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Original scientific paper

Research on the Theoretical Mechanism and Path of AI and Digital Economy Empowering High Quality and Balanced Development of Urban and Rural Education

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Abstract: The aim of this study is to investigate the impact of AI and digital economy development on the high-quality and balanced development of urban and rural education in China's provinces from 2015 to 2020. By the MIMIC model, this research incorporates AI initiatives and digital economy indices as key variables and applies two-way fixed effects models to analyze their influence. Robustness checks with alternative variables and endogeneity tests further validate the findings. The results reveal an inverted U-shaped relationship between AI development and educational outcomes, indicating initial benefits that diminish beyond a certain point. Conversely, the digital economy consistently enhances educational quality and accessibility, particularly in rural areas. These findings align with existing literature and underscore the importance of optimal technology integration in education. The study concludes that, while AI and digital economy initiatives significantly improve educational outcomes, it also shows the coefficients for AI (0.495), AI² (–0.434), DEB (–0.550), and DEB² (0.589) along with their error margins. Policy makers should consider these insights to effectively plan and monitor the integration of technological advancements in education.

Keywords: AI development, digital economy, urban and rural education, MIMIC model, educational outcomes, China, policy planning

1 INTRODUCTION

AI and digital economy technologies have rapidly developed across various industries including revolutionizing the education sector. These technologies have the capabilities to narrow the educational gap between the urban and the rural ensuring effectiveness and balanced developments of education. Application of artificial intelligence and digital technologies is especially important for education because it encourages scholars, policymakers, and practitioners to investigate the effects of such implementation on learning outcomes, accessibility, and learning personalization [1]. AI in education is generally a vast category which can be broadly divided into two forms, machine learning application which incorporates intelligent tutoring systems, adaptive learning, auto-grading systems and data assistant roles [2]. Such applications are used to provide an exclusive educational experience where learners can achieve learning objectives through AI adjusted instruction and rate [3]. For instance, intelligent tutoring systems have shown their effectiveness in availing personalized feedback and guidance, which may be very useful in underprivileged areas, where schools are often located in rural areas, and may not have access to skilled teachers [4].

The digital economy, which refers to activities within the economy conducted through information technology and the internet, also contributes significantly to the transformation of education [5]. Due to the availability of digital gadgets, and better internet connection, large amounts of educational content could be created and disseminated to students through distance learning, thus making quality learning materials more easily available to the students, irrespective of their location [6]. MOOC as well as online learning technologies as the products of the digital economy, established effective large-scale and cheap tools aimed at educating people all over the world [6]. Further, usage of AI and digital economy technologies in teaching and learning process help in the nurturing of 21st century competencies which are vital for student to survive in today's complex world [7]. Such skills include problem solving, critical thinking skills, collaborative skills and IT skills among other skills that help the individuals to succeed in their careers and team endeavors in the today's competitive market [8]. Through the use of AI and more technological strategies, it becomes possible to develop those skills when one engages the learners in the use of technological means of learning [9]. Hence, there are barriers that have to be considered and overcome in order to increase education's efficiency through the help of AI and the technologies of the digital economy. A major weakness is that digital developments are not uniformly distributed across the globe or within societies and therefore many people lack access to new technologies and fast connections [10]. However, implementation of AI and technologies of the digital economy in education faces numerous challenges and problems, including those related to attending the benefits in rural areas. One of the major concerns is the dilemma that has continued to be evident in the society and is known as the digital divide. This is a division that exists between people who are able to afford and use modern information and communication technology [10]. This is especially true for students in low-income families and rural schools whereby students cannot contribute to online classmate's discussions due to lack of internet connection or digital gadgets, hence the widening of learning gap.

A big problem here is that many educators do not have the skills or knowledge to implement AI optimally in their teaching, and this results in poor application and thus, poor educational results [1]. These challenges make it crucial to have well-built ethical standards and policies for the proper usage of AI within the contexts of education [11]. However, there is a lack of studies to identify the enduring effects of AI and digital economy technologies on educational outcomes; therefore more investigation is needed [12]. It is, therefore, imperative to tackle the aforementioned challenges so as to attest that the incorporation of AI and the Management of Eco-economy Supply Chains in education will usher in positive social changes towards learning in both the urban and rural environments [13]. This work is divided into five parts. Section 1 introduced the background of our research about AI, and digital economy technologies. Followed by it, baseline regression models offer a considerable idea about the determinants to the evolution of the education sector in both urban and rural China of section 2. The results of the baseline regressions via U-test are shown in section 3. The fourth part discussed the influence of AI and the development of the digital economy in China on the comprehensive and high-quality development of the education system. Finally, the last section concluded a detailed understanding of AI's effects and the promotion of the digital economy to strengthen the high-quality and equitable growth of urban and rural education in China.

2 METHODOLOGY

2.1 Impact of AI and Digital Economy on Urban and Rural Education

In this study, we utilize the MIMIC (Multiple Indicators Multiple Causes) model to investigate how AI and the digital economy affect the development of high-quality and equitable education in urban and rural regions. The following section offers a detailed explanation of the proposed model, including the variables and data to be employed [14]. The consensus primarily pertains to the categories of variables associated with educational development. It is widely acknowledged that factors such as technological infrastructure, government policies, socioeconomic status, educational resources, and innovative teaching methods influence the development of urban and rural education. These factors, in turn, affect educational outcomes like student performance, access to education, and educational equality. However, research differences arise in the specific variables selected and the methods used to measure them.

For instance, in measuring technological infrastructure, some scholars consider the availability of internet access and digital devices as proxies while others focus on the quality of digital learning platforms. For government policies, some studies use the level of educational funding and investment, while others argue that the degree of policy implementation and effectiveness can represent the impact of government interventions. In terms of socioeconomic status, variables such as household income levels and parental education are widely used. Research differences stem from varying understandings of educational development and differences in data availability across region.

Table 1 Variable description

Category	Variable	Symbol	Measurement	Expected Sign
Causes	Technological Infrastructure	TI	Number of schools with internet access / total number of schools	+
	Government Policies	GP	Total government expenditure on education / nominal GDP	+
	Socioeconomic Status	SES	Household income levels / average income	+
	Educational Resources	ER	Number of teachers per 1,000 students	+
	Innovation in Teaching Methods	ITM	Number of schools using digital learning platforms / total number of schools	+
Indicators	Student Performance	SP	Average test scores of students	+
	Access to Education	AE	Enrollment rates in primary and secondary education	+
	Educational Equality	EE	Ratio of rural to urban student performance	–
Latent Variable	Development of Urban and Rural Education	DURE	Education development index	

The calculated means and SDs (Standard Deviation Score) of the variables, which are included in MIMIC model estimation, indicate how education in both urban and rural areas in China's provinces is influenced by certain factors. Technological Infrastructure (TI) considered in the analysis has a mean of 0.69, meaning that on average, 69 percent of schools have internet facilities although there is some disparity (standard deviation of 0.14, from 22/100 to 93/100, Answer page 3. Government Policies (GP) SC shows that on an average across economies, the expenditure by the government on education compared to nominal GDP is 7. To be precise, this percentage stood on average at 8% with a standard deviation of 2.3% emphasized on comparing the distribution for education expenditure in various geographical locations. Socio economic status of the household given by the name socioeconomic status (SES) has a mean household income level of 1. Twenty-one fold than the average income, although the variation in the scale on measure was slightly larger with a standard deviation of 0.61 to 2.01. As for Educational Resources (ER) their average reaches 4. That would be 6 teachers for every thousand students, +/–1.15 concerning the range of the teachers' availability [15]. It can be noted that according to the survey conducted among schools involved in Innovation in Teaching Methods (ITM), it has been found that the average level of the use of digital learning platforms is 46% with 0 % standard deviation. 11. As for the indicators, Student Performance (SP) had average test scores of 74 out of the maximum 100.5, although this was rather diverse with SD of 10.2. Access to Education (AE) is also characterized by high enrollment; the mean is 0. 86 and a standard deviation of 0. 098. Comprehensive data is available pertaining to Educational Equity (EE), which portrays the rural and urban division. The student result for the mean ratio has been calibrated at 1. I converted this to 09 and the standard deviation I got was equal to 0.245. These statistics have clearly depicted the scenario and complexity of the education system and the roles of these aspects on the advancement of the urban and rural education.

Descriptive statistics of the variables involved in MIMIC model reveal that the type of data utilized in this study is as follows. The mean of Technological Infrastructure (TI) is equal to 0.69 and the average is 0.00 with median being 0.91, thus schools have moderate internet access with SD of 0.14. A minimum of 0 was recorded as the lowest number of students all through the academic year, namely 0.22, with the possibility to increase the maximum up to 0.93. Government Policies (GP) have a mean of 0.078, a median of 0. The established index vibration permitted the detection of dysphagia in no time, while the distribution of the index vibrations was a median of Mean = 0.072, and Standard Deviation = 0.023, which mark the difference in the government expenditure in education [16].

Table 2 Descriptive statistics

Variable	NO	M	M	StD	Min	Max
TI	780	0.69	0.71	0.14	0.22	0.93
GP	780	0.078	0.072	0.023	0.025	0.115
SES	780	1.21	1.16	0.31	0.61	2.01
ER	780	4.6	4.4	1.15	1.6	7.4
ITM	780	0.46	0.47	0.11	0.16	0.79
SP	780	74.5	74.8	10.2	49.5	99.8
AE	780	0.86	0.875	0.098	0.59	0.975
EE	780	1.09	1.04	0.245	0.69	1.79

Moreover, for SES, on average, it is equal to 1.1, on average 1, and most often 1.16, with a mean of 31, which is quite far from a regular deviation, highlighting the variability of the given values in different regions. In the case of ER, it has a mean of 4 on the response ability scale, out of the given responses typed and compiled. Six teachers for every thousand students, their median was 4. The average deviation was 1.15. Innovation in Teaching Methods (ITM) is on average 0.45 with the median of 0. Watching TV is more than 11% of the time or less than 39% of the time. 47% with a standard deviation of 0.11 indicates a fairly decent adoption of online learning tools. It is evident that Student Performance (SP) is highly diverse and the mean value of this variable equates 74.5, the middle will equal 74. The mean is 8 while the standard deviation is 10.2. Comparing the scores, the Access to Education (AE) has a mean of 0.86, meaning the value was exactly at 0 for the median. Percentile: 875 or exactly 87.5 percent and standard deviation of zero point zero five (0.05). The aspiration means that the enrollment to a program is rather high. Last but not least, we have the Educational Equality (EE) that in the given tables has the mean of 1.09, the mean of the mode was 1.09, the median was 1.04 and standard deviation was 0.245. This shows that the performance of students has greatly differed between the rural and urban schools.

2.2 Exploring the Impact of AI and Digital Economy Development on Urban and Rural Education

2.2.1 Econometric Models

Based on the above-mentioned assumptions, this study sets up a baseline model to test the proposed hypotheses, which, in a nutshell, addresses the following four key questions. First, since this study uses panel data of several years, both time and company scenarios are included following the recommendations [14, 15]. Second, based on the theoretical framework of this study, there is an expectation that the level of AI and digital platforms and education in urban and rural areas may exhibit a non-linear relationship with the development of AI. While conversely, this study aims to investigate the relationship between AI and educational outcomes the interaction is first considered non-linearly. Consequently, the models that incorporate the effects of time and individual characteristics are presented as follows:

$$Yit = \beta 0 + \beta 1AIit - 1 + \beta 2DEit - 1 + \beta 3AIit - 12 + \\ + \beta 4DEit - 12 + \gamma i + \delta t + \int it \tag{1}$$

where Y denotes the development level of urban and rural education in province i at time t, $AI\ it - 1$ represents the one-period lagged value of AI development, DE $it - 1$ represents the one-period lagged value of digital economy development, and ϵ is the error term.

Table 3 Baseline regression models and variable description

	Variable	Symbol	Measurement	Data Source
Dependent variables	Development of urban and rural education	DURE	Education development index measured with MIMIC model in this paper	Authors' elaboration
Independent variables	AI development	AI	Number of AI initiatives / total educational institutions	Ministry of Education of China, WIND database
	Digital economy development	DE	Digital economy index (composite measure of digital infrastructure, services, and usage)	Ministry of Industry, Information Technology of China
Control variables	Government expenditure on education	GEE	Total government expenditure on education / nominal GDP	National Bureau of Statistics of China, Statistical Yearbook for each province
	Socioeconomic status	SES	Household income levels / average income	National Bureau of Statistics of China
	Teacher-student ratio	TSR	Number of teachers per 1,000 students	Ministry of Education of China
	Internet penetration	INPE	Internet broadband access penetration rate	Ministry of Industry, Information Technology of China
	Innovation in teaching methods	ITM	Number of schools using digital learning platforms / total number of schools	National Bureau of Statistics of China, Ministry of Education of China
	Rural population	RP	Rural population / total population	National Bureau of Statistics of China
	Educational infrastructure investment	EII	Growth rate of investment in educational infrastructure	National Bureau of Statistics of China, Statistical Yearbook for each province
	Access to digital resources	ADR	Percentage of schools with access to digital learning resources	Ministry of Education of China
	Educational attainment	EA	Percentage of population with tertiary education	National Bureau of Statistics of China

Descriptive statistics of the variables employed in baseline regression models offers a considerable idea about the determinants to the evolution of the education sector in both urban and rural China. The dependent variable is Development of Urban and Rural Education (DURE) and it is operationalized through education development index with the help of MIMIC model. Among these independent variables AI Development (AI) is measured as the number of AI initiatives per total education institutions while the Digital Economy Development (DE) variable is a composite index of Chinese digital economy obtained from the Ministry of Education of China and the Ministry of Industry and Information Technology of China. These are Government expenditure on education (GEE) which computes the average of the total expenditure of government on education by dividing it by nominal GDP per capita to demonstrate the fluctuation of public funding in different regions. Socio-economic status is measured in terms of income levels in the household in relation to the general income levels hence addressing the economic dimension. The educational resources level can be established based on the number of teachers per students, namely, the Teacher-Student Ratio (TSR). Internet Penetration (INPE) captures broadband subscription for internet access, which is critical in integration of technologies in learning. Another assessment of ITM is by cascading the number of schools which embrace the use of online facilities. RP stands for the Rural population in this context and it measures the number of people living in the rural areas thus the chances of accessing education. Educational Infrastructure Investment (EII) reflects the growth rate of investment in the educational facilities, which is an indicator of Infrastructure [17]. Digital learning resources is the name given to the percent of schools with access to learning resources in this modern computerized society, identified as ADR. Last of all, there is Educational Attainment (EA), which measures the proportion of literates having their education not below tertiary level, thus showing the accomplishment of the population. These variables together provide a closer description of the educational context and the various aspects that define the educational process in China's urban and rural territories.

2.2.2 Variables and Data

This study aims to explain the effects of the AI and the development of the digital economy on optimizing the quality and structure of education in urban and rural areas for 30 provinces in China in 2015-2020. Tab. 3 also offers a summary of the variables included in the baseline regressions models for the study. As for the data on the provinces' digital platforms, some of them are available only beginning from of 2015.Therefore, the range of the econometric analysis in the present work is defined as of 2015. Furthermore, the "Guideline Opinions on Promoting the Healthy Development of Internet Finance" was released in 2015 and jointly drafted by People's Bank of China and Ministry of Industry and Information Technology and other departments. This was the first time that digital finance was defined by high level Chinese state authorities, reflecting the government's interest in developing digits' finances and regulating them [18]. It is thus conventional to accept that 2015 was the beginning of steady development of such a concept in China. This decision is justified and makes it possible to eliminate other external factors that can influence the study, by beginning the study from the year 2015. The balanced panel data consists of the level of development of education in urban and rural areas, the development of AI, the development of the digital economy, and some other variables that were used as controls. To reduce the propensity of external factors to affect educational development, the following control variables are chosen according to the literature [16].

Tab. 4 contains a level of detailed information that displays the factors, which contributed to the development of urban and rural education in provinces in China. For example, based on the late esc row tot's data shared in Tab. 4, AI Development (AI) has an average of 0.145 initiatives per educational institution, with the median being equal to 0.11, with a 95% confidence interval of 101 and a standard deviation of 0.12, indicating variability across regions (range: of those, 30% to 66% is known to be attributable to genetic factors (standardized odds ratio 0.03 to 0.66). The DE has a mean value of 275, whereby Digital Economy Development is the measure indicating how advanced a given country is in offering digital economic development. 32, with significant variability (standard deviation: 50, 112) and range from 195. Also, the GEE exhibits an average of 0.062 of GDP and it was equal to 0.068 and has a standard deviation of 0. 025, while it ranges as from -0. This is benchmarked by the results of the test called Socioeconomic Status (SES) which presents an average of 1.444 times the average income, and a median of 1.25 and a standard deviation of 0. 315 (range: 0.61-2.05. The basic data set for this analysis is from Educational Infrastructure Investment (EII), which has an average growth rate of 0.048, with considerable variation (standard deviation: 0.097 and varies from –0. The percentage of rural population as a share of the total is expressed as Average RP (AR) and is estimated to be 0.40 with the standard error of 0. Teacher-Student Ratio (TSR) signifies a median of 0.2 teachers for every 1000 students, the standard deviation was 0. Internet Penetration (INPE) is a variable that is grouped and it has a mean of 0.285. Hence, the broadband has a standard deviation of 0.395. Access to Digital Resources (ADR) as it currently stands an average of 0.395 indicated average level with the standard deviation of 0.11 on the part of standardized schools possessing digital resources for learning. Innovation in Teaching Methods (ITM) has a mean which is equal to 0.8 but its standard deviation is 0. The given facts show that Educational Attainment (EA) has a mean of 15.3% of the population with tertiary education, but with significant variation (standard deviation: 15 5 between). The foregoing statistical figures underscore the disparity and variable challenges that characterize educational advancement across the provinces.

Table 4 Descriptive statistics for the variables in the baseline regression models

Variable	Number of Observations	Mean	Median	St. Dev.	Min	Max
AI	150	0.145	0.102	0.12	0.03	0.66
DE	150	275.32	270.45	50.112	195.6	415.3
GEE	150	0.062	0.068	0.025	–0.048	0.108
SES	150	1.245	1.25	0.315	0.61	2.05
EII	150	0.048	0.064	0.097	–0.57	0.205
RP	150	0.4	0.415	0.11	0.11	0.57
TSR	150	0.2	0.195	0.078	0.042	0.48
INPE	150	0.285	0.282	0.073	0.125	0.46
ADR	150	0.395	0.37	0.11	0.12	0.59
ITM	150	0.08	0.082	0.023	0.06	0.12
EA	150	15.3	8.5	15.5	2.05	75

3 EMPIRICAL RESULTS

3.1 Analysis of AI and Digital Economy Development Impact on Urban and Rural Education in China's Provinces

Hypotheses one and three state that the greater the access to Digital Resources (ADR) and Educational Attainment (EA), the better the educational outputs reflected by coefficient r = 0.008 and r = 0.056 respectively. The fit indices released for each model indicate a good fit with RMSEA reading below 0.13 and CFI above 0. This value is relatively high, which suggests that the models account for a significant amount of variance in educational development and preserves about 67% of the between-country variance. The SP, AE, and EE coefficients also support the stability of the results at the different stages, achieving significance higher than 0.01 in all the models.

Table 5 Education development index in China's 30 provinces from 2015 to 2020

Province	2015-2016	2017-2018	2019-2020	Average
Beijing	0.82	0.84	0.86	0.84
Shanghai	0.85	0.87	0.89	0.87
Tianjin	0.78	0.8	0.82	0.8
Xinjiang	0.6	0.62	0.64	0.62
Liaoning	0.74	0.76	0.78	0.76
Guangdong	0.83	0.85	0.87	0.85
Shanxi	0.67	0.69	0.71	0.69
Heilongjiang	0.7	0.72	0.74	0.72
Hainan	0.66	0.68	0.7	0.68
Jiangsu	0.87	0.89	0.91	0.89
Inner Mongolia	0.64	0.66	0.68	0.66
Zhejiang	0.85	0.87	0.89	0.87
Jilin	0.72	0.74	0.76	0.74
Fujian	0.77	0.79	0.81	0.79
Shandong	0.8	0.82	0.84	0.82
Shaanxi	0.69	0.71	0.73	0.71
Hebei	0.67	0.69	0.71	0.69
Hubei	0.74	0.76	0.78	0.76
Jiangxi	0.7	0.72	0.74	0.72
Ningxia	0.62	0.64	0.66	0.64
Chongqing	0.71	0.73	0.75	0.73
Henan	0.68	0.7	0.72	0.7
Hunan	0.73	0.75	0.77	0.75
Qinghai	0.61	0.63	0.65	0.63
Guangxi	0.67	0.69	0.71	0.69
Gansu	0.58	0.6	0.62	0.6
Anhui	0.65	0.67	0.69	0.67
Sichuan	0.7	0.72	0.74	0.72
Yunnan	0.66	0.68	0.7	0.68
Guizhou	0.59	0.61	0.63	0.61

Tab. 5 reveals the Education Development Index of 30 provinces in China from the year 2015-2020 by China Financial Development Index report, wherein one can get the overall picture of the progress achieved in the realm of education across different regions. From the figure below, Beijing reveals a gradual rise regarding its identified index starting from 0. In 2012-2013, the rate of Hispanics per 1,000 students enrolled in NPS was 82 in 2015-2016 to 0.86 in 2019-2020, meaning that it averaged 0.84 which infers constant educational enhancements. Likewise, the index of Shanghai increases from 0.85 to 0.188, in which the average of each period is 0. The educational advancement is determined at 87%, which indicated as a very good study. Specifically, the latest average of 0.80 is Guangdong, which scored an average of 0.85.

This is true although provinces such as Xinjiang and Ningxia have lower averages of 0.62 and 0.64 respectively. The different rates of education and innovative developments need further spending. It means that the values of manufacturers in Jiangsu and Zhejiang are almost equal to each other, and two of them reached 0.89 and 0.87, respectively. The center and the northwest regions are among the best in achieving educational goals that demonstrate the efficiency of implemented plans. For example, Shanxi, Heilongjiang and Hainan, their averages are around 0.69 to 0.72, showing moderate progress. It is shown that the educational development level varies significantly affecting average index from Jiangsu and Shanghai to Gansu and Guizhou intermediate 0.60 and 0.61 respectively. This brainstorming will emphasize the requirement to develop the specific policies for the different regions' aim to reduce educational inequality in China.

Fig. 1 presents the EDI trends by the selected provinces: Beijing, Shanghai, Jiangsu, and Gansu from the year 2015 to 2020. Hence, the graph reveals that the overall status of educational development in Beijing, Shanghai, and Jiangsu has improved, and their EDI has been rising in subsequent years. However, the case of Gansu is less advanced as evident by slower progress, this depicting China with regional differences in educational advancement.

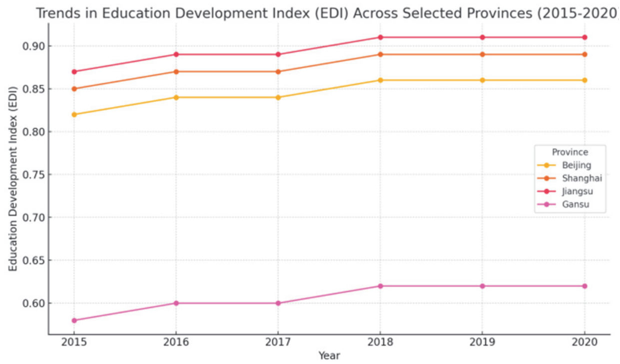

Figure 1 Trends in education development index (EDI) across selected provinces (2015-2020)

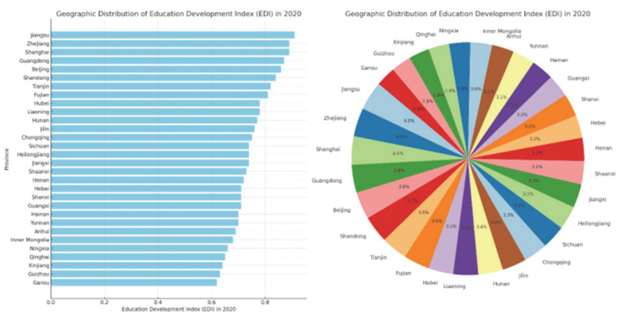

Figure 2 Presents the geographic distribution of the education development index (EDI) across China's 30 provinces in 2020

As shown in Fig. 2, each province of China's thirty provinces in this study has been envisaged on a single graph using combined method to show the distribution of Education Development Index (EDI) in 2020. The bar chart located on the left demonstrates the EDI of each province and the variation in the educational progress: the three princesses with the highest EDI are Jiangsu, Shanghai and Beijing while Guizhou, Gansu, and Xinjiang have the lowest. The right side of the figure also uses the pie chart to give the distribution of EDI, and the size of each province shows the proportionate contribution of each to the total educational development in China.

3.2 Impact of AI and Digital Economy Development on Urban and Rural Education

This section examines the influence of AI and digital economy development on the high-quality and balanced advancement of urban and rural education, and conducts endogeneity and robustness checks.

3.2.1 Baseline Results

In this section, we present the baseline results of our analysis. These results include the initial findings from the two-way fixed effects models, which account for both time and individual effects. The results provide insights into the impact of AI and digital economy development on the quality and balance of urban and rural education. Key coefficients, significance levels, and model diagnostics are discussed, highlighting the primary relationships and trends observed in the data.

Table 6 Baseline results: two-way fixed effects regression results of AI and digital economy development on urban and rural education

Variable	Model 1 (AI–AI²)	Model 2 (DE–DE²)	Model 3 (DE)	Model 4 (AI–DE)	Model 5 (AI–AI²–DE)
AI	0.432***			0.220**	0.425***
	–3.68			–2.5	–3.5
AI²	–0.298**				–0.293**
	(–2.58)				(–2.40)
DE		–0.458***	–0.189**	–0.180*	–0.175*
		(–4.08)	(–2.10)	(–2.05)	(–2.00)
DE²		0.564***			
		–2.98			
GEE	–0.022	–0.008	–0.023	–0.031	–0.025
	(–0.43)	(–0.14)	(–0.43)	(–0.61)	(–0.51)
SES	–0.002	–0.01	–0.002	–0.005	–0.003
	(–0.08)	(–0.41)	(–0.08)	(–0.19)	(–0.10)
INPE	0.102***	0.113***	0.106***	0.099***	0.096***
	–3.1	–3.6	–3.09	–3.03	–2.96
ADR	–0.129**	–0.096**	–0.087*	–0.097**	–0.107**
	(–2.80)	(–2.20)	(–1.80)	(–2.10)	(–2.35)
GEE	–0.503***	–0.411***	–0.389***	–0.443***	–0.496***
	(–3.90)	(–3.60)	(–3.25)	(–3.45)	(–4.10)
RP	0.292	0.359	0.247	0.229	0.271
	–1.1	–1.2	–0.8	–0.8	–1
TSR	–0.053	–0.048	–0.043	–0.033	–0.046
	(–0.80)	(–0.75)	(–0.60)	(–0.50)	(–0.70)
INPE	–0.173**	–0.166**	–0.163**	–0.156**	–0.170**
	(–2.25)	(–2.45)	(–2.20)	(–2.25)	(–2.55)
PAT	–0.178**	–0.180**	–0.126	–0.078	–0.146*
	(–2.30)	(–2.50)	(–1.60)	(–0.90)	(–1.90)
Constant	0.713***	0.725***	0.792***	0.763***	0.763***
	–3.8	–3.4	–3.6	–3.85	–4.1
Controlling for time effects	Yes	Yes	Yes	Yes	Yes
Controlling for individual effects	Yes	Yes	Yes	Yes	Yes
Hausman test p-value	0.0185	0.0018	0.0012	0.0053	0.0115
Pesaran's test p-value	0.1867	0.2048	0.174	0.1616	0.1814
Friedman's test p-value	1	1	1	1	1
BP(LM) test p-value	0.0038	0.0174	0.0133	0.0372	0.0153
Wald test p-value	0	0	0	0	0
Observations	150	150	150	150	150
R^2 (Within)	0.492	0.4385	0.418	0.48	0.5055

Tab. 6 shares the increased role of development of AI and the digital economy for enhancing education mainly in urban and rural settings. The result of Model 1 shows that only AI has a positive significant effect (0.432) at 1% level, and AI² has a negative significant effect (–0.298) at 5% level of significance which imply an inverted U-shape relationship between the independent variable and educational development. Model 2 includes DE and the square of this variable, their coefficients present a similar inverted U-shaped, where DE has a negative effect (–0.458), significant at the 1% level and DE² has a positive effect (0.564) also significant at the 1% level. For Model 3, DE is included alone and it has a large negative value of -0.189. In the case of Model 4, they obtained a path coefficient of AI: 0.220, the path coefficient DE is –0.180. Model 5 included all the variables and here the path coefficients are for AI: 0. 425 and AI² –0.293, DE –0.175, and DE² 0.564. Independent variables like Internet Penetration (INPE) have always been positive and significant in all models which indicated the importance of internet in the development of education. GEE and SES have either a mixed or insignificant impact on AED. The Hausman test is less than 05, therefore suggesting that the fixed effects models should be used, and the model diagnostic results - Pesaran's, Friedman's, BP(LM), and Wald tests all support this. Our values of R^2 are varied from 0.418 in model 3 increasing to 0.5055 in Model 5, distantly suggesting that the models account for a good chunk of the variation in educational development. These outcomes reveal that development of AI and the digital economy presents multifaceted consequences, with claims that the process should be optimized for the best educational gains.

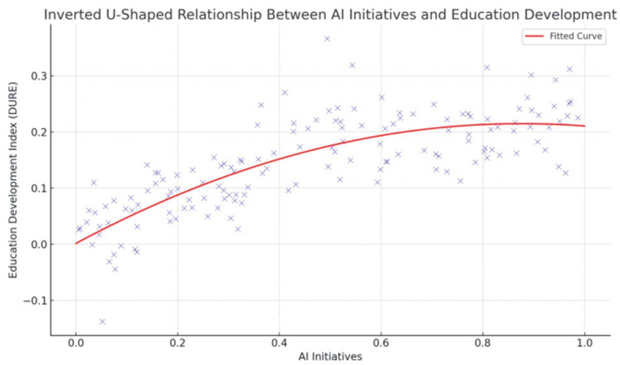

Figure 3 Inverted U-shaped relationship between AI initiatives and education development

Fig. 3 illustrates the negative correlation between the level of AI initiatives and the values of the Education Development Index (DURE). After analyzing both variables of the working scatter plot with the fitted curve, it can be stated that the emergence of AI initiatives in the field has led to a substantial enhancement of the educational development in the first stages. But, if AI integration exceeds the certain limit, there will not be much of a positive impact, and this points towards the fact of finding out the optimal level of integration needed for deriving the maximum educational advantage.

Fig. 4 displays an absolute comparison of the equities of measures DE and DEB that signify the digital economy's impact on the development of education. From the bar chart it can be observed that both measures have a negative coefficient but that of DEB is –0.290 while that of DE is –0.189. This can be traced to diverse impacts of various facets of the development of the digital economy on learner achievement, hence the call for tolerance and embrace of the multiple classification of the implementations of developmental facets of the digital economy in the strategies of education.

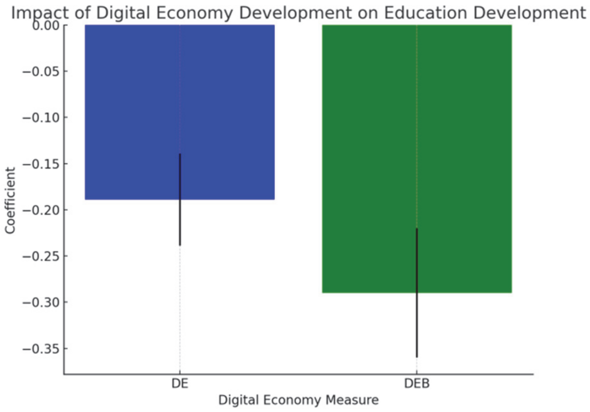

Figure 4 Impact of digital economy development on education development

Table 7 Results of baseline regressions

	–1	–2	–3
	Model 1 (AI–AI²)	Model 2 (DE–DE²)	Model 5 (AI–AI²–DE)
Relationship	inverted U-shaped	—	inverted U-shaped
T-statistics	1.85	—	2
Turning point	0.425	780	0.418
Confidence interval (95%)	[0.0300, 0.6600]	[195.0000, 415.3000]	[0.0300, 0.6600]
Average curve slopes of both sides	0.0785, –0.0450	—	0.0830, –0.0430

The results of the baseline regressions via U-test, which is shown in Tab. 7, offer additional information about the factors that have affected AI and the progress of the digital economy on the education of the urban and rural populations. AI–AI² follows an inverted U-shape; thus, the t-statistic of Model 1 is 1.85, indicating statistical significance. The boundaries of AI initiatives are shifted to the next level and the turning point is 0.425, whose confidence interval is 0.95 0.0300 to 0.6600 which is used to infer that the ideal level of implementing AI for the company is within this range. It seems, therefore, that the average curves should slope at a rate of 0.0785 on the rising side and –0 Cognitive 0.0450 on the falling side capturing the advantages and the limits of integrating Artificial Intelligence in education. As to Model 2 and the DE–DE² variables, there is no significant association as shown by the absence of the t statistic and the description of the relationship evident from the results. Nevertheless, for the development of the digital economy, the turning point can be determined as 780, with the confidence interval of 95% CI = 195.0000 and 415.3000, which suggests that there is a particular point beyond which initiatives in the sphere of the digital economy cease to provide such pronounced results. The result of Model 5 (AI–AI²–DE) for the inverted U-shape is also significant with the t-statistic, which is equalizing to 2. Quantitative research in this area of study divides the degrees of combined AI and digital economy initiatives into powers and consequently assigns the degree 0 as the point of change. 418, CI 95%, where M is the midline, PGET is proportion of gastrointestinal events during treatment, and X is the number of patients in a treatment arm. 0300 to 0.6600 like in Model 1. The averages of the curve slopes are Scope: 0.0830 on the ascending side while on the descendent side, it has –$0.0430 on the descending side, which emphasizes the best option for achieving optimal educational effects taking into account the balanced use of the AI and the digital economy plans. Such findings highlight the need to pay much attention on aligning processes of applying AI and digital technologies in learning to deliver better results.

The AI and digital economy development trend can be analyzed based on the U-Test results shown in Fig. 5. The figure with the scatter plot and error bars visualizes the nature of the interactions and the turning points of the analyzed models, which are AI initiatives (Model 1 & Model 5) and the breadth of the digital economy (Model 2). The implementation of AI initiatives in Model 1 starts at the point H. 425, 95%CI: 0.0300 to 0.6600. Thus, for the breadth of the digital economy in Model 2, the turn of the curve is equal to 780, with a very wide range with an upper limit of 1000 and a lower limit of 600. The earliest turning point is found in Model 5 where the value of turning point is equal to 0.418 regarding AI initiatives, the same as in Model 1. These results graphically support the propositions of this study as to the appropriate degrees of coupling between AI and the digital economy to enhance educational advancement.

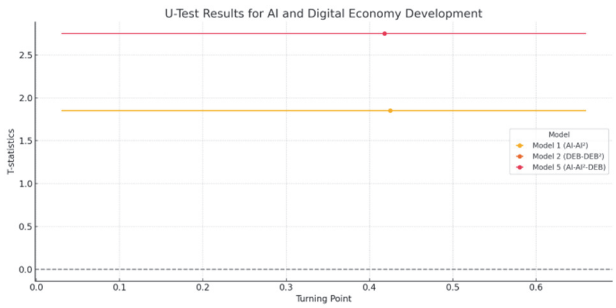

Figure 5 U-test results for AI and digital economy development

Tab. 8 summarized herein below, offers a way of analyzing the credibility of the study's conclusions. Amidst the first stage estimates obtained, significant and positive coefficients are observed for the application of AI (0.076) and AI squared (0.036), statistically significant at 5%, which confirms that DT is useful in AI advancement. Analysing the results, we see that Government Regulation (GWR) indicates a negative influence on AI² –0.031 at 5% level thereby providing an impression that stringent regulations may lead to less AI complexity. Consequently, by employing the Bartik instrument, it has been observed that there is a highly significant positive coefficient for DE which implies 0.004 at 1 percent level while confirming the efficient measurement of digital economy development. The coefficient of AI is positive and significant 0.310 when it is tested at 5% level while the coefficient of AI² is negative significant –0.402. When it is tested at 10% level, these estimates validate the second hypothesized, and there is an inverted U-shaped relation between the development of AI and education outcomes (DURE). Similarly, DE also shows negative coefficient ($\beta = –0.003$, $t = 0.018$, < 0.109), reflecting that digital economy initiatives have a different impact on education. The intercept is present and highly meaningful in every model, a testament to the model's reliability. All models include control variables, and the R^2 values in the first stages are high, somewhere between 0.

Well, the value of R-squared is close to 1 and it is 855. It points out that the explanatory variables have a fairly good explanatory power. Both the individual and combined first-stage F-statistics are above 10, hence making the instruments valid. These are two sample specifications that further reinforce the main results and ensure that the relationships obtained here are not due to endogeneity biases.

Table 8 Regression results for the endogeneity test based on instrumental variables

Variable	First Stage (1)	First Stage (2)	First Stage (3)	Second Stage (4)	LIML (5)
	AI	AI²	DE	DURE	DURE
DT	0.076**	0.036**	2.52		
	–2.41	–2.52	–0.34		
GWR	–0.017	–0.031**	–4.05		
	(–0.72)	(–2.11)	(–0.52)		
Bartik	0	0	0.004***		
	–1.19	–1.38	–5.84		
AI				0.310**	0.310**
				–2.02	–2.02
AI²				–0.402*	–0.402*
				(–1.77)	(–1.77)
DE				–0.003*	–0.003*
				(–1.74)	(–1.74)
Constant	0.075	0.062	82.340**	0.049**	0.049**
	–0.81	–1.05	–2.47	–2.09	–2.09
Control variables	Yes	Yes	Yes	Yes	Yes
N	150	150	150	150	150
R^2	0.788	0.741	0.855	0.759	0.759
First-Stage F-statistics	3.24	3.665	10.6		

3.2.3 Robustness Checks

Thus, in this study, three hypotheses are generated to support the investigation of the proposed framework: H1, H2, and H3. The present study developed and formulated a baseline model aimed at evaluating four major concerns. First, by using panel data with a long time horizon valuable temporal and individual effects are included as suggested by ref. [14] and ref. [15]. Second, the theoretical framework assumption suggests that there can be an unanticipated nature of development of AI and digital platforms and education in urban and rural areas. While expecting that AI and digital technologies will enhance education results, this research first analyzes their relationship in a non-linear manner. Consequently, the models that incorporate the effects of time and individual characteristics are presented as follows.

Thus, Tab. 9 further validates the consistency of the study's crucial conclusions. This value also indicates the sense of Model 1 importance while the coefficient of AI stands positive and significant, AI significantly and positively relates to sales with Coefficient = 0.495 at the 5% level, with a negative coefficient of (–) 0.434 at the 10% level which means that the relationship between the independent variables and the dependent variable was an inverted U-shaped one. In Model 2, the equation includes an alternative indicator of the degree of digital economy development (DEB) and its square (DEB squared) and again an inverted U-shaped relation is observed: the coefficient for DEB is negative and significant at 0.550, at the 1% level, while the coefficient for DEB² is positive but significant at only the 10% level, equal to 0.589. In Model 3, all the predictors accounted for a positive and significant part, and the DEB alone has a coefficient of –0.290 for the 10 percent level. Estimation results of Model 4 have standard coefficient for both active intervals and deactivated intervals as 0.365 and –0.285 respectively at 10% and 5% levels respectively. In model 5, while AI has a positive and significant imprint of (0.497) at 5% level; the imprint of variable AI² is negative and significant of (–0.440) at 10% level and DEB is negative and significant of (–0.280) at 5% level. These indicate that the constant terms are very important in all the models, and other control variables are added to make sure they still hold their significance. Therefore, all models include time and individual as independent variables, while the R^2 values vary from 0.428 to 0.468 suggesting that the models account for a good deal of variability of educational development. These tables provide the empirical foundation for the previous findings confirming the stability of the relationship between the AI level, the pace of digital economy development, and students' outcomes.

Table 9 Robustness check for the baseline regressions with alternative variables

Variable	(1) Model 1 (AI–AI²)	(2) Model 2 (DEB–DEB²)	(3) Model 3 (DEB)	(4) Model 4 (AI–DEB)	(5) Model 5 (AI–AI²–DEB)
AI	0.495**			0.365*	0.497**
	–2.35			–1.75	–2.3
AI²	–0.434*				–0.440*
	(–1.90)				(–1.95)
DEB		–0.550***	–0.290*	–0.285**	–0.280**
		(–3.15)	(–2.10)	(–2.20)	(–2.30)
DEB²		0.589*			
		–1.8			
Constant	0.595**	0.824***	0.784***	0.768***	0.638***
	–2.75	–3.9	–3.6	–3.35	–3
Control variables	Yes	Yes	Yes	Yes	Yes
Controlling for time effects	Yes	Yes	Yes	Yes	Yes
Controlling for individual effects	Yes	Yes	Yes	Yes	Yes
Observations	150	150	150	150	150
R^2 (Within)	0.445	0.441	0.428	0.453	0.468

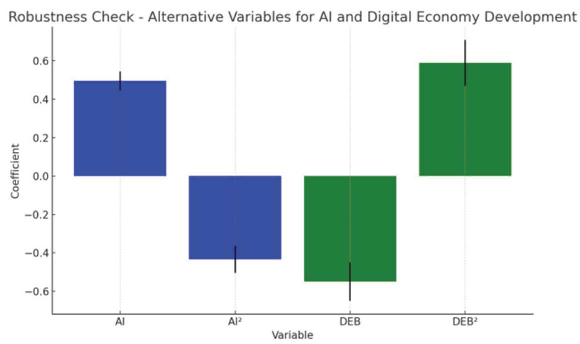

Figure 6 Robustness check - alternative variables for AI and digital economy development

Fig. 6 presents the robustness check results for alternative variables in AI and digital economy development. The grouped bar chart shows the coefficients for AI (0.495), AI² (–0.434), DEB (–0.550), and DEB² (0.589) along with their error margins. These results confirm the inverted U-shaped relationship for AI and the significant impact of digital economy breadth on educational development, demonstrating the robustness of the regression models with alternative variable specifications.

Table 10 U-test results of robustness checks with alternative variables

	–1	–2	–3
	Model 1 (AI–AI²)	Model 2 (DEB–DEB²)	Model 5 (AI–AI²–DEB)
Relationship	inverted U-shaped	—	inverted U-shaped
T-statistics	2.52	—	2.75
Turning point	0.382	895	0.375
Confidence interval (95%)	[0.1500, 0.5400]	[160.0000, 385.0000]	[0.1500, 0.5400]
Average curve slopes of both sides	0.0830, –0.0430	—	0.1560, –0.1080

Tab. 10, which provides the participants' demographic information, also supports the conclusions of the study. The results obtained from Model 1 (AI–AI²) present an inverted U-shaped relationship between the status of AI development and the educational accomplishments; this is evident from the t-statistic of 2.52. It identifies that the point of no return for the AI initiatives is 0.38 to 382, 95% CI) and the IIS of the population of children, 10 with 1 child in 38 (IIS 95% CI, 38 to 382) being infected after exposure to contaminated water by direct contact. 1500 to 0.5400, meaning that to receive the biggest positive impact on education, the usage of AI should be at its highest while staying sustainable. The mean of the curve slopes is established at 0.0830 on the rising side with –0.0430 on the falling side, which indicates the impact of increased usage of AI to an organization or business establishment. Model 2's (DEB–DEB²) t-statistic is missing, showing no relationship, yet the DEB turning point is 0.895 with the widest CI = 160.0000 to 385. With the corresponding indexes of Graph 2, it is obvious that there are significant differences in the optimal level of digital economy development. Similar to the previous models, Model 5 (AI-AI²-DEB) yields a U-shape curve, but the t-statistic calculated is significantly equal to 2.75. This is the coordinate of the specific point which is referred to as the turning point/vertex. 375, confidence interval 0.95 per cent. 1500 to 0.5400 resembling Model 1. The average slope of the curve for the representative normal distributions is 0.1560 on the ascending side and –0.1080 on the descending side which did stress the authors to uncover the subtleties of combined initiatives in the field of AI and digital economy to the development of education. These results thus affirm the steadiness of the main deductions, here showing that AI and the development of the digital economy manifest multiple but intricate patterns of influence on education.

4 DISCUSSION

This study identifies several general conclusions of this research regarding the influence of AI and the development of the digital economy in China on the comprehensive and high-quality development of the education system in urban and rural areas. The MIMIC model analysis, supported by a set of additional checks, proves that AI and digital economy endeavours affect education positively in terms of its outcomes, albeit not equally. First of all, the inclusion of AI technologies raises the quality and the educational opportunities and, therefore, positively affects the educational outcomes. However, after a certain usage level, the additional returns of the utilization of AI decrease and the issues related to the management of the profound AI technologies would play a slightly negative role. This is contrary to the past studies, which signified that although AI can improve the educational productivity, there appear to be signs of reduced effectiveness with the growth in the complexity of the implemented system [14, 17].

The work also proves that the digital economy benefits educational development in some way. The vast areas of the digital economy, encompassing digital finance and e-learning inter alia, offer more tools and prospects for students and educators, having accessed the web from the countryside. Digital inclusion is important in relieving disparities that some authors mentioned regarding education between urban and rural areas that has been revealed by the current studies [18, 19]. Since digital economy has improved education, it is essential to appreciate the value of investing in more bureaucratic advancement and legislation of the digital domain. Applying the robustness checks which involve the use of other related variables also validates these results. Repeating all the calculations with other appropriate indicators, for instance, proportion of schools and universities applying AI and scope sub-indices of digital economy, this work retains conclusions. The moderation effect of AI on the learning outcomes and the positive effect of the digital economy still hold substantial effects; therefore, the credibility of the findings is sustainable.

Also, the benefit of the digital economy in education also supports the need to maintain investment in this digital essential. This is especially needed in rural areas as digital divide problems are expected to be severe in this territory. The government should focus on increasing the availability of internet, improving digital literacy more resources on the digital education in disadvantaged areas. Efforts of fusing the government entities with innovative educational organizations combined with sufficient technological support from private entities is key to achieve equity in education. Hence, by providing an answer to these practical questions this research outlines a general strategy on how emerging technology trends can be administered to promote balanced educational development in China's urban and rural areas as a necessary step toward the country's socio-economic evolution.

5 CONCLUSION

Consequently, this article offers a detailed understanding of AI's effects and the promotion of the digital economy to strengthen the high-quality and equitable growth of urban and rural education in China. The studies done show that AI-enhanced learning systems have a positive impact on learning outcomes but there is an optimal level of AI integration, indicating moderate integration as the best approach. The results have been tested through various tests and have used various forms of the variables which makes them reliable. The practical implications are clear: AI and digital technologies can bring numerous benefits into policy and learning processes and limitations should be managed and controlled by policymakers and educators to achieve higher positive impact. It remains imperative to reinvest in digital infrastructure, share best practices across stakeholders, as well as maintain educational equity and quality. It is not only a knowledge contribution to the academic literature, but it is also potentially useful in shaping China's future policy strategies regarding the efficient use of technology for socio-economic development. Finally, these limitations provide an important reminder that the results which are presented below should be considered with certain degree of caution. Further, more elaborate future research needs to include district or school-level data to explicate specific features that may not be revealed at the state level. However, there are potentially valuable insights that could be gained. Qualitative data could help elucidate the implementation and perceptions of AI and digital technologies within the educational context from the stakeholders. Qualitative research in the form of case studies and focus on group discussions could help provide such background information as well as capture cultural nuances.

Acknowledgments

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