Trends in Student Engagement Among Mainland Chinese Students (2006-2024)

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Abstract

This study adopts a sociocultural perspective on learning engagement, integrated with human capital theory, and employs two sub-studies anchored in three categories of social factors to analyze the longitudinal evolution of learning engagement among students in mainland China, examining the influence of five social factors across three categories—economic (GDP, Gini index, urban unemployment rate), educational (educational expenditure), and internet-related (internet penetration rate)—on learning engagement. Sub-study 1 incorporated 406 studies (n=393,117) for a cross-temporal meta-analysis, revealing that learning engagement primarily demonstrated a year-by-year upward trend, experiencing an overall decline in 2020 followed by a rapid recovery. The Gini index and urban unemployment rate failed to significantly predict learning engagement, whereas the remaining three social factors all exhibited significant positive predictive effects. Sub-study 2 utilized the China Family Panel Studies dataset (n=14,623) for multilevel linear regression, similarly finding that learning engagement among students in mainland China displayed a year-by-year upward trend, with a pronounced increase occurring in 2012. Additionally, except for the inconsistent directional effect of urban unemployment rate on learning engagement, the remaining four factors all significantly positively predicted learning engagement. Collectively, the results from both sub-studies corroborate each other, jointly indicating that the level of learning engagement among students in mainland China exhibits a year-by-year upward trend, with economic development level, educational resource allocation, and internet penetration rate serving as facilitating factors.

Full Text

Longitudinal Changes in Student Learning Engagement in Mainland China (2006-2024)

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Abstract
Drawing on a sociocultural perspective of learning engagement and integrating human capital theory, this study examines the longitudinal evolution of student learning engagement in mainland China through two complementary investigations, analyzing the influence of three categories of societal factors: economic (GDP, Gini coefficient, urban unemployment rate), educational (education expenditure), and internet-related (internet penetration rate). Study 1 conducted a cross-temporal meta-analysis of 406 studies (n = 375,902), revealing a generally upward trend in learning engagement with a temporary decline in 2020 followed by rapid recovery. While the Gini coefficient and urban unemployment rate did not significantly predict learning engagement, the remaining three societal factors emerged as significant positive predictors. Study 2 employed multilevel linear regression on data from the China Family Panel Studies (n = 14,623), which similarly demonstrated a year-over-year increase in learning engagement, marked by a notable surge around 2012. Except for the inconsistent directional effects of urban unemployment, all other factors significantly and positively predicted learning engagement. Collectively, the two studies provide convergent evidence that learning engagement among mainland Chinese students has risen steadily over time, with economic development, educational resource allocation, and internet penetration serving as key facilitators.

Keywords: learning engagement, longitudinal change, multilevel linear regression, linear meta-regression model, cross-temporal meta-analysis

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The traditional Chinese adage "no pains, no gains" reflects the central role of learning engagement in Chinese educational philosophy. Learning engagement refers to students' active participation in the learning process, which fosters optimism, resilience, meaning-making, and creativity while promoting holistic development. It serves as a crucial indicator of positive student psychology (Fang et al., 2008). The sociocultural perspective on learning engagement emphasizes that its examination must be situated within broader macro-level sociocultural contexts (Engeström, 1999; Kahu, 2013). As these contexts—particularly within the educational domain—evolve over time, student learning engagement inevitably undergoes transformation.

Specifically, Confucian ideals of lifelong learning ("learning never ends") and the social schema that "all pursuits are inferior, only learning is noble" have long shaped Chinese society' s profound cultural belief that "knowledge changes destiny." However, as disparities in educational resources between urban and rural areas have widened (Yin, 2022), the notion that "poor families struggle to produce successful children" has quietly gained traction. In recent years, the prevalence of "involution" culture has simultaneously given rise to "Buddhist" and "lying flat" subcultures. In today' s digital era, the rapid dissemination of information via the internet has fueled the "influencer economy" and "live-streaming culture," leading to value distortion among some adolescents and a resurgence of "education is useless" rhetoric (Jia, 2022). Compounded by the COVID-19 pandemic and global economic turbulence, public faith in education has faced severe challenges. Consequently, there is an urgent need to investigate the longitudinal trajectory of learning engagement among mainland Chinese students and its underlying mechanisms.

1.1 Societal Structural Indicators and Student Learning Engagement

Activity Theory offers a sociocultural lens for examining the dynamic relationships among learning subjects, objects, tools, and rules (Engeström, 1999), providing a universal framework for understanding learning activities. Kahu (2013) developed a more focused conceptual framework of engagement, antecedents, and consequences. Both perspectives emphasize how cultural tools and social structures shape learning engagement, positing that engagement is not merely an individual cognitive activity but a dynamic outcome of the interaction between learners and socioculturally constituted activity systems. Human Capital Theory (HCT) provides a more specific analytical framework for understanding learner-environment interactions: learners determine their level of engagement based on assessments of future economic returns and current capital losses (Kodde, 1988). As a macro-environmental variable, economic development directly shapes employment market structures and salary gradients, influencing students' perceived predictability and confidence in educational returns, which ultimately affects their human capital investment strategies. Thus, economic capital and educational resource allocation emerge as core social structural variables that jointly represent key dimensions of the social stratification system. Meanwhile, the internet functions both as a learning environment and a manifestation of sociocultural influence, making it a crucial societal indicator affecting learning engagement.

1.1.1 Positive Effects of Societal Indicators on Mainland Chinese Students' Learning Engagement Research demonstrates that families with higher socioeconomic status have greater access to financial (e.g., income), social (e.g., occupational status), and human (e.g., education) capital, enabling them to provide superior learning conditions and material foundations that promote student engagement (Wang et al., 2024). According to Human Capital Theory (Kodde, 1988) and the Discouraged Student Effect (Micklewright et al., 1990), learning behavior is influenced by three factors: potential educational costs, current wage losses, and future income expectations. When young people encounter media reports about corporate layoffs and shrinking employment opportunities, they dynamically evaluate whether continued educational investment will enhance their employability (Hill et al., 2018). To navigate challenging job markets, students strive to enhance their competitiveness to secure desirable positions (Yuan & Xing, 2021). Consequently, unemployment rates may actually motivate increased learning engagement.

As economies develop, national investment in education continues to grow. Educational funding provides crucial financial support for improving school infrastructure, enhancing teaching staff quality, and optimizing student-teacher ratios. Specifically, instructional expenditures that allocate resources rationally and improve curriculum systems create more opportunities for teacher-student interaction and participation in high-quality educational activities (Pike et al., 2006). Improved compensation for basic education teachers helps attract high-quality talent and enhances teacher stability and professionalism. When teachers' material and psychological needs are met, their teaching enthusiasm and engagement increase (Sun & Chen, 2002). Elevated overall school quality creates a more favorable learning atmosphere, thereby effectively promoting student engagement.

The rapid development of the internet has ushered in an era of knowledge sharing, making personalized online learning a reality. Sustainable online courses play a key role in ensuring educational accessibility and effectiveness (Lasekan et al., 2024). Moreover, online education not only dramatically increases access to knowledge and learning resources but also reduces acquisition costs while enhancing student flexibility and autonomy, thereby facilitating personalized learning (Al Rawashdeh et al., 2021; Getenet et al., 2024). When students encounter learning difficulties, personalized instruction can optimize learning experiences by promptly resolving challenges, thereby effectively stimulating learning motivation and creating a virtuous learning cycle. Research indicates that the autonomous learning opportunities and immediate feedback functions provided by online learning directly enhance student motivation and participation while strengthening students' sense of belonging to online learning, further reinforcing identity and prompting more active engagement (Lund Dean & Jolly, 2012; Wong & Liem, 2022). Additionally, the internet expands access not only to learning resources but also to more suitable teachers. Online learning enables greater flexibility in faculty location, allowing institutions to hire educators with unique expertise who reside elsewhere (Getenet et al., 2024). In short, online learning platforms enhance student engagement (Poon et al., 2024; Vo & Ho, 2024).

In summary, economic level, educational funding, and internet development all positively influence student learning engagement. Superior economic conditions typically provide better learning resources and environments, thereby safeguarding and further promoting engagement. Increased educational funding improves school infrastructure and teacher quality, indirectly enhancing student engagement. Internet popularization drives knowledge sharing and personalized learning, making resource acquisition more convenient and cost-effective while strengthening student motivation and sense of belonging, further elevating engagement. Moreover, sociocultural transformation has profoundly reshaped learning beliefs: traditional exam-oriented "score-only" concepts are gradually shifting toward quality-oriented, lifelong, and internationalized value orientations. This cultural evolution not only alleviates utilitarian learning pressure but also stimulates students' intrinsic motivation through diversified evaluation systems. Accordingly, this study proposes the hypotheses: (H1) Learning engagement among mainland Chinese students shows an upward trend over time; (H2) Societal factors promote this increase in learning engagement.

1.1.2 Negative Effects of Societal Indicators on Mainland Chinese Students' Learning Engagement However, the negative impacts of these societal indicators cannot be ignored. First, sustained economic development has exacerbated money worship among adolescents, with concepts like "money is omnipotent" and "overnight riches" significantly influencing youth values (Liu, 2012). Simultaneously, profit-driven marketing models cater to adolescent consumer psychology, gradually diverting them from core learning objectives (Chen & Wang, 2022). Moreover, employment market volatility intensifies youth anxiety and insecurity, reducing individuals' evaluation of education' s value and raising doubts about whether to continue learning (Hill et al., 2018). Second, while national, societal, school, and family emphasis on education has grown, so have students' academic and time pressures (Chen & Sun, 2022; Wang & Yang, 2022), leading individuals to adopt avoidance strategies when facing learning difficulties (Schmitt et al., 2015) and reducing engagement. Finally, social media development has spawned "Fear of Missing Out" (FOMO; Tanrikulu & Mouratidis, 2023), causing individuals to overfocus on social information, become distracted, and experience learning interference (Al-Furaih & Al-Awidi, 2021), thereby weakening engagement (Tanrikulu & Mouratidis, 2023). Compounded by online media' s amplification of negative narratives like "degree devaluation," which triggers public negativity (Luo & Wang, 2024), these factors undermine Chinese students' belief in education and damage learning engagement (Wu et al., 2023).

In short, economic development fosters impetuous mindsets, rising educational expectations intensify pressure, and internet proliferation distracts student attention—collectively reducing learning engagement. Additionally, online media's sensationalization of negative social events, combined with Generation Z' s identification with "involution," "Buddhist," and "lying flat" cultures, undermines learners' beliefs and destabilizes engagement, causing Chinese citizens' educational faith to decline. Based on this analysis, this study proposes competing hypotheses: (H1') Learning engagement among mainland Chinese students shows a downward trend over time; (H2') Societal factors inhibit the increase in learning engagement. To ensure robust findings, this research designed two complementary studies.

Study 1: Temporal Trends in Learning Engagement—A Cross-Temporal Meta-Analysis Based on the UWES-S Scale (2006-2024)

Study 1 employed cross-temporal meta-analysis to connect disparate studies chronologically, treating existing research as cross-sectional samples of historical development to examine temporal trends in learning engagement and the impact of societal indicators.

2.1 Cross-Temporal Meta-Analytic Method

Unlike traditional approaches that treat cohort effects as error terms, cross-temporal meta-analysis directly analyzes temporal effects. This method was first proposed and applied by American scholar Twenge (2000) and subsequently adopted by Chinese researchers to reveal how societal changes influence group-level psychological indicators (Xin & Zhang, 2009; Konrath et al., 2025; Chen & Sun, 2022). The approach has been used to examine temporal trends in various social-psychological indicators across different populations (Chi & Xin, 2020). This method systematically reveals associations between societal factors and psychological variables underlying temporal effects. This study applied this approach to investigate temporal trends in mainland Chinese students' learning engagement and test how three macro-level indicators—socioeconomic (GDP, Gini coefficient, urban unemployment), educational investment (education expenditure), and internet factors (internet penetration rate)—influence engagement. Based on previous research, if psychological indicators (learning engagement) collected in a given year correlate significantly with societal indicators from that year and from five years prior, an association between societal and psychological changes can be established (Xin & Zhang, 2009). Given that societal factors may have lagged effects, this study followed previous research (Xin & Xin, 2017; Chen & Sun, 2022) by matching annual learning engagement POMP scores with societal indicators from three and one years prior for lagged effect analysis. In short, this study examined how societal factors influence mainland Chinese students' learning engagement by using indicators from five, three, and one years prior, as well as concurrent indicators, to predict current-year engagement.

2.2 Data Sources for Societal Indicators

Based on theory and this study' s scope, GDP, Gini coefficient, and urban unemployment rate were selected as economic indicators; education expenditure served as the educational indicator. Data for these categories were obtained from the National Bureau of Statistics Data Release Database (https://data.stats.gov.cn/easyquery.htm). Internet penetration rate was selected as the network indicator, with data sourced from the China Internet Network Information Center' s (CNNIC) annual "Statistical Report on Internet

Development in China," using reports published in January of the following year as the current year' s indicator. Descriptive information for societal indicators appears in Table 1 .

Table 1 Descriptive Information for Societal Indicators

Indicator	M (SD)	Range	Years
GDP: Gross Domestic Product (trillion yuan)	7.72 (3.74)	1.11–12.05	2001–2022
Gini Coefficient: Income inequality (income disparity/total income × 100%)	46.87 (1.21)	40.50–49.10	2000–2022
Urban Unemployment Rate: Proportion of unemployed in urban labor force	3.28 (1.85)	0.46–6.13	2001–2022
Education Expenditure: Actual government spending on education (trillion yuan)	3.64 (2.13)	0.46–7.56	2002–2022
Internet Penetration Rate: Internet users/total population (%)	40.50 (4.34)	36.00–55.00	2001–2022

2.3.1 Measurement Instrument

Researchers have developed various learning engagement measures, with Schaufeli' s (2002) three- dimensional model being particularly influential. The Utrecht Work Engagement Scale-Student (UWES-S) defines learning engagement as a persistent and broad emotional-cognitive state comprising three dimensions: vigor (energy and resilience in academic activities), dedication (strong sense of meaning, pride, and enthusiasm), and absorption (deep immersion in learning tasks with diminished sense of time). The UWES-S demonstrates good reliability and validity and has been widely used internationally. Chinese scholar Fang (2008) adapted the UWES-S for the Chinese context. This study selected empirical research from 2006 to 2024 that used either Schaufeli' s original or Fang' s revised version.

2.3.2 Scoring Method: POMP Scores

To address the problem of inconsistent scale score meanings across studies with different samples—which prevents direct comparison and calculation—this study adopted POMP (percent of maximum possible scores) scores following previous research (Buecker et al., 2021). POMP scores transform means and standard deviations into percentages of the maximum possible score. This linear transformation reflects the percentage of the theoretical maximum score obtained by individuals or groups (Cohen et al., 1999), enabling direct comparison and integration across different scoring systems. POMP scores are calculated by subtracting the scale' s minimum possible score from each participant' s score, dividing by the scale' s range, and multiplying by 100. This ensures POMP scores reflect relative position on the scale while accounting for different scoring ranges and remaining independent of specific sample characteristics, maintaining strong comparability across cultural backgrounds and time points. Using POMP scores allows researchers to clearly depict temporal trajectories of variables.

2.4.1 Literature Selection Criteria

The following criteria guided literature selection: (1) Participants must be students studying in China, excluding international or exchange students; (2) Participants must hold mainland Chinese household registration, excluding ethnic Chinese and students from Hong Kong, Macao, or Taiwan; (3) Learning engagement must be measured using Schaufeli' s original or Fang' s revised scale, with no restrictions on scoring method; (4) Studies must report sample size (n), mean (M), and standard deviation (SD) for all participants; (5) If subscale scores are reported, these must also be collected; (6) When multiple articles by the same author contain duplicate data, only one is included; (7) Literature collection concluded in August 2024.

2.4.2 Literature Search Results

Literature was searched from CNKI, Wanfang Database, Google Scholar, and Web of Science using terms including "learning engagement," "student engagement," "UWES-S," "school engagement," "learning engagement," and "academic engagement" in titles and abstracts (see screening process in Figure 1 [Figure 1: see original paper]). The final sample comprised 406 studies ($n = 375{,}902$ participants), with males representing 47.00%. Publication years ranged from 2006 to 2024. Following cross-temporal meta-analytic convention, for studies without explicit data collection years, the collection year was calculated as publication year minus two (Twenge, 2000).

2.4.3 Literature Coding

Data were coded in Excel and analyzed using the robumeta package in RStudio (primarily the robu function). Following cross-temporal meta-analytic practice (Twenge, 2000), each study received a unique identifier, and basic data (sample size, engagement means and standard deviations), publication year, data collection year, region, and educational stage were entered into a database. To ensure accuracy, two coders independently coded all studies according to predetermined criteria. Interrater reliability was calculated for 13 indicators including publication year, article type, province, sample size, male proportion, total engagement score, and subscale means and standard deviations, yielding kappa values between 0.82 and 0.95, indicating good agreement (McHugh, 2012). Discrepancies were resolved through discussion.

2.4.4 Data Preparation

For studies reporting only subgroup values (e.g., by gender), overall sample means and standard deviations were synthesized using formulas (1) and (2):

Formula (1)

$$\bar{x} = \frac{\sum x_i n_i}{\sum n_i}$$

Formula (2)

$$S_\tau = \sqrt{\frac{\sum n_i s_i + \sum n_i (x_i - \bar{x})}{\sum n_i}}$$

2.5 Results

2.5.1 Overall Temporal Trends in Learning Engagement To visualize trends, a scatterplot was created with year on the x-axis and POMP scores on the y-axis (Figure 2 [Figure 2: see original paper]). Results show mainland Chinese students' learning engagement has gradually increased. A linear meta-regression analysis was conducted with year as the predictor, publication type as a control variable, and POMP scores for total engagement and its three subdimensions as outcomes. Results indicated a significant positive relationship between year and total engagement (= 0.42, 95% CI [0.18, 0.66], $p < 0.001$). Subdimension analyses revealed similar significant positive trends for vigor (= 0.66, 95% CI [0.35, 0.97], $p < 0.001$), dedication (= 0.64, 95% CI [0.31, 0.97], $p < 0.001$), and absorption (= 0.61, 95% CI [0.31, 0.90], $p < 0.001$) (see Figures 3-B, 3-C, and 3-D).

Figure 2 Temporal Changes in Mainland Chinese Students' Learning Engagement (2006–2024)
Note: Each data point represents a sample's mean POMP score; point size indicates weight in the regression model (larger points = smaller effect size variance). Color figures available in electronic version.

Figure 3 Meta-Regression Trends for Learning Engagement and Subdimensions (2006–2024)
Note: Panels A-D show meta-regression trends with year on the x-axis and POMP scores for total engagement (A), vigor (B), dedication (C), and absorption (D) on the y-axis.

To quantify change, 2006 and 2024 values were substituted into four regression equations (y_total = 0.42x -789.64; y_vigor = 0.66x − 1284.13; y_dedication = 0.64x − 1235.47; y_absorption = 0.61x -1166.38). Means for both years were calculated and divided by the average standard deviation across 19 years to compute Cohen' s d values: total engagement increased by 0.40 SD, vigor by 0.63 SD, dedication by 0.59 SD, and absorption by 0.56 SD. Following Cohen' s (1992) guidelines, d = 0.5 represents a medium effect size, indicating that increases across all dimensions approached medium magnitude.

Finally, a linear meta-regression controlling for gender, data collection region, and educational stage (all dummy-coded) showed these variables were non-significant predictors, while year remained a significant predictor (= 0.37, 95% CI [0.12, 0.63], p = 0.005). In summary, learning engagement among Chinese students has risen over the past 19 years.

2.5.2 Relationship Between Learning Engagement and Societal Indicators To further examine these relationships, societal indicators were plotted on the x-axis against concurrent POMP scores on the y-axis (Figure 4 [Figure 4: see original paper]). Lagged correlation analyses were conducted using societal indicators from the current year and from one, three, and five years prior to predict current engagement (Figure 5 [Figure 5: see original paper]). Results showed stable positive predictions for GDP, education expenditure, and internet penetration rate, while Gini coefficient and urban unemployment showed unstable predictions.

Figure 4 Relationship Between Societal Indicators and Learning Engagement
Note: Panels A-E show meta-regression trends with GDP, Gini coefficient, education expenditure, internet penetration rate, and urban unemployment on the x-axis and total engagement POMP scores on the y-axis.

Figure 5 Societal Indicators' Prediction of Learning Engagement (UWES-S)
Note: Red indicates significant effects; blue indicates non-significant effects.

Study 1 yielded two conclusions: (1) H1 was preliminarily supported—learning engagement increased over time, with a temporary dip in 2020 followed by rapid recovery; (2) H2 was preliminarily supported—economic, educational, and internet factors positively influenced engagement, though urban unemployment' s effect was unstable.

Study 1' s cross-temporal meta-analysis revealed temporal trends and preliminary evidence for positive effects of economic, educational, and internet factors. However, a limitation is its reliance on secondary data. Study 2 addresses this by using primary data from a publicly available dataset.

Study 2: Temporal Trends in Learning Engagement—Evidence from the China Family Panel Studies

Following Yang et al. (2022), Study 2 utilized seven waves (2010-2020) from the China Family Panel Studies (CFPS) to examine student learning engagement.

3.1 Data Sources for Societal Indicators

Same as Section 2.2.

3.2 Measurement of Learning Engagement

Data came from the 2010-2020 CFPS, a longitudinal survey project implemented by Peking University’ s Institute of Social Science Survey. Following Yang et al. (2022), engagement was measured using four items from the CFPS questionnaire (using 2010 item numbers): S601 “I study very hard,” S602 “I concentrate in class,” S603 “I check my homework multiple times for accuracy,” and S606 “I only play after finishing homework” (all 5-point scales). Total scores were converted to POMP scores. After excluding cases with missing or invalid responses, 14,623 valid cases remained (4,752 males, 4,238 females, 947 unreported). Participants came from 31 provincial-level regions including Shaanxi, Henan, and Guangdong (see Table 2).

Table 2 Participant Geographic Distribution

Region	Percentage
Inner Mongolia Autonomous Region	0.10%
Guangxi Zhuang Autonomous Region	12.9%
Tibet Autonomous Region	10.9%
Ningxia Hui Autonomous Region	0.10%
Xinjiang Uyghur Autonomous Region	13.7%
Others	0.10%

3.3.1 Overall Temporal Trends in Learning Engagement

A ridge plot with POMP scores on the x-axis and year on the y-axis revealed a gradual upward trend, with the most pronounced increase between 2011-2012 (Figure 6 [Figure 6: see original paper]). Because students within the same region show similar learning patterns, violating independence assumptions, multilevel linear regression was conducted with students nested within provinces. Results showed year significantly predicted engagement (= 0.023, 95% CI [0.022, 0.024], $p < 0.001$).

Figure 6 Temporal Changes in Mainland Chinese Students’ Learning Engagement (2010–2020)
Note: X-axis = POMP scores; Y-axis = data collection year. Each ridge curve represents the distribution of POMP scores for that year.

3.3.2 Relationship Between Learning Engagement and Societal Indicators

Study 2 conducted lagged analyses using current engagement scores with societal indicators from five, three, and one years prior, as well as concurrent indicators. Multilevel models with students nested within provinces revealed significant predictions for all economic (GDP, Gini coefficient, urban unemployment), educational (education expenditure), and internet factors (internet penetration rate). However, urban unemployment from three years prior showed opposite directional effects compared to other time lags, indicating unstable prediction (Figure 7 [Figure 7: see original paper]).

Figure 7 Societal Indicators' Prediction of Learning Engagement (CFPS)
Note: Red = significant effects; blue = non-significant effects.

Study 2 concluded: (1) H1 was reaffirmed—engagement increased over time, particularly markedly in 2011-2012; (2) H2 was further supported—GDP, education expenditure, and internet penetration rate showed stable positive predictions, while Gini coefficient and urban unemployment showed unstable predictions.

Although Study 2 used longitudinal primary data from a single institution, providing accurate reflection of true engagement trends, limitations remain: data covered only seven intermittent years (2010, 2011, 2012, 2014, 2016, 2018, 2020), and the lack of recent data limits comprehensive revelation of dynamic changes. Study 1' s continuous data effectively compensates for this limitation, making the two studies mutually complementary.

General Discussion

Combining cross-temporal meta-analysis and multilevel linear regression, this research reveals trends in mainland Chinese students' learning engagement over nearly two decades. Overall, engagement shows a gradual upward trend unaffected by participants' geographic origin, educational stage, or gender. All three subdimensions—vigor, dedication, and absorption—similarly increased. Regarding influencing factors, economic, educational, and internet factors all positively affected engagement.

4.1 Dynamic Trends in Mainland Chinese Students' Learning Engagement Over Two Decades

The sociocultural perspective posits that learning is not merely an individual cognitive process but a sociocultural and mediated practice, emphasizing that optimizing social interaction, cultural tools, and contextual design promotes deep engagement. Different stages' sociocultural characteristics profoundly influence learners' motivation and behavior patterns (Lave & Wenger, 1991), consistent with our findings.

First, Study 2 found a notable increase in engagement around 2012. In the early 21st century, China' s economic structure began upgrading and optimizing, entering a "new normal" with rapid tertiary industry development (Wang, 2013). This optimization not only increased skill demands but also created more career opportunities, enhancing students' future earnings expectations and motivating them to enhance self-worth through learning, thereby increasing engagement. During this period, traditional "excellence in learning leads to officialdom" beliefs merged with modern "knowledge changes destiny" narratives, further strengthening engagement beliefs.

Second, Study 1 found a temporary decline in 2020 followed by rapid recovery. The pandemic shocked socioeconomic structures, devastated employment markets, and fundamentally altered learning environments. While rapid online education expansion alleviated resource shortages, it also created new challenges: information overload, attention fragmentation, and learning outcome uncertainty (Alamri, 2023). The pandemic negatively impacted students' academic and mental health while altering learning beliefs. Fortunately, as social policies adjusted and online learning tools improved, learning beliefs quickly recovered. This demonstrates that while external changes produce short-term effects, policy support and educational technology can effectively mitigate negative impacts, consistent with prior research (Kahu, 2013) showing that external factors like employment and health affect engagement at specific critical junctures rather than continuously.

4.2 Dynamic Relationships Between Learning Engagement and Societal Indicators Over Two Decades

Economic Facilitation. Beyond direct effects through improved material conditions, economic growth indirectly enhances engagement by shaping cognition and emotion. A solid economic foundation fosters values and mindsets that strengthen engagement beliefs (Wang et al., 2024). During economic prosperity, society emphasizes education' s importance and personal achievement, and this value transmission effectively stimulates learning motivation. Research shows high-SES parents hold high expectations for their children that become internalized, enabling long-term future planning and sustained engagement (Wang et al., 2024). Economic growth also boosts citizen wellbeing, which correlates positively with engagement (Yi et al., 2020). China' s rising wellbeing (Li & Li, 2015) has promoted student engagement. The unstable prediction of urban unemployment—sometimes positive, sometimes negative—reflects dual mechanisms: parents and teachers may convert employment pressure into controllable learning goals that motivate students (Hidi & Harackiewicz, 2000), yet online reports about severe employment conditions may demotivate some students toward "lying flat." This instability reflects internet culture's profound influence on student psychology.

Educational Funding as Guarantee. Educational investment significantly predicts engagement, consistent with prior research (Liu et al., 2021). Funding improves teacher motivation and learning environments, enhancing student identity and motivation (Wong & Liem, 2022; Kassab et al., 2024). Funding also supports scholarships and grants that increase engagement (Hayek, 2001). Scholarships provide not only material incentives but also transmit social values recognizing academic achievement, which students internalize through interaction, strengthening responsibility and engagement. Grants alleviate financial pressure, reinforcing learner identity and allowing focus on studies.

Internet as Supplement. From a sociocultural perspective, internet technology as a cultural tool optimizes learning environments and provides new tools and interaction platforms that facilitate knowledge construction and engagement. Integration of offline learning with internet technology enhances teaching effectiveness: human-computer interaction in online courses presents traditional knowledge in more engaging formats, aiding complex concept comprehension and sustaining interest (Lasekan et al., 2024). Internet-based online learning increases learner control and autonomy, creating favorable conditions for knowledge construction and strengthening engagement and outcomes (Martin & Borup, 2022; D. Liu, 2024). Empirical research shows gamification tools integrated with coursework promote knowledge construction through exploration, significantly enhancing interest and motivation (Temel & Cesur, 2024).

Overall, mainland Chinese students' learning engagement has increased gradually over two decades, driven by macro-level socioeconomic development, educational reform, technological advancement, and evolving sociocultural concepts. Through continuous optimization of social interaction, cultural tools, and contextual design, engagement holds important implications for educational practice (e.g., collaborative learning design, cross-cultural teaching).

4.3 Theoretical Contributions and Practical Implications

First, this study expands the sociocultural perspective's explanatory scope through Chinese contextualization, revealing institutional mechanisms of cultural conflict. The "poor families struggle to produce successful children" phenomenon reflects a culture-institution conflict: tension between traditional "excellence in learning leads to officialdom" values and structural contradictions in resource allocation creates cognitive dissonance about "knowledge changes destiny," spawning "defensive learning strategies" (e.g., exam-oriented involution). This confirms Mann's (2001) concept of "academic culture alienation."

Second, this study enriches the sociocultural perspective's conception of cultural tools. Online learning platforms' facilitation of personalized and autonomous learning gradually dismantles traditional classroom authority, expanding the conceptual boundaries of cultural tools through technology-enabled media capital.

Finally, findings support a "Culture-Capital" dual-pathway model revealing synergistic mechanisms: sociocultural factors empower learning through values and beliefs (e.g., "education changes destiny"), while human capital provides behavioral incentives through economic returns (e.g., salary premiums for higher education). Their synergy creates "belief-interest resonance" during high-growth periods, driving collective engagement strengthening. During conflict periods, cultural commitment and capital reality may diverge, causing dual alienation —dismantling traditional values while reducing learning to survival strategies, culminating in "forced involution."

4.4 Limitations and Future Directions

This macro-level investigation of learning engagement reveals a 19-year upward trend and demonstrates significant positive effects of economic, educational, and internet factors, holding important theoretical and practical value. However, limitations exist: First, sample attrition occurred. Multiple engagement measures exist beyond the UWES-S, such as the Student Engagement in School (SES) model (Fredricks, 2004), which has been revised into four- (Veiga, 2016), five- (Lin & Huang, 2018), and six-dimensional versions (Gunuc & Kuzu, 2015). This lack of consensus led us to exclude SES-based studies, resulting in substantial sample loss. Second, although economic, educational, and internet factors were examined, indicators were not comprehensive. Future research should incorporate richer multidimensional societal indicators (e.g., social attitudes, emotions). Finally, future studies could employ multiverse analysis or specification curve analysis to identify primary drivers among numerous factors (Huang et al., 2023).

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Note: Figure translations are in progress. See original paper for figures.