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The Impact of Digital Education on Parental Support for Access to Higher Education under Different Family Economic Background: A Case Study of Nanning City

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Abstract

This study investigates how economic background affects parental support under the era of digital education, the Technology Acceptance Model (TAM) offers significant insights into the acceptance levels of digital educational technology among parents and students. Parents' acceptance of such technology directly impacts their support for their children's education. By comparing the differences between high-income and low-income families, targeted strategies are proposed for the government to achieve educational equity. The research conducts a survey using questionnaire on 400 parents from high-income families and 400 parents from the low-income. The study constructs a structural equation model (SEM) to verify model fit. After comparison, the results indicate that there are significant differences in the factors influencing the level of parental support for higher education between high-income and low-income families. For the high-income, cultural capital(β=0.906) and TAM(β=0.509) positively affect parental support, and the low-income, cultural capital(β=0.661), economic capital(β=0.120) and human capital(β=0.283) positively impact parental support, which indicate that the factors that affect the tow kinds of families are totally different. And all the factors will be further analyzed in subsequent sections of this dissertation.

Keywords: parental support, higher education access, TAM, socioeconomic status, educational equity

Introduction

The digital transformation of China's education system has evolved through three developmental phases: digital infrastructure expansion, which has connected 519,000 schools and serving approximately 293 million students by 2023, network-based resource aggregation, hosting 44,000 K-12 (students' aged 6 to 18) resources and 27,000 MOOCs (online open courses), and AI-driven personalization, improving learning efficiency by 13.6% and reducing parental tutoring time by 0.54 hours daily (Chinese Ministry of Education, 2024). Digital education has emerged as a critical equalizer in addressing spatial and socioeconomic disparities in educational access. A prime example is China's National Smart Education Platform. This infrastructure integrates 500,000 schools and serves 180 million users, including students, educators, and lifelong learners. It delivers 44,000 standardized instructional resources and 6,700 specialized courses. Its cloud-based architecture enables the reliable dissemination of premium content to 97.2% of compulsory education institutions. Notably, it particularly benefits 163 underdeveloped counties through real-time resource sharing and adaptive learning interfaces. In these ways, the platform effectively narrows regional educational quality gaps (Ministry of Education of the People's Republic of China, 2025).

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However, significant regional disparities still persist, exemplified by Shanghai's advanced ecosystem (135.2-billion-yuan education expenditure, 75.6% undergraduate enrollment) versus Nanning's basic limited digital access (only 45.13% provincial enrollment rate) (Elite Exam Network, 2023). Empirical evidence from the 2021 CGSS reveals family capital's multidimensional impact: economic capital and cultural capital demonstrate significant intergenerational transmission effects, while social/political capital mediate institutional resource allocation. Collectively, family capital explains 32.7% of educational achievement variance after controlling for covariates (OR=2.1 for registered residence), underscoring persistent structural inequalities within China's digitally transformed education landscape (CGSS, 2021).

Research Objective

To investigate how digital education and different forms of family capital (cultural economic, human) influence parental support for higher education access, and how these influences differ between high-income and low-income families.

Literature Review

Cultural Capital

According to Pierre Bourdieu's theory (1986), cultural capital encompasses non-financial social assets that facilitate mobility through three interconnected forms: embodied (internalized skills, dispositions, and educational competencies shaped by familial socialization and institutional discipline), objectified (material cultural goods requiring economic capital for acquisition and embodied capital for decoding), and institutionalized (formal educational credentials). Its reproduction through inter-generational transmission reinforces social stratification by perpetuating unequal resource distribution. Embodied capital, marked by physical and diachronic accumulation, forms the basis of identity and symbolic power, while objectified capital operates as a materialized tool of social differentiation through consumption practices. Together, these forms underpin the dual logic of cultural reproduction, where economic and symbolic resources intersect to sustain hierarchical power relations.

Economic Capital

Adam Smith's The Wealth of Nations (1776) articulates a tripartite framework connecting capital accumulation to economic prosperity: (1) Capital expansion operates through dual mechanisms – material investments (machinery, infrastructure) and human capital development (skills/knowledge)–driving productivity via technological adoption and economies of scale, aligning with Kaldor's (1961) growth theory; (2) The fixed-circulating capital dichotomy (durable assets vs. operational liquidity) underpins sustained production cycles through complementary asset allocation; (3) A self-reinforcing growth cycle emerges through specialization-induced efficiency gains, market-driven resource optimization ("invisible hand"), and profit reinvestment that elevates wages, employment, and public welfare. This framework posits minimal state intervention, endogenous growth through capital-technology-labor synergies, and a systemic "accumulation-efficiency-welfare" nexus as capitalism's foundational mechanics (Smith, 1776; Kaldor, 1961).

According to Pishghadam et al. (2023), cultural capital and emo-sensory quotient (ESQ) significantly predict academic achievement in a comparative study of 317 Afghan and Iranian students, with contextual disparities revealing higher cultural capital among Afghan students and greater economic capital/ESQ among Iranian counterparts, highlighting contextualized capital dynamics in educational outcomes (Pishghadam, R., Meidani, E., Momenzadeh, S., Hasanzadeh, S., & Miri, M, 2023).

H_1: Cultural capital positively affects parental support.
H^2: Economic capital positively affects parental support.

Based on the literature review, the researcher of the related research hypothesized that all the stages of cultural capital and economic capital were positively associated with students' academic performances. Specifically, cultural capital and economic capital are positively related to parental support.

Human Capital

In his seminal 1962 work, Gary S. Becker conceptualizes human capital as intangible assets formed through strategic investments in education, experiential learning, and social competencies. The framework identifies three core components: 1) Formal/institutional education coupled with self-directed learning that develops cognitive capacities for problem-solving and technological adaptation; 2) Experience-derived tacit knowledge acquired through

occupational engagement and practical task mastery; 3) Social skill acquisition encompassing interpersonal communication, collaborative teamwork, and network-building abilities critical for organizational effectiveness. Becker emphasizes the multiplicative returns generated when these dimensions synergistically interact, arguing that their integrated development enhances individual productivity, organizational value creation, and long-term socioeconomic outcomes in dynamic environments. The theory establishes human capital as a critical growth engine through deliberate investment in knowledge systems, practical expertise, and relational capabilities.
Kutieshat and Farmanesh (2022) empirically testified through a quantitative study of 450 Jordanian education employees that new human resource management practices significantly improve innovation performance during COVID-19 via organizational innovation and innovative work behavior mediation, advocating policy reinforcement for educational innovation (Kutieshat&Farmanesh, 2022).

H_3: Human capital positively affects parental support.

Based on the literature review, the researcher of the related research hypothesized that all the stages of human resource management were positively associated with educational innovation. Specifically, human capital is positively related to parental support.

TAM

Technology Acceptance Model (TAM) (Davis, 1989) identifies perceived use (PU) and perceived ease of use (PEOU) as dual determinants of IT adoption. PU reflects users' belief that technology enhances task performance, directly predicting behavioral intention through efficiency and productivity gains. PEOU, defined as the perceived effortlessness of system interaction, both directly shapes usage attitudes and indirectly influences intention by mediating PU's effects. Crucially, empirical studies highlight PEOU's gatekeeper role: even highly useful systems face rejection if perceived as complex, as technological utility is contingent on accessibility. These antecedents hierarchically structure user attitudes, which drive adoption behaviors, emphasizing the necessity of optimizing functional value (PU) and usability (PEOU) synergistically. The framework underscores PEOU's dual function as a direct predictor and mediator, amplifying or constraining PU's impact on adoption outcomes (Davis, 1989; Venkatesh & Davis, 2000).

The Ministry of Education of China, in concert with nine other departments, has promulgated the "Opinions on Accelerating the Promotion of Education Digitization," with the objective of bolstering education digitalization to underpin the creation of a robust education system. Rooted in the principles of moral education and talent cultivation, the document advances education digitalization through multiple avenues, such as reinforcing the National Smart Education Public Service Platform, spurring AI - assisted education reform, and magnifying the international reach of digital education. It also outlines steps to enhance infrastructure, formulate standards, and bolster security and organizational execution to realize equitable, high - quality, and lifelong learning. Importantly, digital platforms are leveraged to disseminate high - quality educational resources widely, reducing disparities among urban, rural areas, regions, and schools, and enabling broader access to quality education (Ministry of Education of the People's Republic of China, 2025).

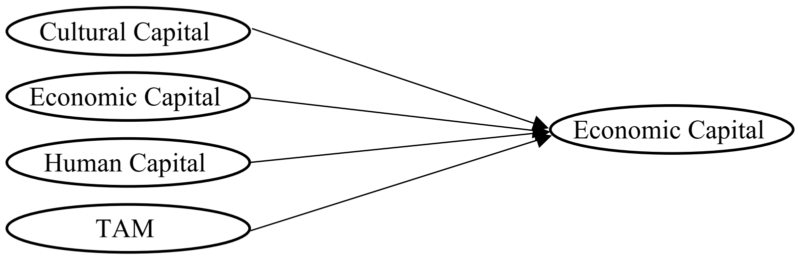
Gupta et al. (2021) extended the Technology Acceptance Model (TAM) to demonstrate that ICT based teaching in engineering education significantly enhances student engagement, academic performance, and learning satisfaction, based on empirical analysis of 300 students across programming courses, advocating for broader multi-institutional and cross-cultural validation (Gupta et al, 2021).

H_4: TAM positively affects parental support.

Based on the literature review, the researcher of the related research hypothesized that all the stages of TAM were positively associated with educational equality and students' engagement. Specifically, TAM is positively related to parental support.

Based on the literature review, the researcher of this paper developed the research framework and established the research hypotheses as follows:

Figure 1. Research conceptual framework



Research Methodology

Population and Sample

This study focuses on Nanning City, Guangxi Zhuang Autonomous Region, People's Republic of China as the research region. According to the statistics of Nanning People's Government network in 2022, Nanning is divided into 7 municipal districts. This research is implemented in the scope of high school students and their families in this region.

According to the "Notice on Basic Data of Nanning City for 2022-2023", the total of 57,000 high school seniors in Nanning are listed. Therefore, this study is based on a sampling survey of 57,000 people and their families in Nanning, Guangxi. And the sample size can be calculated based on Yamane formula (Yaman, 1973). And the 57,000 will be separated into two groups, namely: the high-income and the low-income. According to the 2023 Statistical Bulletin on National Economic and Social Development released by the National Bureau of Statistics, the per capita disposable income of the high-income group is 95,055 yuan per year, which means that if a family's per capita annual income exceeds this figure, the family can be categorized as a high-income one, translating into a monthly per capita disposable income of approximately 7,921 yuan for high-income households. Meanwhile, the per capita disposable income of the low-income group stands at 9,215 yuan annually, implying that a family with a per capita annual income lower than this amount can be classified as a low-income family, with the average monthly disposable income per capita for low-income families being roughly 769 yuan (National Bureau of Statistics, 2024). After calculation, the sample of this paper is 397.21 each, and the researcher had sent over 1,000 questionnaires for the two types of family. In order to randomize the samples, the street encounter strategy was used to group the samples according to different family incomes, so that the ratio of high and low family income students reached 1:1.

Research Tools

The data was collected through an online questionnaire which was spread by social media in order to ensure randomness and consisted of six parts. The first part collected information from general respondents, including monthly family income, educational level, and occupation, while the second part collected parents' views on the impact of cultural capital on their children's knowledge acceptance. The third part, economic capital on children's knowledge acceptance, the fourth part, human capital, and the fifth part, TAM and part six: Parental support.

The pre-test involved 40 respondents from both high and low-income families, and the internal consistency of the questionnaire was tested using Cronbach's Alpha. According to Nunnally (1978), a reliability coefficient of 0.70 or higher is generally considered acceptable. The pre-test yielded a Cronbach's Alpha score of high-income family is 0.904, and low-income family, 0.925, indicating the high reliability of the research instrument for the actual data collection process for both high and low-income family.

Research Tools Development

The general data analysis included variables such as monthly income, educational level, occupation, and the levels of influence of cultural capital, economic capital, human capital and TAM on parental support.

The researcher collected Likert-scale data and analyze using descriptive statistics (mean, percentage, range, SD). Assess normality through skewness (-3 to +3) and kurtosis (-7 to +7) following Kline's (2015) standard.

Structural Equation Modeling (SEM) was utilized to examine the effects of cultural capital, economic capital, human capital, and the Technology Acceptance Model (TAM) on parental support, with hypothesis testing conducted through a two-stage analytical process employing AMOS and SPSSAU software. And the two stages are as follows:

Confirmatory Factor Analysis (CFA) validated measurement indicators through standardized factor loadings (>0.50 threshold) (Hair et al., 2010).

Structural model evaluation employed latent path analysis with fit criteria: $\chi^2/df < 2$, RMSEA <0.05, SRMR <0.05, and CFI ≥0.90 (Schumacker & Lomax, 2010).

Statistical Techniques

An online questionnaire (via Wenjuanxing) targeting parents of high school students yielded 425 responses from high-income families, with 406 retained after validity checks by the utilization of SPSS for deleting outliers. Demographic distribution showed: Educational level: junior high school or below (n=9), high school (n=27), junior college (n=52), undergraduate degree (n=290), and postgraduate (n=28). Monthly income: 5,001-6,000 yuan(n=65), 6,001-7,000 Yuan (n=92), and above 7,000 yuan (n=249). No respondents reported earnings≤5,000 yuan. Occupational distribution: unemployed (n=4), workers (n=18), government official (n=307), merchants (n=32), teachers (n=36), and medical staff (n=9).

A total of 398 low-income questionnaires were collected through the same way as the foregoing mentioned. And 381 valid questionnaires were retained after data cleaning by using SPSS for outlier elimination. Educational composition comprised: junior high school or below (93), high school (191), junior college (65), undergraduate (31), and postgraduate (1). Monthly income distribution showed: ≤3000 yuan (298), 3001-4000 (30), 4001-5000 (10), 5001-6000 (14), 6001-7000 (13), and >7000 yuan (16). Occupational categories included: unemployed (90), workers (210), government official (30), merchants (22), teachers (26), and medical staff (3).

In terms of classification criteria, mean ≥ 4.0 indicates "strongly agree", 3.5 ≤ mean<4.0 indicates "agree", and 3.0 ≤ mean<3.5 indicates "neutral".

Table 1: The interpretation of high-income family

Factor	S.D.	Skewness	Kurtosis	Mean	Interpretation
CC: Cultural Capital	0.63297	-0.357	1.101	3.7381	Agree
ECC: Embodied Cultural Capital	0.81492	-1.011	1.415	3.9745	Agree
ICC: Institutionalized Cultural Capital	0.70107	-0.159	0.204	3.5016	Agree
EC: Economic Capital	0.59527	-0.945	3.303	3.3302	Neutral
SE: Social Economy	0.79274	-0.013	-0.138	3.1174	Neutral
RM: Resource Management	0.64073	-0.648	1.299	3.4828	Agree
WC: Working Capital	0.74328	-0.497	0.780	3.3904	Neutral
HC: Human Capital	0.54697	-0.032	0.840	3.8684	Agree
Ed: Education	0.77439	-0.933	2.364	3.7463	Agree
Ex: Experience	0.68605	-1.555	5.160	4.4261	Strongly Agree
SK: Social Skills	0.54937	-0.678	0.981	3.4329	Agree
TAM: Technological Acceptance Model	0.54975	-0.731	2.336	3.5449	Agree
PU: Perceived Use	0.58855	-0.731	2.366	3.2937	Neutral
UA: User Acceptance	0.62962	-0.237	0.810	3.7783	Agree
PEOU: Perceived Ease of Use	0.64969	-0.836	3.801	3.5626	Agree
PS: Parental Support	0.56106	-0.752	2.061	3.9880	Agree
ES: Esteem Support	0.64339	-1.243	4.363	4.0337	Agree
IS: Informational Support	0.69573	-1.286	3.860	4.1486	Agree
EmS: Emotional Support	0.68868	-1.068	6.118	4.2553	Strongly Agree
TS: Tangible Support	0.71066	-0.752	2.061	3.8202	Agree
GS: Guidance Support	0.53952	-1.387	4.726	3.6823	Agree

Source: surveys and calculations

The analysis reveals a consensus among respondents, with factor ratings ranging from 3.1174 (Socioeconomic Status, SE) to 4.4265 (Experience, Ex) on a Likert scale. Notably, experiential capital (Ex: M=4.4261) and emotional support systems (EmS: M=4.2553) emerged as predominant determinants for high-income households, demonstrating their reliance on accumulated practical knowledge and affective resources. Conversely, institutionalized cultural capital (ICC: M=3.5016) and economic capital (EC: M=3.3302) exhibited comparatively lower valuation, suggesting these variables may demonstrate context-dependent efficacy or generate divergent interpretations regarding their income-generating potential.

Table 2: The Interpretation of Low-income Family

Factor	S.D.	Skewness	Kurtosis	Mean	Interpretation
CC: Cultural Capital	0.84167	-0.596	0.657	3.3792	Neutral
ECC: Embodied Cultural Capital	1.05344	-0.580	-0.147	3.4584	Agree
ICC: Institutionalized Cultural Capital	0.80977	-0.303	0.700	3.2999	Neutral
EC: Economic Capital	0.83501	-0.127	0.258	3.1648	Neutral
SE: Social Economy	0.97857	0.129	-0.388	3.0639	Neutral
RM: Resource Management	0.88149	-0.377	0.426	3.3010	Neutral
WC: Working Capital	0.96944	-0.107	-0.162	3.1942	Neutral
HC: Human Capital	0.78847	-0.571	0.971	3.3792	Neutral
Ed: Education	1.01439	-0.602	0.161	3.4751	Agree
Ex: Experience	0.88149	-0.337	0.125	3.3010	Neutral
SK: Social Skills	0.81879	-0.323	0.760	3.3615	Neutral
TAM: Technological Acceptance Model	0.78019	-0.371	0.905	3.4591	Agree
PU: Perceived Use	0.85986	-0.257	0.682	3.3097	Neutral
UA: User Acceptance	0.79664	-0.582	1.029	3.6142	Agree
PEOU: Perceived Ease of Use	0.84907	-0.321	0.413	3.4535	Agree
PS: Parental Support	0.81507	-0.825	1.341	3.7119	Agree
ES: Esteem Support	0.95500	-0.571	0.319	3.5766	Agree
IS: Informational Support	0.89231	-0.761	0.710	3.7647	Agree
EmS: Emotional Support	0.94000	-0.747	0.580	3.8023	Agree
TS: Tangible Support	0.94239	-0.871	0.832	3.8749	Agree
GS: Guidance Support	0.83080	0.676	1.372	3.5413	Agree

Source: surveys and calculations

The data of low-income families presented in Table 4-2, encompassing 21 observed factors across five dimensions: cultural capital, economic capital, human capital, technology acceptance, and parental support. The data were collected through questionnaire surveys and quantitative calculations, measured using a 5-point Likert scale. Central tendency analysis revealed that factor means ranged from 3.06 to 3.87 (theoretical midpoint: 2.5). The highest mean values were observed in tangible support (TS = 3.87), emotional support (EmS = 3.80), and informational support (IS = 3.76), while the lowest means corresponded to social economy (SE = 3.06), economic capital (EC = 3.16), and working capital (WC = 3.19).

Based on the statistics form two types of families, high-income families show a high consensus (standard deviation 0.54-0.81) and extreme positive attitudes (left skewed, peak distribution) towards cultural capital and social support (such as emotional support EmS=4.26, experiential Ex=4.43), but a conservative evaluation of social economic resources (SE=3.12); Low income families are more concerned about economic factors (such as economic capital EC=3.16), but their evaluation of economic capital is neutral and their attitude differentiation is significant (standard deviation 0.78-1.05). The data distribution is close to symmetry (skewness<0.6, kurtosis≈0). The results indicate that high-income groups are more inclined towards value identification of non-economic resources, while low-income groups exhibit cognitive heterogeneity under economic constraints, highlighting the systematic impact of socioeconomic status on resource perception and attitude consistency (based on the 5-point Likert scale, neutral value=3).

Results and Discussion

Results of High and Low-income Family

The observed variables exhibit acceptable univariate normality, with skewness values ranging from -3 to+3 and kurtosis values ranging from -7 to+7, meeting the parameter estimation criteria in structural equation modeling (Kline, 2015). The results of confirmatory factor analysis (CFA) confirmed the structural validity of the latent variables, indicating that all measurement models have sufficient model fit indices (see Table 3&4). These psychological measurement characteristics confirm the applicability of the data for subsequent structural analysis, ensuring the robustness of parameter estimation in testing hypothesis relationships.

Table 3. Structural Validity Test Results of Using CFA to Measure Latent Variables in High-income Family

	χ2df	GFI	RMSEA	CFI	TLI
standard	<3	>0.9	<0.10	>0.9	>0.9
Result	2.628	0.938	0.063	0.970	0.956

Table 4. Structural Validity Test Results of Using CFA to Measure Latent Variables in Low-income Family

	χ2df	GFI	RMSEA	CFI	TLI
standard	<3	>0.9	<0.10	>0.9	>0.9
Result	2.564	0.939	0.064	0.978	0.965

The structural equation modeling (SEM) analysis, validated through standard criteria (Tables 3-4), revealed significant causal relationships between economic capital and parental support through path analysis, with factor loadings and model outcomes detailed in Figures 2-3.

Figure 2. The Structural Equation Model of Factors Influenced by Economic Background on Parental Support of High-income Family.

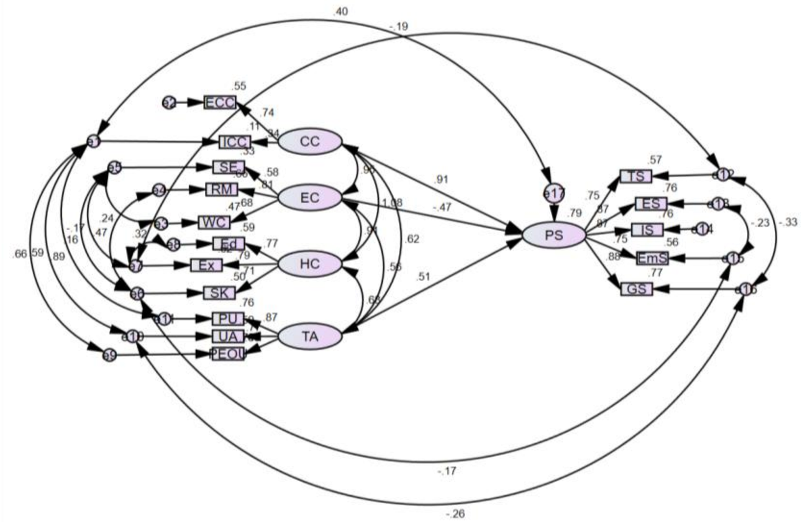


Figure 3. The Structural Equation Model of Factors Influenced by Economic Background on Parental Support of Low-income Family.

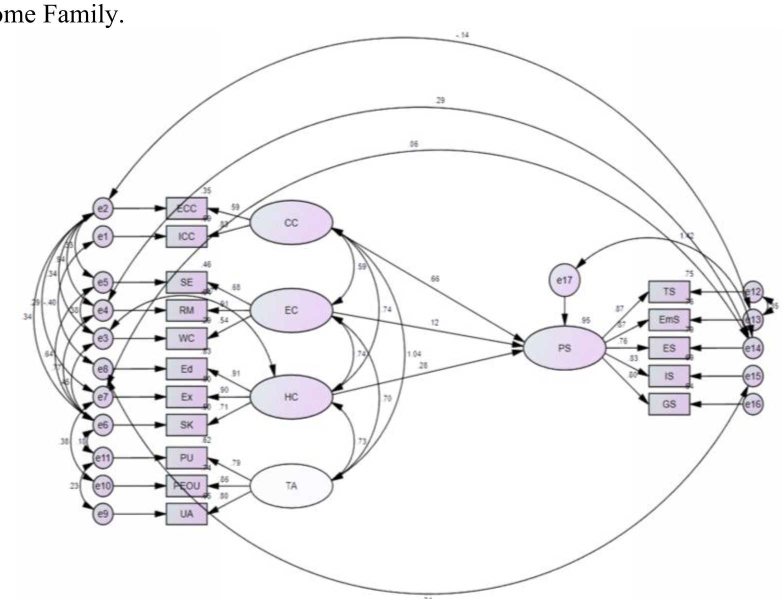


Table 5: Factor Loading Value of High and Low-income Family

Coefficient Comparative Table			
Factor	**High-income**		**Low-Income**
CC to PS	0.906	>	0.661
EC to PS	-0.471	<	0.120
HC to PS	NO		0.283
TAM to PS	0.509		NO
CC to ECC	0.744	>	0.588
CC to ICC	0.336	<	0.830
EC to SE	0.575	<	0.676
EC to RM	0.810	<	0.914
EC to WC	0.684	>	0.539
HC to Ed	0.766	<	0.910
HC to Ex	0.788	<	0.895
HC to SK	0.707	<	0.708
TAM to PU	0.872	>	0.786
TAM to UA	0.765	<	0.803
TAM to PEOU	0.862	=	0.862
PS to TS	0.752	<	0.867
PS to ES	0.869	>	0.763
PS to EmS	0.749	<	0.874
PS to IS	0.870	>	0.829
PS to GS	0.876	>	0.798

This study employs multi-group structural equation modeling (SEM) to reveal the moderating role of family income levels in the mechanisms through which cultural capital (CC), economic capital (EC), human capital (HC), and the technological acceptance model (TAM) influence parental support (PS). Key empirical findings demonstrate: (1) The positive effect of cultural capital on parental support is significantly stronger in high-income families (β=0.906) than in low-income families (β=0.661), with notably superior efficiency in converting CC to embodied cultural capital (ECC) among high-income households (β=0.744); (2) Economic capital exhibits income-specific heterogeneity, showing a negative association with PS in high-income groups (β=-0.471) versus a positive relationship in low-income groups (β=0.120); (3) Human capital significantly affects PS only in low-income families (β=0.283), while demonstrating stronger educational investment effects (β=0.910) compared to high-income counterparts (β=0.766); (4) The TAM-to-PS relationship is significant exclusively in high-income families (β=0.509), with superior path coefficients for perceived use (β=0.872) and perceived ease of use (β=0.862) relative to low-income groups. Further analysis reveals divergent support strategies: high-income families prioritize esteem support (β=0.869) and informational support (β=0.870), whereas low-income families emphasize tangible support (β=0.867) and emotional support (β=0.874). These findings illuminate structural disparities in family resource endowments and support strategies, providing novel theoretical insights into educational investment mechanisms through the lens of social stratification.

In summary, the Structural Equation Modeling (SEM) analysis confirmed the differential impact of various forms of capital and technology acceptance on parental support across different income groups. Both models demonstrated an acceptable fit (High-income: CFI = 0.970; RMSEA = 0.063. Low-income: CFI = 0.978; RMSEA = 0.064), confirming structural validity.

For the high-income, the result showed as follows:

(1) Cultural capital had the strongest positive effect on parental support (β=0.906).

(2) Economic capital was negatively associated with parental support (β=–0.471), suggesting that economic abundance may reduce perceived necessity for active involvement. The transformation of resource allocation strategies, disparities in educational expectations and support approaches, the diminishing marginal returns of economic capital, the growing prominence of social and cultural capital, as well as the combined effects of educational competition and differentiation strategies, collectively contribute to a situation where high-income families tend to convert their economic capital into other forms. This enables them to concentrate on offering non - economic support, thereby weakening the role that economic capital plays in parental support.

(3) Human capital did not show a significant effect, indicating limited influence of human resources in high-income households.

(4) Technology Acceptance Model (TAM) also significantly influenced parental support (β=0.509).

For the low income, the result revealed as listed:

(1) Cultural capital had a moderate positive effect (β=0.661).

(2) Economic capital had a small but positive effect (β=0.120), highlighting financial resources as critical in constrained environments.

(3) Human capital significantly impacted parental support (β=0.283), emphasizing the role of education, experience, and skills.

(4) TAM did not show a significant effect, indicating limited influence of digital tools in lower-income households.

Support types also varied:

(1) High-income parents emphasized esteem(β=0.869) and informational support(β=0.870).

(2) Low-income parents prioritized tangible(β=0.867) and emotional support(β=0.874).

Discussion

Existing research reveals marked differences in family capital allocation and educational perceptions between the high and low-income, which distinctly shape children's academic outcomes via divergent pathways. Here's a concise yet detailed summary:

(1) Cultural capital: It exerts the most significant influence, especially in the high-income, where it strongly predicts parental support and student achievement (Jin et al., 2022; Tan et al., 2023). The high-income are inclined to adopt innovative educational methods and integrate technology. In contrast, the low-income, constrained by limited technological access and cognitive resources, opt for traditional approaches and rely more on social capital utilization.

(2) Economic capital: A paradoxical stratification exists. The high-income plays down its direct educational impact, while disadvantaged families are acutely aware of financial limitations as persistent barriers to education.

(3) Human capital: Perceptions differ markedly. The low-income stresses the efficacy of networking, whereas the high-income focuses on self-directed learning strategies. These divergences mirror the underlying structural inequalities in educational resource allocation and intergenerational capital transmission.

(4) TAM: The patterns of technology acceptance and usage among high-income and low-income families that reveal significant disparities influenced by economic capital and access to technological resources. And the differences are listed as follows:

(4.1) High-Income Families

- High Level of Technology Acceptance: The high-income demonstrates exceptional performance across all dimensions of the Technology Acceptance Model (TAM). They achieve an average User Acceptance (UA) score of 3.7783, signifying a strong inclination to utilize digital tools, such as online learning platforms. The average Perceived Ease of Use (PEOU) score is 3.5626, reflecting a clear comprehension of the convenience offered by technological tools. However, the average Perceived Usefulness (PU) score for technology is relatively conservative, at 3.2937.

- Positive Technology Usage Behavior: High-income families often integrate online and offline learning, employing technology as a supplement rather than a replacement. They are inclined to establish a “positive cycle of technological capital” and utilize ample resources, such as purchasing educational software, to enhance learning efficiency.

- Influencing Factors of Technology Acceptance: The technological acceptance of high-income families is underpinned by their abundant economic resources. They not only have easy access to advanced technological equipment but also provide a favorable environment for technological usage and guidance for their children.

(4.2) Low-Income Families

- Low Level of Technology Acceptance: The average User Acceptance (UA) score of low-income households is 3.6142, indicating a lower willingness to use digital tools. There is a relatively high degree of variation in technology acceptance, and some families find it difficult to participate in technology-assisted learning due to the lack of basic equipment such as computers.

- Limited Use of Technology: Low-income families often restrict the use of technology to basic communication functions and primarily rely on traditional channels to obtain educational resources, making it challenging to fully utilize digital educational resources.
- Obstacles to Technology Acceptance: Low-income families face a dual deficiency in equipment and skills, leading to the dilemma of "technological exclusion". Their economic circumstances limit the acquisition of technological equipment and the development of digital literacy, and they hold a neutral or skeptical attitude toward the role of technology in education.

Contribution

Theoretical Contribution

This study provides empirical evidence for governments to formulate differentiated educational policies and optimize resource allocation for both the high-income and the low-income:

(1) For High-income families, the approaches to enhance educational support effectiveness are listed as follows:

- Advance digital transformation of cultural capital (e.g., virtual cultural resource repositories)
- Refine technology acceptance models (e.g., intelligent education platform development)

(2) For Low-income families, the measures that are able to effectively address structural constraints are listed as follows:

- Strengthen economic capital compensation mechanisms (e.g., scholarship programs)
- Promote human capital development initiatives (e.g., vocational skill development programs)
- Improve the realization of technology acceptance.

Managerial Contribution

The results demonstrate the heterogeneity of family capital types and educational support strategies. Future research should focus on the following aspects:

(1) Expand research into analyses of urban-rural gradient disparities.

(2) Construct dynamic panel models to track the interactive effects of digital technology iterations on multidimensional capital.

This approach will provide a spatiotemporally adaptive theoretical framework for equitable education policymaking.

Limitations and Future Research Directions

(1) The conclusions of this research are subject to the following limitations:

- The research is geographically constrained, relying solely on single - city sampling in Nanning.
- The cross-sectional design depends on self-reported measures, which may lead to social desirability bias and prevent causal inference.
- There are omitted moderating variables, such as community resources and policy interventions.
- The validation of the Technology Acceptance Model (TAM) in resource-scarce settings is insufficient.

(2) Future research directions are proposed as follows:

- Prioritize multi-regional stratified sampling to assess urban-rural and cultural-economic variations.
- Adopt mixed-method approaches, including longitudinal data collection and qualitative interviews, to explore the dynamic mechanisms in household education decisions.
- Integrate extended theoretical frameworks, such as the UTAUT, to enhance the predictive power in digital adoption studies.
- Establish cross-cultural comparative paradigms to systematically investigate the interactions between family capital and policy interventions, thereby advancing the theoretical universality across different contexts.

Reference

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy, 70*(5), 9–49.

Bourdieu, P. (2011). The forms of capital (1986). *Cultural Theory and Art, 1*, 81–93.

CGTN. (2024, February 1). China advances digital technology integration in education. https://news.cgtn.com/news/2024-02-01/China-advances-digital-technology-integration-in-education--1qQclg2OAYo/p.html

China Academy of Educational Sciences. (2024). China Academy of Educational Sciences releases Global Digital Education Development Index and China Smart Education Development Report 2023. https://www.cnaes.edu.cn/post/8538

China Education Daily. (2024, January 30). Digital education leads the future: A review of positive achievements in China’s education digitalization work. http://www.moe.gov.cn/jyb_xwfb/s5147/202401/t20240130_1113352.html

China Internet Science. (2024, January 25). Beijing Normal University School of Statistics and Homework Help jointly release report: Intelligent educational technology enhances learning ability. http://science.china.com.cn/2024-01/25/content_42682988.htm

CSTNet. (2023). *The Blue Book of China’s Smart Education: Smart Education is a New Form of Education in the Digital Age.* http://www.moe.gov.cn/jyb_xwfb/xw_zt/moe_357/2023/2023_zt01/mtbd/202302/t20230214_1044497.html

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Education Examination Network. (2023, August 10). Shanghai’s college entrance examination undergraduate admission rate and annual admission situation: Attached are the number of students admitted in each province in 2023. http://www.jdxzz.com/gkzx/2023/0810/10121129.html

Gupta, C., Gupta, V., & Stachowiak, A. (2021). Adoption of ICT-based teaching in engineering: An extended technology acceptance model perspective. *IEEE Access, 9*, 58652–58666. https://doi.org/10.1109/ACCESS.2021.3072580

Jin, H., Ma, X., & Jiao, S. (2022). Cultural capital and its impact on academic achievement: Sustainable development of Chinese high school students. *Sustainability, 14*(22), 14976. https://doi.org/10.3390/su142214976

Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kutieshat, R., & Farmanesh, P. (2022). The impact of new human resource management practices on innovation performance during the COVID-19 crisis: A new perception on enhancing the educational sector. *Sustainability, 14*(5), 2872. https://doi.org/10.3390/su14052872

Ministry of Education of the People's Republic of China. (2025). *Opinions of the Ministry of Education and eight other departments on accelerating education digitalization*. https://www.gov.cn/zhengce/zhengceku/202504/content_7019045.htm

Ministry of Education of the People's Republic of China. (2025). China smart education white paper released - Ministry of Education of the People's Republic of China. https://www.moe.gov.cn/jyb_xwfb/xw_zt/moe_357/2025/2025_zt06/dongtai/202505/t20250517_1190910.html

Nanning Daily. (2021, March 16). Accumulated investment of over 500 million yuan! Nanning City, Guangxi Province solidly promotes the construction of educational informatization. https://www.edu.cn/xxh/focus/df/202103/t20210316_2084846.shtml

Nanning Municipal People’s Government. (2021). *Notice from the Office of the People’s Government of Nanning City on Issuing the 14th Five-Year Plan for the Development of Digital Nanning*. https://www.nanning.gov.cn/zwgk/fdzdgknr/zcwj/zfwj/t5048940.html

National Bureau of Statistics. (2024). Resident income and consumption expenditure in 2023. https://www.stats.gov.cn/sj/zxfb/202401/t20240116_1946622.html

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.

Pishghadam, R., Meidani, E., Momenzadeh, S., Hasanzadeh, S., & Miri, M. (2023). Economic, social, and cultural capital and ESQ in academic achievement: A comparison of Afghan and Iranian students. *Frontiers in Psychology, 14*, Article 1087480. https://doi.org/10.3389/fpsyg.2023.1087480

Shanghai Education. (2024, March 22). *2023 Shanghai Education Work Annual Report*. https://edu.sh.gov.cn/xxgk2_zdgz_jygzydynb_02/20240322/130af0e8f8424bdab6ad78fe46ec403e.html

Smith, A. (1937). *The wealth of nations. Modern Library*. (Original work published 1776)

Zhang, X., & Wang, B. (2023). Research on the impact of family capital on education acquisition: Empirical analysis based on CGSS2021. *Operations Research and Fuzzy Learning, 13*(4), 3441–3449. https://doi.org/10.12677/ORF.2023.134347