transfer payments into a unified accounting framework, linking government fiscal revenue and expenditure with the resource allocation of the household sector.

3.5 Final Goods Sector and Market Clearing

To connect household labor supply, education service production, and final consumption, this paper introduces a final goods sector and describes the resource allocation relationship in the economy through the clearing conditions of the goods market and labor market.

3.5.1 Final Goods Sector

Assuming final goods are produced by competitive firms, the production function is:

$$Y_t = A_{Y,t} N_{Y,t} \tag{36}$$

where Y_t is the output of final goods, $A_{Y,t}$ is the labor productivity of the final goods sector, and $N_{Y,t}$ is the labor input of this sector.

To simplify the model, assume that the productivity of the final goods sector is constant, $A_{Y,t} = \bar{A}_Y$, and normalize the price of final goods to 1. Firms choose labor input according to the profit maximization principle, yielding:

$$w_t = \overline{A_Y} \tag{37}$$

Therefore, the labor productivity of the final goods sector determines the wage level per unit of effective labor. Under this specification, the wage does not change with factors other than the productivity of the final goods sector, while household labor income is still affected by differences in human capital and labor time.

3.5.2 Goods Market Clearing

Final goods are used to satisfy household consumption demand. Considering the population shares of the three types of households, the final goods market clearing condition is:

$$Y_t = \sum_{i\in\{H,M,L\}} \lambda_i {C_t}^i \tag{38}$$

The online education market clearing condition is:

$$\sum_{i\in\{H,M,L\}} \lambda_i {O_t}^i = O_t = {A_{O,t}}^{eff} N_{O,t} \tag{39}$$

The offline tutoring market clearing condition is:

$$\sum_{i\in\{H,M,L\}} \lambda_i {S_t}^i = S_t = A_{S,t} N_{S,t} \tag{40}$$

Public education supply follows the exogenous process described earlier, and its price adjusts according to the relative relationship between public education demand and supply; therefore, no separate market clearing condition is imposed.

3.5.3 Labor Market Clearing

Households earn income by providing labor, while the final goods, online education, and offline tutoring sectors use labor input for production. Assuming that labor inputs in all sectors are measured in effective labor units, the labor market clearing condition is:

$$\sum_{i\in\{H,M,L\}} \lambda_i {H_t}^i {L_t}^i = N_{Y,t} + N_{O,t} + N_{S,t} \tag{41}$$

where the left-hand side represents the weighted total effective labor provided by all types of households, and the right-hand side represents the labor demand of the final goods, online education, and offline tutoring sectors, respectively. This condition connects household labor supply with the labor demand of each production sector.

In summary, this paper establishes a dynamic analytical framework for the impact of digital education on household educational investment and human capital accumulation through household decision equations, education service supply equations, government fiscal constraints, and product and labor market clearing conditions. Under this framework, digital literacy affects households' effective use of educational

resources, the supply technology and prices of different educational channels affect household educational choices, and educational investment and family background jointly affect human capital accumulation, ultimately affecting the labor income and its gap among different income groups.

4. Calibration

To ensure that the model has reasonable steady-state characteristics and can capture the heterogeneity of households at different income levels in educational choice, digital literacy accumulation, and human capital formation, this paper calibrates the model parameters. Parameter values are determined based on three types of information: first, reference to existing theoretical and empirical studies; second, steady-state targets determined according to data characteristics such as Chinese household income, education consumption, and time use; third, heterogeneity parameters set in combination with the research mechanism of this paper. For parameters lacking direct empirical estimates, they are set under the premise of ensuring the feasibility of the model's steady state and reasonable economic meaning, and their distributional effects are examined through policy simulations later. Details are provided in Table 1.

Table 1. Calibration of Model Structural Parameters

Parameter	Definition	High-Income	Middle-Income	Low-Income	Calibration Source
β	Discount factor	0.985	0.985	0.985	Standard in the literature
θ	Education utility weight	0.25	0.25	0.25	Steady-state education expenditure share
φ	Inverse Frisch elasticity	2.0	2.0	2.0	Chetty et al. (2011)
σ	Elasticity of substitution across education services	2.0	2.0	2.0	Goldin & Katz (2008)
ε	Price elasticity of study time	1.7	1.5	1.3	Xing et al. (2013)
α	CES weight on public education	0.15	0.30	0.60	China household education consumption structure
β	CES weight on online education	0.35	0.40	0.35	China household education consumption structure
γ	CES weight on offline	0.50	0.30	0.05	China household

Parameter	Definition	High-Income	Middle-Income	Low-Income	Calibration Source
	tutoring				education consumption structure
η_G	Digital literacy elasticity of public education	0.55	0.50	0.45	PISA 2022
η_O	Digital literacy elasticity of online education	0.35	0.30	0.25	PISA 2022
η_S	Digital literacy elasticity of offline tutoring	0.15	0.10	0.07	PISA 2022
δ_D	Digital literacy depreciation rate	0.025	0.030	0.035	PISA 2022
v_O	Digital literacy accumulation efficiency of online education	0.055	0.050	0.045	PISA 2022
λ_H	Education-to-human-capital conversion efficiency	0.140	0.130	0.115	PISA 2022
δ_H	Human capital depreciation rate	0.05	0.05	0.05	Becker & Tomes (1979); Cunha & Heckman (2007)
μ_G	Quantity contribution of public education purchases	0.3	0.3	0.3	Mechanism-based specification
μ_O	Quantity contribution of online education purchases	0.3	0.3	0.3	Mechanism-based specification
μ_S	Quantity contribution of offline tutoring purchases	0.2	0.2	0.2	Mechanism-based specification
ψ_G, ψ_O, ψ_S	Baseline conversion efficiency	1.0	1.0	1.0	Normalization
ξ	Public education supply-demand elasticity	0.30	0.30	0.30	Mechanism-based specification
ρ	Online education network effect strength	0.20	0.20	0.20	Studies on Chinese digital platforms
δ_N	Online education user retention rate	0.15	0.15	0.15	Mechanism-based specification
ρ_A	Persistence of online education productivity shock	0.60	0.60	0.60	Persistence of digital education technology shocks
ρ_{Tr}	Transfer payment smoothing parameter	0.80	0.80	0.80	Policy mechanism specification
φ_{Tr}	Transfer payment response coefficient	0.50	0.50	0.50	Policy mechanism specification
gap^{target}	Policy target gap level	0.20	0.20	0.20	Policy mechanism specification

Note: Parameters are calibrated based on existing literature, Chinese household data, and model steady-state targets. Heterogeneity parameters reflect differences across income groups in educational preferences and digital literacy accumulation.

5. Distributional Effects of Digital Education and Policy Simulations

5.1 Distributional Effects of Online Education Productivity Shocks

To investigate the income distribution effects of digital education technology progress, this paper introduces a positive productivity shock to the online education sector, assuming the shock follows a first-order autoregressive ($AR(1)$) process. In the baseline scenario, the elasticity of substitution across educational services is set to 2.0. This paper measures changes in income distribution by the deviation of the log income gap between high-income and low-income households, and between middle-income and low-income households, relative to their steady-state levels. A positive value indicates that the corresponding income gap has widened; a negative value indicates that the income gap has narrowed.

Figure 1 shows that although higher online education productivity reduces the price of educational services, it widens the income gap among households at different income levels. This indicates that digital education technology progress does not necessarily bring about improvements in income distribution; its impact also depends on the educational investment structure and digital literacy levels of different households. Specifically, the decline in online education prices prompts all three types of households to increase online education investment, but at the same time may crowd out other educational investments. Under the model specification, low-income households rely relatively more on school education, and school education has a stronger effect on digital literacy accumulation than online education. Therefore, the increase in online education investment fails to fully compensate for the losses caused by reduced school education investment, and the digital literacy of low-income households actually declines. In contrast, high-income households, relying on their relatively favorable educational investment structure and higher initial digital literacy, can more effectively convert technological progress into learning outcomes, thereby obtaining relatively greater benefits.

The decline in digital literacy also affects subsequent human capital formation through the dynamic accumulation mechanism. Simulation results show that the human capital of low-income households may still show a positive response in the early stage of the shock due to stock inertia, but then gradually turns negative and further transmits to labor income. At the same time, the income gap in Figure 1 remains

persistently above the steady-state level, indicating that the distributional effect of the online education productivity shock has a certain degree of persistence.

In summary, although online education technology progress can reduce education costs and promote an increase in online education investment, differences across households in the structure of educational investment and digital literacy may cause their benefits to be unequal, thereby widening income inequality. Therefore, the inclusive development of digital education depends not only on technological progress and the expansion of educational resources, but also on whether households at different income levels can effectively use digital education resources. Furthermore, when returns to education generally decline, will the relative advantage of high-income households weaken, and how will the income gap change? The next section examines this issue through a counterfactual scenario of declining returns to education.

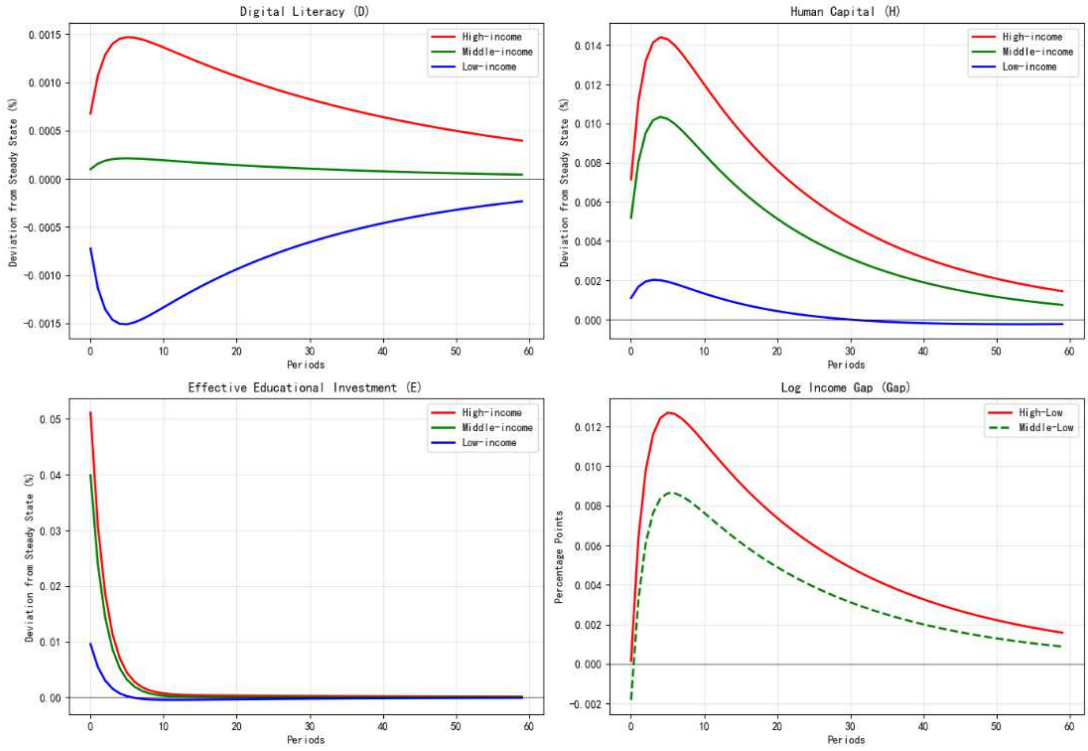


Figure 1. Distributional Effects of Online Education Productivity Shocks

5.2 Distributional Effects of Declining Returns to Education

The previous section shows that households at different income levels differ in their ability to convert educational investment into human capital, and online education technology progress may therefore widen income inequality. Furthermore, if the value of human capital formed through educational investment generally declines, will the income gap narrow accordingly? To investigate this issue, this paper constructs

a counterfactual scenario in which the human capital conversion efficiency of all households is uniformly reduced by 30%, to simulate the impact of declining returns to education.

Figure 2 shows that the impact of declining returns to education on income distribution has distinct phases. In the initial period of the shock, the income gaps between high-income and low-income households, and between middle-income and low-income households, are both below their steady-state levels; subsequently, the income gap turns positive and reaches a peak, before eventually declining as the shock gradually dissipates. This indicates that declining returns to education may narrow the income gap in the short run, but this effect is not persistent.

This pattern is related to the initial conditions and dynamic adjustment processes of households at different income levels. A decline in human capital conversion efficiency weakens the ability of all types of households to convert educational investment into human capital. In the early stage of the shock, high-income households have a higher initial level of human capital accumulation, and their absolute losses may be larger, thereby temporarily narrowing the income gap. However, as dynamic adjustment unfolds, high-income households may still maintain their relative advantage by virtue of higher initial human capital and digital literacy, while low-income households, constrained by initial conditions, may have a relatively slower adjustment process, ultimately leading to a re-widening of the income gap.

The above results indicate that a short-term narrowing of the income gap is not equivalent to an improvement in the welfare of low-income households. If the narrowing of the gap is mainly due to losses among high-income households, rather than an improvement in the development capacity of low-income households, then such a change is unlikely to produce sustained distributional improvement. Therefore, declining returns to education are not a reliable mechanism for narrowing income inequality. In contrast, enhancing the ability of low-income households to convert educational investment into effective learning and human capital is an important direction for promoting the inclusive development of digital education.

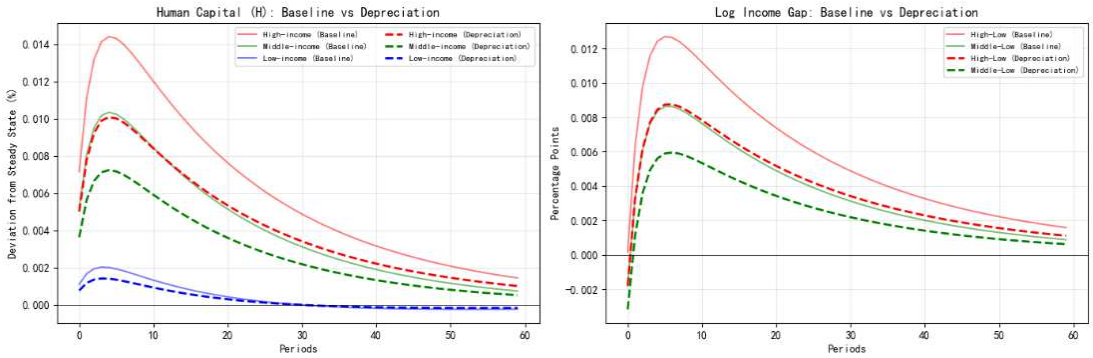


Figure 2. Distributional Effects of Declining Returns to Education

5.3 Pathways and Conditions for Inclusive Digital Education Development

The previous two sections show that online education technology progress may widen income inequality by changing the structure of household educational investment, while the short-term narrowing of the gap caused by declining returns to education does not mean that the situation of low-income households has improved. Therefore, digital education policy needs not only to promote the development of education technology, but also to optimize the structure of education supply and enhance the ability of low-income households to use digital education resources. This paper examines the policy effects of reducing the elasticity of substitution across educational services, raising the digital literacy accumulation efficiency of low-income households, and a combination of both.

First, this paper reduces the elasticity of substitution across educational services from 2.0 in the baseline scenario to 1.0, to examine the impact of reducing the degree of substitution among different forms of education. Simulation results show that the digital literacy and human capital of all three types of households turn positive, with the human capital of low-income households shifting from a negative response in the baseline scenario to positive. This indicates that reducing the elasticity of substitution across educational services can alleviate the crowding-out of school education by online learning, enabling low-income households to accumulate digital literacy and human capital more effectively. However, the improvement in the absolute level of low-income households does not simultaneously translate into a narrowing of the relative income gap, suggesting that optimizing the education supply structure alone is still insufficient to reverse the trend of widening income inequality.

Second, this paper increases the digital literacy accumulation efficiency parameter of low-income households from 0.045 to 0.060, to examine the policy effect of enhancing their ability to utilize digital education. The results show that the magnitude of the negative response of low-income households' digital literacy and human capital is reduced, but has not yet turned positive. This means that improving digital literacy accumulation efficiency can alleviate the adverse effects faced by low-income households, but if the structure of educational investment is not adjusted accordingly, losses caused by the crowding-out of school education may still limit the policy effect.

Finally, this paper simultaneously reduces the elasticity of substitution across educational services and raises the digital literacy accumulation efficiency of low-income households, to examine the synergistic

effects of the two policies. Simulation results show that under the combined policy, the digital literacy and human capital of all three types of households respond positively, and the human capital of low-income households also shifts from a negative response in the baseline scenario to positive, with their absolute level significantly improved. However, the widening of the income gap under the combined policy is roughly comparable to the scenario of reducing the substitution elasticity alone, and the relative income gap still has not narrowed. This indicates that improving the human capital accumulation conditions of low-income households does not necessarily change the relative benefit distribution across income groups.

Taken together, the three sets of policy simulations show that optimizing the education supply structure can reduce losses caused by the substitution of educational investment, while raising digital literacy accumulation efficiency helps enhance the ability of low-income households to use digital education resources, and the combination of the two can further improve the human capital accumulation of low-income households. But these policy effects are still insufficient to eliminate the trend of widening relative income inequality. Therefore, evaluating the effectiveness of digital education policy requires attention to both the absolute improvement of educational conditions and human capital for low-income households, and the relative benefit changes among different income groups.

Furthermore, optimizing the education supply structure and enhancing digital literacy can also be combined with income redistribution policies. Since this paper has not yet characterized the specific impact of transfer payments on the allocation of household education budgets, the existing simulations cannot directly determine the effects of redistribution policies. Future research can further introduce the transmission mechanism between transfer payments and household education decisions, examining whether fiscal support can alleviate the educational investment constraints of low-income households, and whether different policies can form synergies, thereby balancing the improvement of living standards for low-income households and the narrowing of the income gap.

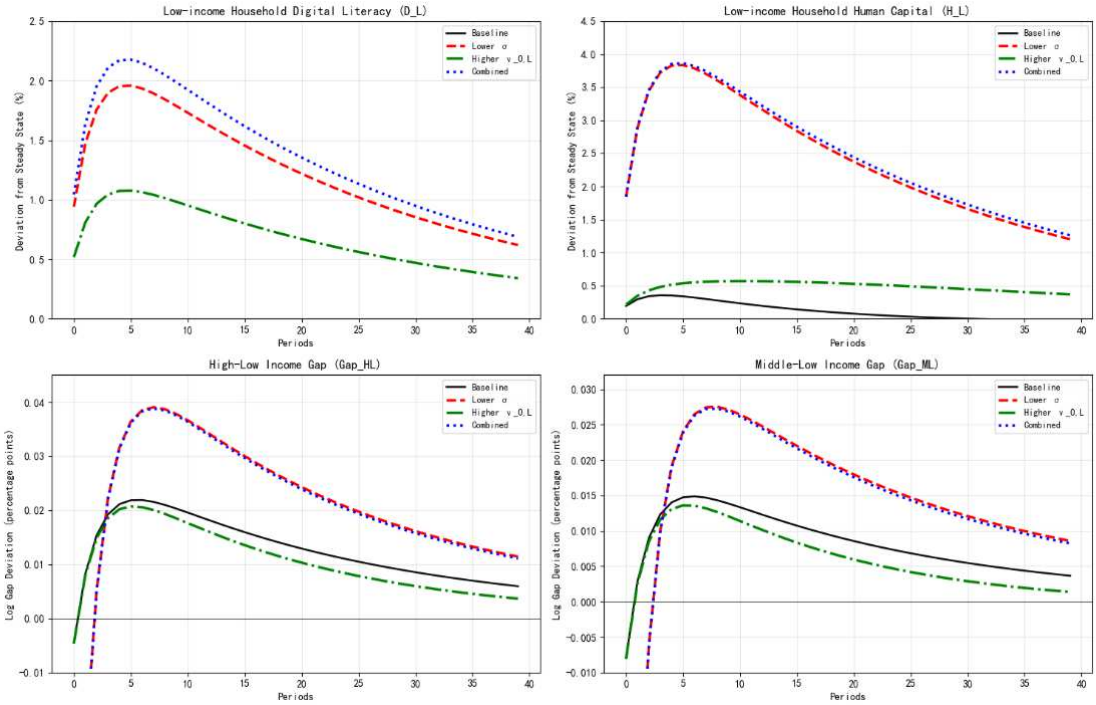


Figure 3. Pathways and Conditions for Inclusive Digital Education Development

6. Empirical Evidence on Digital Education and Income Inequality

6.1 Data and Variables

This paper uses PISA 2022 data to test whether there is income heterogeneity in the returns to digital learning. PISA 2022 covers 80 countries and economies and approximately 610,000 15-year-old students. This paper integrates student questionnaires, ICT questionnaires, and cognitive test scores. After excluding observations with missing key variables, the final sample consists of 303,305 students across 47 countries and economies. The PISA data are cross-sectional.

The dependent variable is mathematics achievement. PISA uses a matrix sampling design, in which each student completes only a subset of test items, and 10 plausible values ($PV1MATH$–$PV10MATH$) are generated by item response theory. This paper estimates regressions using all 10 plausible values separately, and combines coefficients and standard errors according to Rubin's rules. The key explanatory variable is the digital learning index ($digital\ \ _{i}ndex$), constructed and standardized using principal component analysis based on digital activities related to learning purposes in items $IC170$ and $IC171$.

The moderator variable is a low-income dummy (low_income), defined as the bottom 25% of $ESCS$. Control variables include gender, relative grade, and grade repetition. All regressions are weighted using the student final weight W_FSTUWT, and standard errors are clustered at the country level.

Table 2. Variable Definitions and Descriptive Statistics

Variable	Definition	Mean	Std. Dev.	Min	Max
PV1MATH	Mathematics score	466.88	99.88	128.70	943.04
PV1READ	Reading score	464.05	106.21	35.46	938.68
PV1SCIE	Science score	476.99	102.49	74.63	902.72
digital_index	Digital learning index (standardized)	0.01	0.99	-2.63	3.01
ESCS	Economic, social and cultural status index	-0.18	1.05	-6.84	7.38
low_income	Low-income dummy	0.21	0.40	0	1
female	Gender (female = 1)	0.49	0.50	0	1
GRADE	Relative grade (standardized)	-0.07	0.55	-3	4
REPEAT	Grade repetition	0.08	0.28	0	1

6.2 Empirical Strategy

This paper employs an interaction-term regression to test the income heterogeneity of digital learning returns:

$$Y_{ic} = \alpha + \beta_1 Digital_{ic} + \beta_2 LowIncome_{ic} + \beta_3 (Digital_{ic} \times LowIncome_{ic}) + \gamma' X_{ic} + \delta_c + \varepsilon_{ic} \quad (42)$$

where Y_{ic} is the mathematics achievement of student i in country c, and δ_c is the country fixed effect. β_1 is the marginal effect for the high-income group, $\beta_1 + \beta_3$ is the marginal effect for the low-income group, and β_3 is the difference between the two groups. If β_3 is significantly negative, it indicates that the academic returns to digital learning are significantly lower for low-income households.

6.3 Empirical Results

Table 3 reports the main regression results. Column (1) includes only the digital learning index, with a coefficient of 5.309, significantly positive at the 1% level. Column (2) adds the low-income dummy, with a coefficient of -43.002, significantly negative at the 1% level, indicating that students in the low-income group have significantly lower mathematics achievement. Column (3) adds the interaction term: the coefficient on the digital learning index is 3.928, significantly positive at the 1% level; the

interaction term coefficient is -2.941, with a standard error of 1.353, significantly negative at the 5% level.

The interaction term is significantly negative. According to the estimation results in column (3), for each one-standard-deviation increase in the digital learning index, mathematics achievement increases by 3.928 points for the high-income group ($SE = 1.055,\ p < 0.01$); the marginal effect for the low-income group is:

$$\hat{\beta}_1 + \hat{\beta}_3 = 3.928 - 2.941 = 0.987 \tag{43}$$

A linear combination test shows that the standard error of this marginal effect is 1.528, $p = 0.522$, which is not significantly different from zero at conventional significance levels. This means that the conditional association between digital learning and mathematics achievement for the low-income group is not only significantly weaker than for the high-income group, but also statistically indistinguishable from zero itself. Digital learning has almost no detectable positive association with the academic achievement of students from low-income households.

This paper further conducts robustness checks by replacing the dependent variable, using split samples, and replacing the construction method of the digital learning index. The direction of the interaction term is consistent, and some tests reach the 10% significance level. Detailed results are provided in the appendix table.

Table 3. Digital Learning, Household Income, and Academic Achievement

Variable	(1)	(2)	(3)
digital_index	5.309***	2.995***	3.928***
	(1.092)	(1.053)	(1.055)
low_income	—	-43.002***	-43.251***
	—	(2.641)	(2.491)
digital_index × low_income	—	—	-2.941**
	—	—	(1.353)
female	14.541***	13.386***	13.402***
	(1.784)	(1.939)	(1.952)
GRADE	19.880***	18.816***	18.842***
	(2.209)	(2.075)	(2.092)
REPEAT	-52.122***	-48.000***	-48.132***
	(4.684)	(4.244)	(4.221)
Country FE	Yes	Yes	Yes

N	303,305	303,305	303,305
R^2	0.278	0.308	0.308

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

6.4 Correspondence with Model Mechanisms

The empirical results are broadly consistent with the core mechanism of the theoretical model. In the DSGE model, digital education technology shocks induce households to adjust their educational investment structure by changing the relative prices of educational services. Because low-income households have a higher weight on public education in their educational consumption, their public education time is more significantly crowded out when online education prices fall. Since the digital literacy accumulation efficiency of public education is higher than that of online education, this substitution process causes the digital literacy of low-income households to decline rather than rise, further dragging down human capital accumulation and labor income.

The significantly negative interaction term in the PISA data, along with the marginal effect for the low-income group being close to zero, is consistent with the direction of the above mechanism: although low-income households similarly participate in digital learning, their ability to convert digital learning into academic returns is significantly weaker. This means that an increase in digital learning activities alone is not sufficient to improve the academic performance of low-income households; the ability to convert returns is the key constraint.

7. Conclusion and Policy Implications

The development of digital education has provided new pathways for expanding access to educational resources, but its income distribution effects depend on the structure of household educational investment and digital learning capabilities. This paper constructs a dynamic stochastic general equilibrium (DSGE) model with three types of heterogeneous households—high-, middle-, and low-income—to examine the effects of online education productivity shocks, the elasticity of substitution across educational services, and digital literacy accumulation efficiency on household human capital and income inequality, and uses PISA 2022 microdata to test the income heterogeneity of the relationship between digital learning activities and academic achievement. The main conclusions are as follows.

First, online education technology progress does not necessarily narrow income inequality. Higher online education productivity can reduce education costs and promote online education investment, but may also change the structure of household educational investment. When different forms of education have a substitution relationship, low-income households may face impaired digital literacy and human capital accumulation due to the crowding-out of school education investment. Because households at different income levels differ in their ability to convert digital education resources into effective learning outcomes, the cost advantage brought by technological progress may not translate into equal educational benefits, and may further widen income inequality.

Second, the impact of declining returns to education on income distribution is dynamic. Model simulations show that a decline in human capital conversion efficiency may cause the income gap to narrow in the short run, then re-widen and gradually decline. A short-term narrowing of the gap does not mean that the absolute situation of low-income households has improved; it may also stem from differences in the shocks experienced by households at different income levels. Therefore, evaluating the distributional effects of education policy requires attention to both the relative income gap and the human capital accumulation and actual economic conditions of different households.

Third, optimizing the education supply structure and improving digital literacy accumulation efficiency help to improve the human capital accumulation of low-income households. Policy simulations show that reducing the elasticity of substitution across educational services can improve the human capital response of low-income households, but is insufficient on its own to narrow the relative income gap; raising the digital literacy accumulation efficiency of low-income households can alleviate their adverse effects, but the effect is limited when implemented alone. The combination of the two policies can further improve the human capital accumulation of low-income households, but still has not reversed the trend of widening income inequality. This indicates that improving the absolute development situation of low-income households and narrowing the relative income gap are not the same goal.

Fourth, PISA 2022 evidence supports the income heterogeneity of digital learning returns, although the cross-sectional design limits causal interpretation. The regression results show a significant positive correlation between the digital learning index and mathematics achievement, but this association is significantly weaker among students from low-income households. This result resonates with the model's specification of heterogeneity in household digital learning ability, but since the empirical analysis is based on cross-sectional data, it cannot confirm the causal relationship between digital learning and academic

achievement, nor can it directly validate all transmission mechanisms in the model.

Based on the above findings, this paper proposes the following policy recommendations:

First, optimize the allocation of educational resources and promote the coordinated development of different forms of education. Digital education policy should not only focus on the quantity, coverage, and usage scale of online education resources, but also pay attention to its relationship with school education and after-school tutoring. High-quality digital education resources should be effectively connected with classroom teaching, the role of school education in basic knowledge instruction and learning support should be leveraged, and unreasonable substitution among different forms of education should be reduced, so that digital education becomes an effective complement to traditional education.

Second, enhance the digital literacy and digital learning capabilities of low-income households. Digital learning guidance should be strengthened to help students improve their abilities in information screening, self-directed learning, and problem solving, and the efficiency of using digital education resources should be improved through teacher guidance and personalized learning support. For households with relatively insufficient digital education resources, necessary equipment, internet access, and learning support should also be provided, reducing barriers from resource access to effective application of digital education, so that low-income households can more fully share the benefits of digital education development.

Third, establish a differentiated education support mechanism for low-income households. Addressing differences across income groups in educational investment and digital literacy accumulation requires the rational allocation of public education resources, and the strengthening of digital learning tutoring and necessary educational support. When advancing digital education platform construction and education resource allocation, attention should be paid to the actual benefits of different income groups, avoiding that improvements in average coverage mask differences in learning outcomes across groups.

Fourth, improve the evaluation system for digital education policy. Policy evaluation should not be limited to the scale of resource supply and frequency of use, but should also comprehensively examine indicators such as the structure of educational investment, digital literacy, academic achievement, and human capital accumulation, and distinguish between improvements in the absolute level of low-income households and changes in the relative income gap. Meanwhile, future research can use longitudinal tracking data and more identification-robust empirical designs to further test the impact of digital education on the learning outcomes and long-term income of households at different income levels,

providing more reliable empirical evidence for policy optimization.

In summary, digital education technology progress has created conditions for improving access to educational resources, but its distributional effects depend on the education supply structure and households' digital learning capabilities. Only by expanding the supply of digital education resources while promoting the coordinated development of different forms of education and enhancing the ability of low-income households to convert digital learning into human capital can the inclusive role of digital education be more fully realized.

Statements and Declarations

Funding

This work was jointly supported by the 2025 Humanities and Social Sciences Research Planning Fund of the Ministry of Education of the People's Republic of China (Grant No. 25YJA790094); the 2025 Key Program of the Zhejiang Provincial Natural Science Foundation of China (Grant No. LZ25G030002); and the 2027 Major Project of Zhejiang Provincial Philosophy and Social Sciences Planning (Leading Talent Cultivation Program) (Grant No. 27CXTD006ZD).

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Zheyan Zheng and Xinmiao Zhou. The first draft of the manuscript was written by Zheyan Zheng. Kai Zhang and Fujun Lai contributed to the model construction, interpretation of results, and critical revision of the manuscript. All authors commented on previous versions of the manuscript and read and approved the final manuscript.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. The PISA 2022 data are publicly available from the OECD.

Code Availability

The code that supports the findings of this study is available from the corresponding author upon reasonable request.

Ethics Approval

Not applicable. This study uses publicly available, de-identified data from the PISA 2022 database.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

References

Acemoglu, D.: Technical change, inequality, and the labor market. J. Econ. Lit. 40(1), 7 – 72 (2002)

Acemoglu, D., Autor, D.H.: Skills, tasks and technologies: implications for employment and earnings. In: Ashenfelter, O., Card, D. (eds.) Handbook of Labor Economics, Vol. 4, pp. 1043 – 1171. Elsevier, Amsterdam (2011)

Autor, D.H.: Why are there still so many jobs? The history and future of workplace automation. J. Econ. Perspect. 29(3), 3 – 30 (2015)

Autor, D.H., Goldin, C., Katz, L.F.: Extending the race between education and technology. Am. Econ. Rev. Insights 2(3), 347 – 362 (2020)

Autor, D.H., Katz, L.F., Kearney, M.S.: Trends in U.S. wage inequality: revising the revisionists. Rev. Econ. Stat. 90(2), 300 – 323 (2008)

Autor, D.H., Levy, F., Murnane, R.J.: The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118(4), 1279 – 1333 (2003)

Becker, G.S., Tomes, N.: Child endowments and the quantity and quality of children. J. Polit. Econ. 84(4), S143 – S162 (1976)

Becker, G.S., Tomes, N.: An equilibrium theory of the distribution of income and intergenerational mobility. J. Polit. Econ. 87(6), 1153 – 1189 (1979)

Becker, G.S., Tomes, N.: Human capital and the rise and fall of families. J. Labor Econ. 4(3, Part 2), S1 – S39 (1986)

Bettinger, E.P., Fox, L., Loeb, S., Taylor, E.S.: Virtual classrooms: how online college courses affect student success. Am. Econ. Rev. 107(9), 2855 – 2875 (2017)

Bettinger, E., Fox, L., Loeb, S., Taylor, E.: Equity in online learning. National Bureau of Economic Research, Cambridge, MA (2022)

Cai, F., Lan, G., Song, F.: From “digital literacy” to “digital citizenship”: the evolutionary logic, construction path of the EU digital competence framework and its implications for China. E-Government 1 – 12 (2025)

Che, H.: The construction path of a learning society under digital transformation—an analysis based on China’s macroeconomic education policy. J. Yanbian Educ. Coll. 39(5), 24 – 28 (2025)

Chen, L., Gao, Y., Yu, L.: How does artificial intelligence change firms’ labor demand? Evidence from big data on recruitment platforms. Manag. World 2024(6), 74 – 93 (2024)

Chen, W., Huang, L., Shu, S.: Social polarization, family educational expectations and class mobility—an empirical study based on the China Family Panel Studies. J. Xiamen Univ. (Arts Soc. Sci.) 75(5), 143 – 157 (2025)

Chetty, R., Hendren, N., Katz, L.F.: The effects of exposure to better neighborhoods on children: new evidence from the Moving to Opportunity experiment. Am. Econ. Rev. 106(4), 855 – 902 (2016)

Chetty, R., Jackson, M.O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R.B., et al.: Social capital I: measurement and associations with economic mobility. Nature 608(7921), 108 – 121 (2022)

Cunha, F., Heckman, J.J.: The technology of skill formation. Am. Econ. Rev. 97(2), 31 – 47 (2007)

Cunha, F., Heckman, J.J.: Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. J. Hum. Resour. 43(4), 738 – 782 (2008)

Ding, Y., Wang, Y., Guo, Y.: The experience of upward intergenerational class mobility strengthens system-justifying beliefs. In: Proceedings of the 26th National Academic Conference of the Chinese Psychological Society, pp. 152 – 153 (2025)

Fang, F., Tian, G., Zhang, X.: Digital infrastructure and upward intergenerational income mobility—a quasi-natural experiment based on the “Broadband China” strategy. Econ. Res. J. 2023(5) (2023)

Goldin, C., Katz, L.F.: Long-run changes in the wage structure: narrowing, widening, polarizing. Brook. Pap. Econ. Act. 2008(2), 135 – 165 (2008)

Han, J., Lu, X., Wright, S.D.: Macroeconomic fluctuations and the distribution of consumption. NBER Macroecon. Annu. 31, 139–173 (2016)

Hargittai, E.: Second-level solutions to the digital divide. Inf. Commun. Soc. 10(3), 415–429 (2007)

Hulleman, J.M., van der Maas, H.L.J., Jolles, J.: Does homework pay off? On the relationship between homework and academic performance. Educ. Res. Rev. 5(1), 6–15 (2010)

Ichino, A., Riphahn, R.T.: The heterogeneous-agent approach to macroeconomics: a review essay. J. Econ. Perspect. 25(3), 195–216 (2011)

Jackman, M.L., Kuhfeld, M.A., Ruzek, E., Bauer, S.: Learning during the COVID-19 pandemic: a review of research. Learning Policy Institute, Palo Alto, CA (2020)

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., Liu, J.: The COVID-19 slide: what summer learning loss can tell us about students' academic outcomes this fall. NWEA Research Brief, Portland, OR (2020)

Leeper, E.M., Walker, T.B., Yang, S.-C.S.: Fiscal foresight and information flows. Econometrica 85(3), 1115–1145 (2017)

Liu, D., Yuan, Y.: Artificial intelligence, skill stripping and firm income inequality. J. Finance Econ. 52(1), 123–137 (2026)

Schwerdt, G., Wößmann, L.: The effect of private tutoring on students' academic achievement. IZA Institute of Labor Economics, Bonn (2017)

van Deursen, A.J., van Dijk, J.A.: The digital divide and social stratification. In: The Digital Divide, pp. 15–30. Routledge, London (2019)

van Deursen, A.J., van Dijk, J.A., ten Klooster, P.M.: Internet skill gaps and the relation to socio-demographics and internet use. Inf. Commun. Soc. 14(7), 1005–1025 (2011)

Wang, Y., Yan, X., Gu, Y.: The impact of artificial intelligence development on economic growth and the gap between rich and poor. Mod. Bus. 2025(17), 31–34 (2025)

Wei, Q., Chen, Z.: How family digital literacy optimizes pension asset allocation—from the perspectives of insufficient effective financial demand and household consumption expectations. Financ. Theory Pract. 2026(6), 80–103 (2026)

Xie, T., Chen, Y.: Educational digitalization, family supplementary education consumption and macroeconomic policy effects: evidence from the National Smart Education Platform for Primary and Secondary Schools. China Educ. Technol. 2026(5), 33–40 (2026)

Xing, S., Zhang, J., Chen, L.: The value implication, practical challenges and promotion path of digital-intelligent integration empowering the digital transformation of vocational education. J. Ningbo Polytech. Univ. 30(5), 73 – 79 (2026)