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ARTICLE

The Protective Role of Integrated Social Media Access and Perceived Social Resources on Student Mental Health: Evidence from China

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ABSTRACT: Backgrounds: The mental health consequences of social media use remain debated. Drawing on the "rich-get-richer" perspective, this study examines whether social media access interacts with perceived social resources to shape depression risk among Chinese students. **Methods:** We analyze nationally representative data from the 2020 and 2022 waves of the China Family Panel Studies (CFPS), constructing a two-period unbalanced student panel. High-dimensional fixed effects linear probability models are estimated with province and year fixed effects and province-specific linear trends. Mediation analyses follow the Baron and Kenny framework and are supplemented by Sobel-Goodman and bootstrap tests. Heterogeneity is examined by sex and urban–rural residence. **Results:** Students with both social media access and high perceived social resources exhibit a significantly lower probability of depression ($\beta \approx -0.06$, $p < 0.01$). Trust in strangers partially mediates this association, accounting for approximately 5% of the total effect. In contrast, greater perceived entertainment value functions as a suppressor, slightly attenuating the protective relationship. The association is stronger among male and urban students. Robustness analyses using life satisfaction as an alternative outcome yield consistent patterns. **Conclusions:** Findings support the "rich-get-richer" hypothesis: digital engagement amplifies existing social advantages in mental health outcomes. Rather than exerting uniform effects, social media appears to reinforce underlying social inequalities. Policies should therefore move beyond access expansion toward strengthening trust-building mechanisms and mitigating entertainment-driven risks.

KEYWORDS: Social media access; depression; perceived social resources; trust; entertainment perception; mental health; students

1 Introduction

As digital connectivity has become a common feature of contemporary society, social media has evolved into a ubiquitous social environment, exerting a significant influence on everyday lives [1]. In China alone, over 1 billion users engaging with platforms such as WeChat and Douyin [2]. Notably, social media use among Chinese students is almost universal. Social media use among Chinese students is nearly universal, and survey evidence suggests that many regard it as an indispensable part of daily life. For this group, digital participation is not only widespread but also highly intense. For students, social media has become deeply embedded in everyday routines and social interactions [3]. Integrating digital interaction seamlessly into students' daily lives has made social media the primary environment for social evaluation and identity negotiation. Because digital interaction is now seamlessly integrated into students' daily lives, social media has become a key arena for social evaluation and identity negotiation. This close interweaving of digital habits with daily life has led to in-depth academic research on how these media interactions affect mental health, with a particular focus on the mechanisms underlying the formation of depressive symptoms.

Current research consistently underscores the complex and often contradictory nature of this relationship, frequently described as a "double-edged sword" [4,5]. On one hand, social media can serve as a powerful tool for building and sustaining social networks, strengthening interpersonal connections, fostering a sense of belonging, and enabling access to mental health information and support communities [6]. On the other hand, upward social comparison on social media undermines self-esteem and elicits feelings of inadequacy, which ultimately leads to an increase in depressive symptoms [7].

Given these conflicting findings, scholars have increasingly shifted their focus from asking whether social media affects mental health to examining for whom and how it exerts its influence [8,9]. The Differential Susceptibility to Media Effects Model (DSMM), proposed by Valkenburg and Peter, provides a systematic framework for understanding this conditionality. It posits that media effects are not uniform across users but depend on three categories of susceptibility variables: dispositional (e.g., personality traits, sex), developmental (e.g., age, cognitive maturation), and social-contextual factors (e.g., peer relationships, family dynamics) [10].

Among these dimensions, social-contextual factors have received growing attention due to their proximal influence on how individuals interpret and respond to digital social environments. Research indicates that these influences operate through multiple mechanisms. For example, individuals' subjective perceptions of social affordances—such as perceived social connectivity and system interactivity—critically shape their engagement with digital platforms [11]. Likewise, the interplay of quality of interactive services, user identification, and feelings of belongingness further modulates psychological outcomes, including satisfaction and continued engagement [12]. Additionally, pre-existing social positions can moderate these effects. Arampatzi et al. found that users experience social disconnection and loneliness often report lower well-being, even when overall time spent on social networking sites (SNSs) is unrelated to general happiness [13].

Despite these advances, one important social-contextual factor remains understudied: perceived popularity, which reflects an individual's standing within peer networks and may shape the mental health consequences of social media use. This gap is particularly salient for student populations, who engage extensively with social media and exhibit heightened responsiveness to peer-related cues and social evaluation, potentially amplifying the psychological impact of online feedback [14].

Accordingly, this study examines whether the relationship between social media access and depression among students depends on their perceived social resources. Specifically, this study investigates whether students who both use social media and perceive themselves as socially popular exhibit different risks of depression compared with other students. Building on the rich-get-richer perspective, we hypothesize that students with both social media access and higher perceived popularity will face a lower risk of depression than their peers. In addition, the study explores two potential psychological mechanisms—trust in strangers and perceived entertainment value of the internet—through which such relationships may operate.

To address these questions, we draw on nationally representative data from the China Family Panel Studies (CFPS), focusing on student respondents from the 2020 and 2022 survey waves. Using panel data methods that account for regional and temporal heterogeneity, this study investigates the association between social media access, perceived social resources, and depression risk among Chinese students.

By focusing on the interaction between digital access and perceived social resources, this study contributes to the literature in several ways. First, it extends existing research on social media and mental health by highlighting the importance of heterogeneous effects conditioned by individuals' social capital.

Second, it contributes to the broader literature on social capital and psychological well-being by examining how perceived social standing interacts with digital environments. Finally, the findings may provide useful insights for policymakers seeking to design more targeted strategies to promote healthy social media engagement among adolescents.

2 Theoretical Framework and Research Hypotheses

2.1 Rich-Get-Richer vs. Poor-Get-Richer Hypotheses

Two dominant theoretical frameworks offer competing predictions about who benefits from social media use.

The rich-get-richer hypothesis posits that individuals who already possess abundant social skills and resources are best positioned to benefit from online social interaction [15]. They can use digital platforms to efficiently maintain and expand their large social networks, thereby gaining greater social support [16]. Given the well-established positive relationship between social support and mental health, online interaction may further amplify the psychological advantages associated with social competence among individuals with higher perceived popularity [17].

In contrast, the poor-get-richer hypothesis suggests that individuals who feel socially disconnected and lonely may turn to online platforms to compensate for these deficiencies [18,19]. The internet, with its reduced social cues and potential for anonymity, provides a less intimidating environment to practice social skills, form relationships, and access support that may be difficult to obtain offline, thereby potentially enabling socially disadvantaged individuals to derive greater benefits from online interaction. However, it is crucial to note that while the compensatory use of the internet might be motivated by a desire for connection, empirical evidence is mixed on its success, with some studies suggesting it can lead to problematic use and negative psychological outcomes if offline interactions remain challenging [20].

Based on this reasoning, we propose the following hypothesis:

H1: *Individuals with both social media access and strong perceived social resources will demonstrate a lower risk of depression compared to others.*

2.2 The Role of Trust and Entertainment Perception

Beyond determining whether social media use benefits or harms students with varying levels of perceived social resources, it is crucial to understand the mechanisms through which these effects operate. Our study examines two potentially important mediators: trust in strangers and the perceived importance of the internet for entertainment purposes.

Trust, as a crucial cognitive dimension within social capital, links the intensity of social media usage to students' overall life satisfaction and civic participation. According to Social Baseline Theory [21], individuals who perceive themselves as having strong social resources tend to view the social world as less threatening and more supportive. This perception may extend beyond their immediate social circle to encompass a broader sense of safety in interpersonal encounters, including interactions with strangers. Indeed, research suggests that those who feel socially connected are more likely to hold positive expectations about others' benevolence [22]. When such individuals engage in online environments—where interactions with unfamiliar others are common—their heightened trust in strangers may facilitate more positive exchanges and reduce the cognitive burden of hypervigilance, a factor known to contribute to depressive symptoms [23]. As Valenzuela et al. [24] argue, purposeful interaction within social networking sites can cultivate a general sense of trust, and this trust, in turn, enhances an individual's psychological well-being by strengthening the perception of available social resources. Thus, trust may alleviate the psychological burden associated with social vigilance and foster more meaningful online connections, thereby reducing the risk of depression [25].

Hence, it is hypothesized that:

H2: *The protective effect of internet use on depression risk among individuals with strong perceived social resources will be mediated by greater trust.*

Additionally, students' perception of the utility of the internet—especially their subjective valuation of the internet's entertainment functions—may also affect their mental health. According to the Use and Gratification Theory [26], individuals select and use media based on their specific needs and motivations, and the alignment between these motivations and the gratifications provided by the media plays a crucial role in shaping psychological outcomes. As prior research suggests, entertainment-oriented use provides a sense of escapism and enjoyment without the pressures of maintaining or seeking social validation, which can positively influence mental health [27].

For individuals who perceive themselves as having sufficient social resources, offline interactions may adequately satisfy their interpersonal needs. Consequently, when these individuals engage with the internet, they may assign greater value to its entertainment functions rather than relying on it as a compensatory means of fulfilling unmet social needs [28,29]. This greater valuation of entertainment may be associated with more positive online experiences characterized by enjoyment rather than anxiety about social standing, thereby contributing to better mental health outcomes [30].

Thus, we hypothesize:

H3: *The protective effect of internet use among individuals with strong perceived social resources on depression risk will be mediated by greater perceived entertainment value of the internet.*

These hypothesized mechanisms are summarized graphically in Fig. 1.

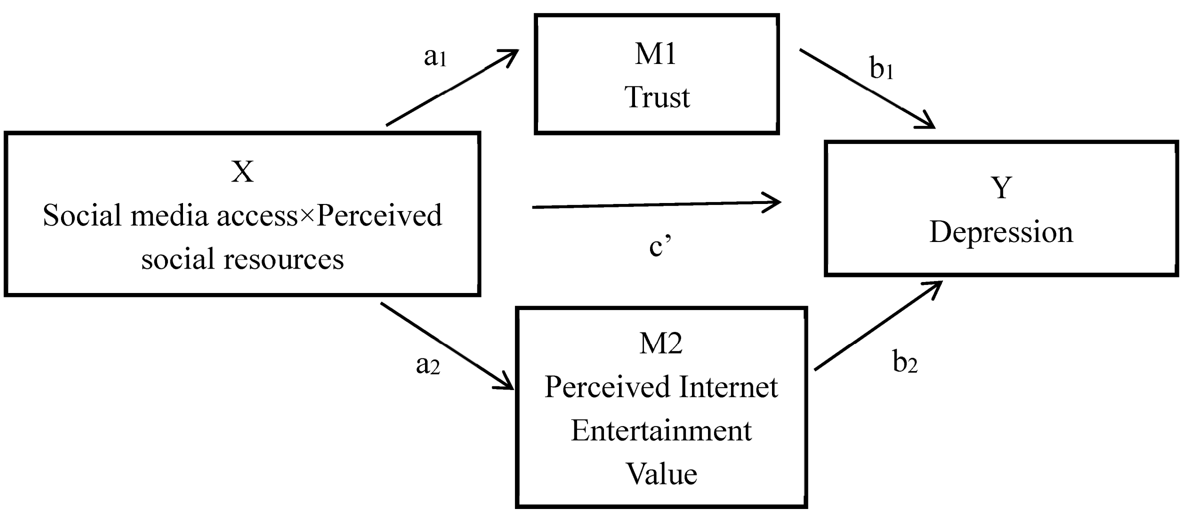

Figure 1: Theoretical framework of the effects of integrated social media use and perceived social resources on students' mental health. X: social media access × perceived social resources (HighPopularity_Access); M1: trust in strangers; M2: perceived importance of the internet for entertainment; Y: depression; a1: effect of X on M1; a2: effect of X on M2; b1: effect of M1 on Y; b2: effect of M2 on Y; c': direct effect of X on Y after controlling for mediators.

3 Methods

3.1 Data

3.1.1 Data Source

Data for this study are drawn from the China Family Panel Studies (CFPS), a nationally representative longitudinal survey administered by the Institute of Social Science Survey (ISSS) at Peking University. Launched in 2010, the CFPS employs a multistage probability proportional-to-size (PPS) sampling design, stratified by region and urban-rural status, covering 25 provinces across China that collectively represent approximately 95% of the national population. The survey collects comprehensive information on individual, family, and community-level characteristics, including demographic attributes, socioeconomic status, health outcomes, and social behaviors. The CFPS protocol was approved by the Institutional Review Board (IRB) of Peking University (Approval No. IRB00001052-14010). All participants provided written informed consent prior to participation. The present study uses publicly available anonymized secondary data and therefore did not require additional ethical approval.

The target population of the CFPS consists of all resident families and their household members living in the 25 sampled provinces of China. An eligible household is defined as an independent economic unit residing in a residential community, with at least one family member holding Chinese nationality. Family members are defined as financially dependent immediate relatives, or non-immediate blood, marital, or adoptive relatives who have lived with the household for more than three consecutive months and are financially related to the sampled household. The sampling design employs a three-stage probability-proportional-to-size (PPS) sampling strategy: primary sampling units (PSUs) are administrative districts or counties; secondary sampling units (SSUs) are administrative villages or neighborhood communities nested within the selected districts or counties; and tertiary sampling units (TSUs) are households within the selected villages or communities. In the baseline 2010 survey, the CFPS successfully interviewed 14,960 households and 42,590 individuals. By the 2022 wave, the sample had expanded to approximately 20,000 households and 75,000 individuals across more than 1000 counties or districts due to the tracking of gene members and natural population changes.

The CFPS employs a unique "gene member" tracking rule to maintain longitudinal representativeness. All members listed in the baseline 2010 family roster are defined as "gene members", and children subsequently born to or adopted by these gene members are also identified as gene members. All gene members are permanently followed throughout their lifetimes, regardless of whether they move or form new households. In each follow-up wave, the non-gene immediate relatives of gene members (i.e., parents, spouses, and children living in the same household) are defined as "core members" for that specific wave; they are eligible for interviews during that wave but are not permanently tracked if they leave the household. Family members who are neither gene members nor core members are not eligible for personal interviews. Regarding interview eligibility, all individuals aged 9 and above in sampled households are eligible for personal interviews, while for children aged 0–15, questionnaires are completed by their guardians as proxy respondents. The baseline survey achieved a household-level response rate of 81.25% and an individual-level response rate of 84.14%.

The source population of the present study comprises all respondents who successfully completed the individual questionnaire in the 2020 and 2022 waves of the China Family Panel Studies (CFPS). These two waves represent the most recent publicly available survey rounds and simultaneously contain the core variables required for this study, including mental health assessments (CES-D scale), internet usage indicators, measures of social perception, and relevant control variables. Accordingly, we append the

2020 and 2022 datasets to conduct the analysis and construct a two-period unbalanced panel dataset. An unbalanced panel indicates that not all individuals are observed in both survey waves; however, all eligible person-wave observations meeting the study criteria are retained in the analytical sample.

Within this source population, the analytical sample is restricted to respondents classified as students. Specifically, individuals who reported being currently enrolled in an educational institution at the time of the survey—including those attending during the academic term or temporarily on school break—were defined as students. This classification is based on the standardized education-status categories provided in the CFPS questionnaire, thereby ensuring objectivity and replicability in sample identification.

After identifying the student subsample, we further applied predefined inclusion and exclusion criteria to ensure data completeness and internal consistency of variable measurement. Detailed eligibility and exclusion criteria are presented in Sections 3.1.2 and 3.1.3. Following systematic sample screening procedures, the final analytical sample used for empirical estimation was obtained.

3.1.2 Inclusion Criteria

1. Population Eligibility: Participants must be students, defined as those enrolled during the semester or on school break.
2. Data Completeness: Participants must have complete data for all core variables, including:
   (1) Outcome variable: Valid depression status (depressed) based on converted CES-D scores.
   (2) Explanatory variable: Composite indicator of social media access and perceived social resources (HighPopularity_Access).
   (3) Mediating variables: Trust in strangers (trust) and perceived importance of the internet for entertainment (entertainimp).
   (4) Control variables: Age, sex, urban/rural residence, family size, logarithm of household income, and education level.
3. Survey Wave Participation: The participant sample is drawn from the 2020 and 2022 waves of CFPS data. These two waves are appended to construct a two-period unbalanced panel dataset for analysis.
4. Valid Mental Health Assessments: Participants must have valid CES-D scores, converted from the original 1–4 scale to the standard 0–3 scale and then to a total score ranging from 0 to 60.

3.1.3 Exclusion Criteria

1. Non-Student Status: Individuals not classified as students are excluded.
2. Missing Core Data: Participants with missing values in any core variable are excluded to avoid bias.

3.2 Variable Measurement

3.2.1 Dependent Variable

The dependent variable is depression, measured with the 20-item Center for Epidemiologic Studies Depression Scale (CES-D). The original CES-D assesses affective, somatic, and interpersonal symptoms experienced during the past week across four dimensions: depressive affect, somatic symptoms, interpersonal difficulties, and positive affect (reverse coded). Each item is rated on a four-point scale ranging from 0 ("rarely or none of the time") to 3 ("most or all of the time"). Item scores are summed to produce a total score between 0 and 60, with higher scores indicating more severe depressive symptoms.

In the CFPS, however, items are coded on a 1–4 scale rather than the standard 0–3 scale, yielding a raw total score between 20 and 80. To ensure comparability with the standard CES-D used in prior research, we linearly transformed the CFPS scores to the standard 0–60 metric by subtracting 20 from the raw total score. Subsequently, we applied the clinical cut-off recommended by Radloff [31]: total scores of 16 or above are classified as indicating clinically significant depressive symptoms (coded as 1), while scores below 16 are classified as not meeting the threshold for clinically significant depressive symptoms (coded as 0).

3.2.2 Independent Variable

To capture the joint presence of social media access and perceived social resources, we constructed a composite indicator, HighPopularity_Access. Social media access is proxied by Internet accessibility, measured by two items asking whether the respondent uses a mobile device or a computer to access the Internet. Respondents reporting the use of either device are coded as having social media access (1), and 0 otherwise.

Perceived social resources are assessed using self-rated popularity based on the question "How good are your interpersonal relationships?" Responses range from 0 to 10, and scores of 5 or higher are coded as high perceived social resources (1), while lower scores are coded as low (0).

Finally, the composite variable takes the value of 1 if a student has both social media access and high perceived social resources, and 0 otherwise.

3.2.3 Mediating Variables

(1) Trust

The trust variable is derived from the social trust module of the CFPS. It is measured by the following direct question: "How much do you trust strangers?" Responses are recorded on an 11-point scale ranging from 0 ("completely distrust") to 10 ("completely trust"). In our analysis, the raw response is treated as a continuous variable.

(2) Entertainment Perception

This variable is drawn from the CFPS module assessing attitudes toward internet use. It is measured by the item: "How important is the internet for leisure and entertainment?" Responses are recorded on a 5-point Likert scale (1 = "not important at all", 5 = "very important"). This item captures the subjective importance respondents assign to the entertainment function of the internet and reflects their cognitive tendency to view it primarily as a tool for leisure. In the analysis, it is treated as an ordinal variable.

These mediating variables are both operationalized through single-item self-report measures. This measurement strategy is primarily based on two considerations. First, as a nationally representative multi-topic longitudinal study, the CFPS must balance respondent burden against data breadth; thus, it employs efficient single-item measures for complex constructs—a standard practice in large-scale surveys such as the WVS. Second, recent methodological research further suggests that a conceptually clear single item can offer greater logical transparency than multi-item scales that mechanically aggregate responses. Nonetheless, we acknowledge the inherent limitations of single-item measures regarding reliability and the capture of multidimensionality, which are addressed in Section 7.2 (Limitations).

3.2.4 Control Variables

We also include key demographic and socioeconomic covariates which may influence depression risk: age, sex (1 = female, 0 = male), urban residence (1 = urban, 0 = rural), family size, logarithm of annual household income (lnincome), and education level (edu), in order to reduce confounding and isolate the effects of primary predictors.

Detailed definitions and coding of all variables employed in the empirical analysis are summarized in Table 1.

Table 1: Definitions of variables.

Type of Variable	Variable	Definition
Dependent variable	depressed	Depressive status: 1 = clinically significant depressive symptoms; 0 = otherwise
Independent variable	the composite indicator	Social media access with high perceived social resources: 1 = yes; 0 = no
Mediating variables	trust	Trust in strangers (range: 0–10)
	entertainimp	Perceived importance of Internet for entertainment (range: 1–5)
Control variables	age	Age of the student
	female	Sex: 1 = female; 0 = male
	urban	Residence: 1 = urban; 0 = rural
	family size	Number of household members
	lnincome	Natural logarithm of total annual household net income (in Chinese Yuan)
	education	Current stage of formal education: 1 = Primary school; 2 = Junior high school; 3 = High school/Vocational school; 4 = Junior college; 5 = Undergraduate program; 6 = Master's program; 7 = Doctoral program

3.2.5 Operationalization

To address the research questions, we estimated a series of high-dimensional fixed-effects models to reduce potential omitted variable bias and account for complex correlation structures in the error term. The econometric specification takes the following form:

$$\mathrm{Depressed}_{ipt} = \beta_0 + \beta_1 \mathrm{Pophigh\_access}_{ipt} + \beta_2 X_{ipt} + \mu_p + \lambda_t + \delta_p \cdot t + \epsilon_{ipt} \tag{1}$$

where: i, p and t denote individual, province, and year, respectively. $\mathrm{Depressed}_{ipt}$ measures depression; while $\mathrm{Pophigh\_access}_{ipt}$ is the key explanatory variable indicating simultaneous social media access and high perceived popularity. X_{ipt} represents a vector of individual controls including age, sex, urban residence, family size, household income, and education level. μ_p denotes province fixed effects, λ_t denotes year fixed effects and $\delta_p \cdot t$ represents the provincial linear trends. β_0 is the intercept, β_1 and β_2 represent the coefficients of the corresponding variables, and ϵ_{ipt} is the idiosyncratic error term.

To further examine the underlying mechanism, we referred to the Baron and Kenny [32] three-step mediation framework. The models are specified as follows:

Step 1: Using Eq. (1), test whether the combined variable of social media access and perceived social resources influences student mental health.

Step 2: Test whether this combined variable influences trust and entertainment perception, the two mediating variables, as specified in Eq. (2):

$$M_{ipt} = \beta_0 + \beta_1 \mathrm{Pophigh\_access}_{ipt} + \beta_2 X_{ipt} + \mu_p + \lambda_t + \delta_p \cdot t + \epsilon_{ipt} \tag{2}$$

Step 3: Simultaneously include the combined variable, the mediators, and mental health in the model, as given by Eq. (3):

$$\mathrm{Depressed}_{ipt} = \beta_0 + \beta_1 \mathrm{Pophigh\_access}_{ipt} + \beta_2 M_{ipt} + \beta_3 X_{ipt} + \mu_p + \lambda_t + \delta_p \cdot t + \epsilon_{ipt} \tag{3}$$

In Eqs. (2) and (3), the variables $\mathrm{Depressed}_{ipt}$, $\mathrm{Pophigh\_access}_{ipt}$, X_{ipt} have the same meanings as in Eq. (1). M_{ipt} represents the mediating variable (trust or the perception of the internet as a tool for entertainment). The terms μ_p, λ_t, and $\delta_p \cdot t$ capture the province fixed effects, year fixed effects, and the provincial linear trends, respectively. β_0, β_1, β_2 and β_3 are the model parameters to be estimated, while ϵ_{ipt} denotes the error term.

3.2.6 Statistical Analysis

All statistical analyses were performed using Stata 17.0 (StataCorp LLC, College Station, TX, USA). Descriptive statistics were first computed to summarize the distribution of all study variables. Categorical variables are presented as frequencies and percentages, while continuous variables are reported as means and standard deviations. To examine the relationship between social media access, perceived social resources, and student mental health, we employed a series of high-dimensional fixed effects linear probability models estimated using the reghdfe command [33]. This approach efficiently absorbs province fixed effects, year fixed effects, and province-specific linear trends to mitigate omitted variable bias arising from time-invariant regional heterogeneity and divergent regional development paths. Standard errors were clustered at the province level to account for potential serial correlation and heteroskedasticity, as well as correlated shocks within geographic units over time [34]. Mediation effects were tested using the Baron and Kenny [32] three-step framework, supplemented by Sobel-Goodman tests and bootstrap resampling methods (with 1000 replications) to assess the statistical significance of indirect effects. Heterogeneity analyses were conducted by stratifying the sample by sex and urban-rural residence. Statistical significance was set at $p < 0.05$ (two-tailed).

4 Results

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics of all variables included in this study.

Table 2: Statistical description.

Variable	Obs	Min	Max
Categorical Variables	N (%)		
depressed	7318 (22.8%)	0	1
the composite indicator	7318 (76.8%)	0	1
female	7318 (47.9%)	0	1
urban	7318 (45.1%)	0	1
edu	7318	1	7
Education Level	N (%)		
primary school	2335 (31.9%)	1	1
junior high school	1872 (25.6%)	2	2
high school/vocational	1572 (21.5%)	3	3
junior college	614 (8.4%)	4	4
undergraduate program	823 (11.2%)	5	5
master's program	81 (1.1%)	6	6
doctoral program	21 (0.3%)	7	7
Continuous Variables	Mean (SD)		
trust	2.642 (2.143)	0	10
entertainimp	3.319 (1.061)	1	5
age	15.59 (4.493)	9	44
family size	4.979 (1.889)	1	16
lnincome	11.202 (1.012)	0	15.613

Approximately 22.8% of the participants reported clinically significant depressive symptoms, indicating a non-negligible prevalence of mental health issues among Chinese adolescents. Additionally, 76.8% of the sample was classified into the "HighPopularity_Access" group, indicating a high prevalence of both social media and a strong perceived social resources. This pattern not only aligns with the high level of internet penetration in China but may also reflect relatively advantaged social resource endowment among the respondents. The relatively large standard deviation of this binary indicator (SD = 0.422) further indicates notable dispersion in the distribution of this characteristic within the sample.

Additionally, Table 2 illustrates the distribution of respondents by their current level of education. The sample displays a decreasing distribution across successive educational stages, with the largest proportion of participants at the primary school level, followed by progressively smaller shares at higher educational levels. This pattern suggests that our findings may predominantly reflect individuals with lower educational attainment.

4.2 Main Regression Results

Table 3 presents the core findings from our empirical analysis, examining the impact of integrated social media access and perceived popularity on depression using three progressively rigorous model specifications. Consistent with H1, across all specifications, the coefficient for our key variable of interest remains statistically significant and negative, confirming that individuals with simultaneous social media access and relatively strong perceived social resources exhibit a lower likelihood of depression compared with other participants.

Table 3: The impact of integrated social media access and perceived popularity on depression.

		Depressed	
	(1) Fixed Effect	**(2) Fixed Effect**	**(3) Fixed Effect**
The composite indicator	-0.060^{***} (0.018)	-0.062^{***} (0.018)	-0.062^{***} (0.018)
Age	0.009^{***} (0.002)	0.008^{***} (0.002)	0.008^{***} (0.003)
Female	0.007 (0.009)	0.009 (0.010)	0.010 (0.010)
Urban	−0.010 (0.012)	−0.010 (0.012)	−0.009 (0.012)
Family size	0.008^{**} (0.004)	0.006 (0.004)	0.006 (0.004)
Lnincome	−0.004 (0.005)	−0.005 (0.004)	−0.005 (0.004)
Edu	−0.009 (0.008)	−0.005 (0.008)	−0.004 (0.008)
Constant	0.165^{***} (0.058)	0.189^{***} (0.049)	0.193^{***} (0.050)
Year fixed effect	YES	YES	YES
Province fixed effect	NO	YES	YES

Table 3: *Cont.*

	Depressed (1) Fixed Effect	(2) Fixed Effect	(3) Fixed Effect
Provincial linear trends	NO	NO	YES
Observations	7070	7070	7070
R-squared	0.008	0.019	0.025

Note: Standard errors, clustered at the province level, are in parentheses. $^{**}p < 0.05$, $^{***}p < 0.01$.

In our most parsimonious specification, controlling only for year fixed effects (Column 1), students with both social media access and high perceived popularity show a 6-percentage-point lower probability of depression, which is statistically significant at the 1% level. This protective effect persists when accounting for time-invariant regional heterogeneity through province fixed effects (Column 2; $\beta = -0.062$, $p < 0.01$) and remains substantively unchanged when further incorporating province-specific linear trends to control for diverging regional development paths (Column 3; $\beta = -0.062$, $p < 0.01$).

4.3 Mediation Analysis Results

The mediation results for H2 (mediator: trust) and H3 (mediator: perceived entertainment value) are presented in Table 4.

Table 4: Mediation analysis results for trust and entertainment perception pathways.

	(1) Depressed	**(2) Trust**	**(3) Depressed**	**(4) Depressed**	**(5) Entertainimp**	**(6) Depressed**
The composite indicator	-0.063^{***} (0.013)	0.304^{***} (0.060)	-0.060^{***} (0.013)	-0.156^{***} (0.020)	0.107^{**} (0.045)	-0.160^{***} (0.020)
Trust			-0.010^{***} (0.002)			
Entertainimp						0.034^{***} (0.005)
Observations	7069	7069	7069	6051	6051	6051
R-squared	0.025	0.156	0.027	0.034	0.114	0.040
Sobel test		Mediator: trust $p = 0.002$			Mediator: entertainimp $p = 0.026$	
Control				Yes		

Note: Standard errors, clustered at the province level, are in parentheses. $^{**}p < 0.05$, $^{***}p < 0.01$. All regressions include year fixed effects, province fixed effects and province-specific linear trends.

Supporting H2, we find that individuals with internet access and high perceived popularity exhibit higher levels of trust in strangers (Column 2: $\beta = 0.304$, $p < 0.01$) compared to their peers. This enhanced trust is, in turn, associated with a notable reduction in depression risk (Column 3: $\beta = -0.010$, $p < 0.01$). However, our findings regarding the perceived entertainment value of the internet directly contradict H3. While the composite indicator predicts a higher entertainment valuation (Column 5: $\beta = 0.107$, $p < 0.05$), this valuation is unexpectedly linked to an increase in depression risk (Column 6: $\beta = 0.034$, $p < 0.01$).

The Bootstrap three-step regressions confirm both pathways are significant: trust operates as a positive mediator, while entertainment perception exhibits a suppressing effect (Table 5), reinforcing the reliability of our mechanism analyses.

Table 5: Mediation analysis results for trust and entertainment perception pathways.

	(1) Depressed	(2) Trust	(3) Depressed	(4) Depressed	(5) Entertainimp	(6) Depressed
The composite indicator	-0.0625^{***} (0.0128)	0.3038^{***} (0.0598)	-0.0597^{***} (0.0124)	-0.0625^{***} (0.0128)	0.1069^{**} (0.0476)	-0.1596^{***} (0.0205)
Trust			-0.00974^{***} (0.0025)			
Entertainimp						0.0344^{***} (0.0056)
Observations	7070	7069	7069	7070	6051	6051
R-squared	0.025	0.156	0.027	0.025	0.115	0.040
Control			Yes			

Note: Standard errors, clustered at the province level, are in parentheses. $^{**}p < 0.05$, $^{***}p < 0.01$. All regressions include year fixed effects, province fixed effects and province-specific linear trends.

However, several methodological limitations warrant acknowledgment when interpreting these Bootstrap results. First, given the pronounced province-level clustering in our panel data structure, conventional individual-level Bootstrap resampling would disrupt within-province error dependencies and invalidate our province-clustered standard errors. Second, while the Wild Cluster Bootstrap method theoretically offers a superior alternative by resampling residuals at the cluster level to preserve provincial dependencies, practical implementation proved infeasible: the ‘boottest’ command in Stata is incompatible with ‘reghdfe’ models that absorb multiple fixed effects (province, year, and province-specific linear trends) or include interaction terms. Consequently, our reported Bootstrap estimates rely on standard non-clustered resampling and should be interpreted with caution, as they do not fully account for the hierarchical structure of the CFPS data.

Table 6 shows the results of Sobel-Goodman mediation test. We confirm that the indirect effect through trust is statistically significant ($\beta = -0.003$, $p < 0.01$; Table 6), accounting for approximately 5.0% of the total effect. This suggests that the generalized constitutes one pathway through which social media access combined with strong perceived social resources reduce depression risk. In terms of entertainment, the indirect effect is positive and significant by Sobel-Goodman test ($\beta = 0.004$, $p < 0.05$), indicating a classic suppression effect rather than a mediating mechanism. It is noteworthy that the magnitude of this suppression effect is relatively modest in substantive terms, accounting for only 2.3% of the total effect. This suggests that while the suppression is statistically detectable, its practical significance in the overall relationship is limited.

Table 6: Effect table of mediation effect regression.

	Effect Value	Std. Err.	p Value	Effect Proportion
Total effect				
trust	−0.063	0.013	2.1e−06	0.047
entertainimp	−0.156	0.020	1.1e−14	−0.024
Direct effect				
trust	−0.060	0.013	6.4e−06	1.050
entertainimp	−0.160	0.020	1.8e−15	0.977
Indirect effect				
trust	−0.003	0.001	0.002	0.050
entertainimp	0.004	0.002	0.026	−0.023

Given that the Sobel-Goodman test assumes normally distributed indirect effects—a condition often violated in finite samples—we additionally employed Bootstrap resampling methods to validate our findings non-parametrically. The bootstrap results are presented in Tables 7 and 8.

Table 7: Mediation effect test of trust.

Effect	Coefficient	BootSE	Bootstrapping			
			Bias-Corrected 95% CI		Percentile 95% CI	
			Lower	Upper	Lower	Upper
Total Effect	−0.06	0.014	−0.084	−0.029	−0.085	−0.03
Indirect Effect	−0.003	0.001	−0.005	−0.001	−0.005	−0.001
Direct Effect	−0.057	0.014	−0.08	−0.024	−0.082	−0.027

Table 8: Mediation effect test of entertainment.

Effect	Coefficient	BootSE	Bootstrapping			
			Bias-Corrected 95% CI		Percentile 95% CI	
			Lower	Upper	Lower	Upper
Total Effect	−0.155	0.02	−0.19	−0.113	−0.193	−0.116
Indirect Effect	0.004	0.002	0.001	0.008	0.001	0.008
Direct Effect	−0.159	0.02	−0.195	−0.119	−0.195	−0.12

For the trust mediation path, the bootstrap results confirm a significant indirect effect ($\beta = -0.003$, 95% BC CI [−0.005, −0.001]), consistent with H2 and the theoretical framework positing that students with robust social networks develop trust in strangers, thereby alleviating psychological burden and reducing depression risk.

However, regarding the entertainment perception path, the bootstrap analysis reveals a significant positive indirect effect ($\beta = 0.004$, 95% BC CI [0.001, 0.008]). Specifically, higher perceived entertainment value slightly weakens the protective effect of social media use on depression. This finding contradicts H3, suggesting that entertainment-oriented use may introduce certain negative moderating mechanisms at the psychological level.

In summary, these bootstrap findings reinforce our primary conclusions: the trust pathway operates as a genuine mediator, while the entertainment pathway functions as a suppressor, with both results demonstrating robustness across alternative estimation methods.

5 Heterogeneity Analysis

To gain a comprehensive understanding of the impact of social media use on the mental health of Chinese students, we conduct a detailed heterogeneity analysis by stratifying the sample along two dimensions: sex and residential area. All the results are presented in Table 9. This approach allows us to identify the differential effects of the composite variable "HighPopularity_Access" (integrating social media access and high perceived social resources) across distinct subgroups.

Table 9: The result of the heterogeneity analysis.

	Female	Male	Urban	Rural
The composite indicator	-0.045^{**} (0.020)	-0.078^{***} (0.020)	-0.075^{**} (0.028)	-0.055^{**} (0.022)

Table 9: *Cont.*

	Female	Male	Urban	Rural
Age	0.008** (0.004)	0.007* (0.004)	0.007** (0.003)	0.009** (0.004)
Female			−0.004 (0.014)	0.020* (0.011)
Urban	−0.019 (0.017)	0.001 (0.013)		
Family size	0.009* (0.005)	0.003 (0.005)	0.011*** (0.004)	0.003 (0.004)
Lnincome	−0.003 (0.009)	−0.006 (0.005)	−0.001 (0.006)	−0.009 (0.008)
Edu	−0.006 (0.011)	0.000 (0.014)	0.005 (0.010)	−0.014 (0.012)
Constant	0.155 (0.113)	0.222*** (0.063)	0.122* (0.078)	0.274** (0.101)
Observations	3376	3692	3197	3871

Note: Standard errors, clustered at the province level, are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. All regressions include year fixed effects, province fixed effects and province-specific linear trends.

5.1 Sex Heterogeneity

Among girls, the composite indicator of integrated social media access and high perceived social resources lowers the probability of depressive symptoms by 4.5 percentage points ($p < 0.05$); among boys, the reduction is 7.8 percentage points ($p < 0.01$). This can be attributed to differences in the level of activity, social interaction patterns, and psychological needs between males and females on digital platforms. Previous research suggests that males may be more likely than females to seek support through online social networks, which may provide them with greater psychological security [35]. Additionally, sex differences may also relate to the tendency of males to seek more external resources in the face of stress, while females may rely more on internal social support systems.

5.2 Urban–Rural Heterogeneity

Urban students exhibit a larger protective effect (−7.5 percentage points, $p < 0.05$) compared with their rural peers (−5.5 percentage points, $p < 0.05$). Urban adolescents are generally more likely to have easier access to online social resources, which may play a significant role in protecting their mental health. Ahlborg et al. [36] found a significant association between social capital and mental health, with urban adolescents being more likely to receive psychological support through online social networks, thereby experiencing a greater protective effect.

6 Robustness Test

To evaluate the robustness of our baseline results, we perform an alternative outcome test by replacing the CES-D depression score with a conceptually related but independently measured indicator—life satisfaction. In the CFPS, life satisfaction is assessed on a five-point ordinal scale (1 = "very unsatisfied" to 5 = "very satisfied"). To ensure analytical clarity and comparability with our main specification, we recode this measure into a binary variable, with scores of 1–3 classified as low satisfaction (0) and 4–5 as high satisfaction (1).

This robustness check enables us to examine whether the observed effects of integrated social media access and perceived popularity hold consistently across alternative measures of mental health, thus mitigating concerns about measure-specific artifacts and providing additional empirical support for our findings.

The results, presented in Table 10, reveal a statistically significant positive effect of the key variable on life satisfaction across all model specifications. Specifically, in the most parsimonious model with year fixed effects only (Column 1), students with both social media access and high perceived popularity exhibited an approximately 0.029-unit increase in life satisfaction ($p < 0.05$). This effect remains statistically significant after incorporating province fixed effects (Column 2; $\beta = 0.029$, $p < 0.05$) and province-specific linear trends (Column 3; $\beta = 0.029$, $p < 0.05$), indicating that the positive association is not driven by unobserved regional heterogeneity or trends.

The consistency of these results with our main regression—where the composite indicator negatively predicted depression—strengthens the validity of our hypothesis (H1). It suggests that the combination of social media access and high perceived social resources enhances overall mental well-being, manifesting as both reduced depression and increased life satisfaction. Furthermore, the coefficients for control variables generally align with expectations, though some lose significance, underscoring the distinct yet complementary nature of these mental health measures. Overall, this robustness check confirms that our core findings are not an artifact of the specific depression metric and reinforces the "rich-get-richer" dynamic in digital contexts.

Table 10: The impact of integrated social media access and perceived popularity on life satisfaction.

		Life Satisfaction	
	(1) Fixed Effect	**(2) Fixed Effect**	**(3) Fixed Effect**
The composite indicator	0.029**	0.029**	0.029**
	(0.014)	(0.013)	(0.013)
Age	−0.009***	−0.007***	−0.007***
	(0.002)	(0.002)	(0.002)
Female	−0.028**	−0.028**	−0.028**
	(0.012)	(0.012)	(0.012)
Urban	0.003	0.001	0.000
	(0.013)	(0.013)	(0.013)
Family size	0.000	0.003	0.003
	(0.004)	(0.004)	(0.004)
Lnincome	0.001	0.001	0.001
	(0.007)	(0.008)	(0.008)
Edu	−0.021**	−0.026***	−0.024***
	(0.008)	(0.008)	(0.008)
Constant	0.940***	0.911***	0.913***
	(0.076)	(0.083)	(0.082)
Year fixed effect	YES	YES	YES
Province fixed effect	NO	YES	YES
Provincial linear trends	NO	NO	YES

Table 10: *Cont.*

	Life Satisfaction		
	(1) Fixed Effect	(2) Fixed Effect	(3) Fixed Effect
Observations	5077	5076	5076
R-squared	0.027	0.038	0.043

Note: Standard errors, clustered at the province level, are in parentheses. $^{**}p < 0.05$, $^{***}p < 0.01$. All regressions include year fixed effects, province fixed effects, and province-specific linear trends.

7 Discussion

7.1 Findings

Drawing on CFPS data, this study moves beyond the simplistic "good versus bad" framing of social media and provides more nuanced evidence on how social media access interacts with perceived social resources to shape mental health. The empirical results reveal three core findings:

First, the results strongly support the rich-get-richer hypothesis [15]: students with both social media access and high perceived popularity are less likely to experience depression. The benefits of digital access appear to accrue primarily to those who already possess social advantages. Their digital interactions seem to complement and enhance their already rich social lives, leading to better mental health outcomes. This finding challenges the notion that social media primarily serves a compensatory function for socially disadvantaged groups, and is consistent with research suggesting that personal social capital is crucial for online experiences [8].

Second, the analysis clarifies underlying mechanisms. The results partially support our hypotheses about how this effect occurs. The trust pathway functions as expected. Individuals with both access and popularity report higher trust in strangers, which is in turn linked to lower depression, demonstrating a significant mediating effect ($\beta = -0.003$, $p < 0.01$). The finding for the entertainment perception pathway is surprising and contrary to our hypothesis. Although students possessing both access to social media and robust social resources report a significantly heightened perception of the internet importance for entertainment, this perception paradoxically associated with a higher risk of depression, suggesting a suppressive indirect effect ($\beta = 0.004$, $p < 0.05$). This pattern may be explained by the design of entertainment-focused platforms, which employ algorithmic recommendation systems to maximize user engagement. Such designs can foster habitual or addictive usage, potentially eliciting negative affect—such as guilt, regret, or perceived loss of control—that counteracts the anticipated hedonic benefits of online entertainment [37,38]. However, this harmful suppressive indirect effect is substantially outweighed by the considerably larger direct protective effect of integrated social resources.

Finally, heterogeneity analyses demonstrate that, across both sex and residential area dimensions, the interaction between social media access and perceived social resources reduces depressive symptoms, while the magnitude and statistical precision of this protective effect are greatest among (i) male students and (ii) urban students. This result underscores the context-dependent nature of these digital-social dynamics.

However, it is important to acknowledge that the observed effect sizes are small in absolute magnitude ($R^2 < 0.05$), despite reaching statistical significance. This indicates that the combined effect of social media access and perceived social resources represents only one of many factors influencing students' mental health outcomes. Such low R^2 values are common in large-scale social and epidemiological research, where complex psychological outcomes are typically shaped by numerous measured and unmeasured personal and environmental influences [39]. Despite the small effect sizes, the results nevertheless provide statistically detectable and replicable evidence of a directional association at the population level [40].

While the practical significance of these effects should not be overstated, they do not necessarily translate into clinically meaningful differences at the individual level.

7.2 Limitations and Future Research

While this study advances understanding of social media and mental health, several limitations remain. First, our measure of social media access is binary and does not account for variations in usage patterns, intensity, or platform type. Future research should incorporate more fine-grained measures to differentiate among distinct forms of online engagement (e.g., active versus passive use). Second, our sample is testricted to Chinese students and overrepresenting individuals at earlier educational stages. This cultural and educational imbalance limits the diversity of the data and may constrain the extent to which the findings generalize to other populations. Conducting studies with more balanced samples across cultures and educational levels would be an important step toward improving external validity. Third, although the mediating effects we identified were statistically significant, their magnitudes were relatively small. This suggests the existence of additional mechanisms—such as online self-presentation strategies or fear of missing out (FoMO)—that deserve closer examination.

Finally, the most notable limitation of this study lies in its reliance on single-item measures for the core predictor and mediator variables, with the exception of depressive symptoms, which were assessed using the standardized CES-D scale. As noted earlier, while this represents a necessary trade-off for feasibility within the context of a large-scale social panel survey, and while single items offer clarity in directly capturing core concepts, their psychometric properties (e.g., reliability, validity) have not been systematically evaluated. This approach may indeed introduce measurement error and limit the ability to capture the full richness of constructs such as “social resources” and “trust”. This limitation reflects a pervasive tension in contemporary social science research: the choice between efficiency and depth in measurement tools when navigating the space between investigating macro-level trends and micro-level mechanisms.

This limitation, however, points to valuable directions for future research. First, subsequent studies could, where feasible, incorporate brief yet psychometrically superior scale instruments while maintaining survey efficiency to cross-validate the findings of this study. Second, researchers could explore the use of measurement models to perform latent variable modeling on multiple related single-item indicators, thereby partially correcting for measurement error while leveraging existing large-scale social survey data. Finally, we call for closer collaboration between measurement methodologies and social scientists during the design phase of large-scale surveys to develop a minimal yet optimal battery of measurement tools that balances efficiency with reliability and validity, thereby advancing this line of research toward greater precision.

8 Conclusions

Overall, this study offers a more nuanced understanding of digital inequality in student mental well-being based on large-scale empirical evidence from China. By examining the interaction between social media use and perceived social resources, the analysis shows that the psychological consequences of digital engagement are socially conditioned. Students who perceive themselves as possessing greater social capital appear to benefit more from digital connectivity, whereas the compensatory effects fail to materialize for those with lower perceived social standing. These findings reconceptualize the digital divide, suggesting that it should no longer be viewed merely as a matter of differential access, but also as a mechanism capable of reinforcing existing social disparities. Crucially, the identification of trust- and entertainment-based pathways, together with systematic differences across sex and urban–rural contexts, further clarifies the psychological processes through which digital participation influences well-being.

Although the observed effect sizes are small and caution against overinterpretation, they nonetheless reveal statistically detectable and theoretically meaningful patterns. From a practical perspective, platform designers, educators, and public health practitioners may therefore consider how online environments might be more deliberately structured to foster genuine social connection and trust, rather than passive or algorithmically driven consumption—particularly for male students and those from rural areas. More broadly, the study invites renewed reflection on how digital practices are embedded within the broader social contexts that shape individuals' psychological experiences.

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Availability of Data and Materials: The data that support the findings of this study are openly available in China Family Panel Studies at https://cfpsdata.pku.edu.cn/#/home.

Ethics Approval: The China Family Panel Studies (CFPS) was approved by the Institutional Review Board (IRB) of Peking University (Approval No. IRB00001052-14010). Written informed consent was obtained from all participants by the CFPS survey team. The present study is a secondary analysis of fully anonymized, publicly available CFPS data; therefore, no additional ethical approval or informed consent was required for this study.

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