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Toward a Nuanced Understanding of Digital Skills and Perceived Social Mobility: An Exploratory Study Among Chinese Youth

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Abstract

It is generally believed that the acquisition of digital skills is associated positively with socioeconomic empowerment. Policies and programs have been implemented to equip young people with skills in various digital technologies. However, the association between different types of digital skills and young people's socioeconomic outlook is unclear. Drawing on data from a nationally representative survey conducted in China, this article reveals that overall digital skill level (DSL) and basic digital skills are not significantly associated with young adults' perceived future mobility (PFM). Rather, the mastery of advanced digital skills is what matters. Individuals with only basic digital skills tend to exhibit more pessimistic expectations about their future mobility than those who possess both basic and advanced skills. In particular, the association between DSL and PFM varies across different levels of socioeconomic status (SES), suggesting that DSL correlates more strongly with perceived mobility for youth with lower SES than it does for their wealthier peers. This study suggests the existence of a digital skills underclass among young people, a relatively small yet significant group at risk of being left behind. The findings offer new perspectives for policymakers seeking to promote inclusive and sustainable youth development in the digital age.

Keywords

China; digital divide; digital skills; perceived future mobility; young adults

1. Introduction

With the development of ICTs, governments and nongovernmental organizations have proactively promoted digital upskilling programs (e.g., ITU, 2020; OECD, 2019; UNESCO, 2018; Vuorikari et al., 2022). Digital skills are considered critical to the success of young people, underpinning scholarly performance, easing transitions into the workforce, and fostering active participation in democratic processes (e.g., Vuorikari et al., 2022). Policymakers generally assume that equipping the workforce with digital competencies will enable individuals, and particularly disadvantaged individuals, to secure better-paid employment and achieve greater social mobility.

On the one hand, empirical studies have shown that digital skills are associated with improved economic returns (Falck et al., 2021) and upward income mobility (Wang, 2025). On the other hand, this optimistic assumption does not seem to apply to young people. Despite widespread access to digital technologies, some studies have reported that younger generations are not uniformly equipped for their technology-rich future, which means that various forms of digital divides persist and correlate strongly with the digital futures of younger generations (Iivari et al., 2020).

In addition, a few studies have argued that the types of digital skills matter. For example, a recent work indicated that unequal digital skill acquisition may relate to deeper forms of preexisting social exclusion (e.g., health inequalities and the income gap) among young adults (C. Qin et al., 2024). Au (2024) reported that digital technologies tend to benefit already privileged groups while leaving disadvantaged groups further behind when they do not have advanced skills, such as information management skills, and who therefore experience a greater degree of objective socioeconomic deprivation. By distinguishing between types of digital skills and examining the moderating role of socioeconomic status (SES), this article aims to explore whether upskilling policies act as a genuine ladder for everyone, especially vulnerable people.

In the Chinese context, national programs such as "Broadband China" and "Digital China" have made it much easier for people to access the internet (C. Liu, 2012; C. Liu & Wang, 2021; Xia, 2010, 2022). According to the latest statistical report in China, young people account for nearly half of the Chinese internet user population of 1.123 billion (CNNIC, 2025). This massive digital expansion provides a unique contextual setting when compared to other regions. Unlike young adults in many Western countries, who often report relatively low mobility expectations, Chinese youth have traditionally shown high optimism regarding their future socioeconomic trajectories (Whyte, 2010). However, this unique intersection of widespread digital access and personal aspirations clashes increasingly with rigid offline social stratification. In reality, young Chinese people today face a highly competitive labor market and unequal educational resources (Mok & Wu, 2016). As noted by van Deursen and van Dijk (2014), widespread access without strategic skills often fails to correlate with capital-enhancing benefits. For Chinese youth, the following question remains: To what extent can digital skills enhancement be translated into real-world outcomes?

Despite the growing literature on socio-digital stratification, a research gap remains. Most studies treat digital skills as a uniform generic tool and focus primarily on objective socioeconomic outcomes. Few studies have investigated how specific dimensions of digital skills operate within the broader socio-digital stratification process to shape subjective social mobility expectations. This article addresses this gap by offering an incremental empirical contribution to the research.

2. Literature Review

2.1. Definitions and Determinants of Social Mobility

Social mobility can be defined in two ways: objective social mobility and subjective social mobility. Objective social mobility refers to horizontal changes in objective conditions, including an individual's occupation, education, and economic status (Anderson, 2018; Bian, 2002; Tiffin et al., 2005; Tooth & Mishra, 2013). Subjective social mobility refers to an individual's perception of their opportunities for upward social mobility based on personal initiative and effort (Su et al., 2015). This includes perceived present mobility, perceived future mobility (PFM), and perceived intergenerational mobility (Du et al., 2021; Song, 2024).

At the individual level, researchers have explored how parental *SES*, gender, *hukou* classification (in China), and the expansion of higher education relate to perceptions of social mobility (Huang, 2020; Mok & Wu, 2016; Song, 2024). The findings indicate that most respondents, irrespective of prior experiences of upward or downward mobility, tend to perceive an upward trajectory in social mobility. These perceptions align consistently with various individual-level sociodemographic factors and broader societal and economic conditions, including economic growth, low unemployment rates, and GDP performance, alongside *hukou* reforms (C. Chen & Qin, 2014; Du et al., 2021; Gugushvili & Zelinska, 2023; Huang, 2020). However, some scholars adopt a more critical stance and contend that the expansion of higher education in China exhibits a weakened association with perceived upward social mobility and that family background demonstrates a more robust correlation (Mok & Wu, 2016). Similarly, M. Jackson et al. (2005) concluded that educational attainment, both in terms of its level and the institution attended, weakens the direct link between digital skills and social mobility. Recent studies suggest that the significance of parental achievements and *hukou* status in predicting upward social mobility in China is gradually declining (C. Chen & Qin, 2014).

2.2. Digital Skills and Perceptions of Social Mobility

Over the past two decades, the relationship between digital skills and social stratification/inclusion has been discussed thoroughly. Scholars have considered digital skills not only as useful tools (e.g., communication and entertainment) but also as important forms of cultural and economic capital in societies where digital mediation is common (Merisalo & Makkonen, 2022; Ragnedda & Ruiu, 2020; Rodríguez-Camacho et al., 2024; van Laar et al., 2018). Digital skills are considered a type of social capital that is linked closely to life outcomes, aspirations, and future trajectories (Ragnedda, 2018; Ragnedda & Ruiu, 2020; Rodríguez-Camacho et al., 2024; Verwiebe & Hagemann, 2025). Digital skills are of greater importance for young adults who are entering an unstable job market, where being good at digital capacities is no longer just a plus but often a requirement for obtaining a good job and moving up in the world (Hargittai, 2010; Vuorikari et al., 2022). Digital skills have emerged as important competencies, particularly for young adults navigating the transition from education to employment and engaging in the digital facets of social life (van Deursen & Helsper, 2015; van Laar et al., 2017, 2018).

Empirical research that investigates the correlation between digital skills and perceptions of social mobility has produced mixed results. One perspective posits that digital skills enhance optimism with respect to advancement. Advocates have asserted that these skills bolster the belief in merit-based advancement by facilitating access to valuable information, expanding networks, and offering new resources (DiMaggio & Bonikowski, 2008; Robinson et al., 2015; van Laar et al., 2018). A contrasting point of view warns that unequal access and skill levels can make social divides worse. Scholars have observed that this process frequently entails unfavorable comparisons with others online, potentially exacerbating disillusionment regarding one's prospects for success (Helsper, 2021). Research by Hargittai (2010) revealed that individuals who possess only fundamental internet skills frequently perceive the online realm as presenting fewer opportunities. Studies showed that digitally disadvantaged youth from lower socioeconomic backgrounds are more susceptible to algorithmic isolation and information cocoons (Hargittai, 2021; Zuiderveen Borgesius et al., 2016). Other studies have indicated minimal to no effect, which suggests that digital proficiency alone is inadequate to transform entrenched beliefs regarding mobility without the implementation of comprehensive institutional reforms (Hout, 2014; Torche, 2014).

In the Chinese context, the relationship between digital competencies and individuals' perceptions of social mobility warrants further scholarly attention. Over the past two decades, national initiatives such as Broadband China and Digital China have subsidized digital infrastructure heavily, making basic technology widely accessible (C. Liu, 2012; C. Liu & Wang, 2021; Xia, 2010, 2022). According to recent statistical reports, young adults now account for a massive portion of the internet user population in China (CNNIC, 2025). However, this rapid universalization of internet access occurs alongside enduring offline structural challenges, including a highly competitive job market and unequal educational opportunities (Au, 2024).

Although basic connectivity is nearly universal, the capacity to use technology and the tangible benefits derived from it remain stratified. These digital divisions align consistently with established offline inequalities in geography, class, and education (Qiu, 2009). Recent empirical evidence reflects this socio-digital stratification. For example, higher digital literacy levels are associated with better economic outcomes and employment stability in rural areas (Zhou et al., 2024). Similarly, higher levels of digital skills correlate positively with better health outcomes among urban, affluent, and younger populations (C. Qin et al., 2024). However, among rural-to-urban migrant students, G. L. Liu (2025) recently observed offline identity challenges and structural obstacles related strongly to how these youth perceive the empowering potential of digital literacies.

3. Theoretical Framework and Hypotheses

Socio-digital stratification theory serves as the theoretical foundation for this study. Different from early views that saw digital adoption as a universal equalizer (Bell, 1973), the socio-digital stratification perspective highlights a bidirectional feedback loop between digital and social inequalities (Helsper, 2012; Ragnedda, 2020). As Helsper (2012) explained through the corresponding fields model, offline social hierarchies (e.g., class or education) dictate individuals' access to and usage of technologies, which reproduce and often amplify preexisting structural disadvantages in the digital realm. This process often reproduces and amplifies existing structural disadvantages in the digital realm (Ragnedda & Ruiu, 2020). Within this stratification process, the academic focus has shifted from the first- and second-level digital divides (access and basic usage) to the third-level digital divide (Ragnedda & Ruiu, 2017). This divide specifically examines the unequal capacity to translate digital engagement into tangible offline outcomes (Scheerder et al., 2017; van Deursen et al., 2017).

To understand how digital skills operate within this stratification process, the concept of digital capital offers a useful analytical lens (Ragnedda, 2018). Building on Bourdieu's (1986) theory of capital, scholars note that digital capital has two distinct dimensions. The objectified dimension involves material resources and technological access, whereas the embodied dimension consists of internalized digital dispositions and competencies (Ignatow & Robinson, 2017; Ragnedda & Ruiu, 2020). Therefore, digital skills are not simply technical tools but also serve as the embodied state of digital capital. This embodied capital helps individuals convert online resources into offline socioeconomic benefits, empowering them to obtain the competencies demanded by the modern labor market (Vuorikari et al., 2022), better career prospects, and improved social status (Rodríguez-Camacho et al., 2024). Accordingly, the following hypothesis is proposed:

> H1: Digital skills are positively associated with PFM.

However, not all digital skills have the same capital for social advancement, which may obscure the realities of the socio-digital stratification. Users acquire digital skills sequentially, moving from operational abilities to strategic competencies that are more complex (van Dijk & van Deursen, 2014). In the framework of digital capital, the distinguishing value of a resource declines when it becomes universally accessible (Ragnedda, 2017). Because basic digital skills are now ubiquitous among young people, particularly in China (CNNIC, 2025), such skills no longer act as a competitive advantage. Instead, real digital capital is concentrated among users who have advanced skills to control algorithmic rules and verify complex information (Verwiebe & Hagemann, 2025). Possessing these advanced skills allows young adults to accumulate distinct forms of digital capital that yield social prestige and economic returns (van Deursen et al., 2014), which genuinely enhances their mobility expectations. Consequently, a digital underclass (DU) emerges. This group includes individuals who are technically connected but who lack the strategic competencies needed to convert their digital engagement into beneficial outcomes (Ragnedda, 2020). Without effective engagement, these disadvantaged groups struggle to obtain capital returns (Lutz, 2019; Park, 2017). Thus, the following hypotheses are proposed:

> H2a: Advanced digital skills are positively associated with PFM, whereas basic digital skills are not significantly related.

> H2b: Compared with individuals who possess both basic and advanced digital skills, individuals who possess only basic digital skills exhibit lower PFM.

Existing theories offer competing arguments regarding who benefits the most from digital capital. According to socio-digital stratification processes and the corresponding fields model, offline privileges are frequently amplified in the digital domain (Helsper, 2012). This stratification hypothesis suggests that individuals with a higher SES are better able than others are to extract offline benefits from their digital skills due to their existing structural advantages (Au, 2024; Rodríguez-Camacho et al., 2024). In contrast, the resource substitution hypothesis posits that personal resources are marginally related more strongly with outcomes for individuals who lack structural advantages (Ross & Mirowsky, 2006). From this perspective, embodied digital capital might serve as a crucial alternative pathway for disadvantaged youth to overcome offline barriers. To test these conflicting theoretical narratives within the specific context of Chinese youth, the following competing hypotheses are proposed regarding the moderating role of SES:

> H3a: The positive relationship between digital skills and PFM is stronger for young people with a higher SES.

H3b: The positive relationship between digital skills and PFM is stronger for young people with a lower SES.

4. Data and Measures

4.1. Sample

The data used for this study were derived from the Chinese General Social Survey (CGSS), which was conducted by Renmin University of China. The CGSS is a nationally representative survey that includes respondents from 30 provinces (municipalities and autonomous regions) in China, and it has been widely used in numerous previous studies (e.g., Du et al., 2021; Hao & Ke, 2024; Huhe, 2014; Zhang & Jiang, 2019). The CGSS 2017 data covered 783 variables and a sample of 12582 participants, all aged 18 years and older.

Within this total sample, we identified 4455 young adults, accounting for 35.41% of the respondents. This age category, defined as individuals ≤44 years old, aligns with the classification of young adults as defined by both the WHO and China's National Bureau of Statistics and is consistent with the categorizations employed in many existing Chinese studies (e.g., C. Liu et al., 2023; G. Qin & Li, 2024; Xiong & Yu, 2024; Zhu et al., 2020). Notably, 4165 of these young adults were internet users, representing a high internet penetration rate of 93.49%. After we dropped cases with missing or invalid variables, our final valid sample consisted of 1317 young adults.

This high internet penetration rate among young adults provides a crucial background. By 2017, basic digital access was nearly universal among Chinese youth. However, this digital expansion occurred alongside rigid offline social stratification (Wu, 2019). Young adults faced a highly competitive labor market and unequal educational resources (Mok & Wu, 2016). Therefore, the CGSS 2017 survey captures a unique transitional period, showing how young adults tried to use new digital skills to overcome real social barriers.

In the final sample, 50.05% of the respondents were female, and 49.95% of the respondents were male. The relatively balanced sex distribution that resembles the proportional ratios typically observed in samples from other studies (e.g., B. Jackson et al., 2007) demonstrates the reliability of the sample. Finally, negative-order variables were recoded as positive-order. The sample selection and attrition flow diagram is shown in Figure 1.

4.2. Measures

4.2.1. Dependent Variable

The dependent variable is PFM. The CGSS 2017 employed the MacArthur Scale of Subjective Social Status, which requires participants to indicate their present social standing and predict their status a decade later using a pictorial 10-step ladder, where the bottom (1) and top (10) represent the lowest and highest positions, respectively. The visual scale has been widely utilized and validated in recent social mobility research within the Chinese context (e.g., Du et al., 2021; C. Liu et al., 2023). Following Du et al. (2021), PFM is derived by subtracting the current status (SS_1) rating from the estimated score 10 years later (SS_2) and thus provides a longitudinal perspective on self-perceived mobility ($M = 1.391$, $SD = 1.406$; Cheng & Wen, 2019).

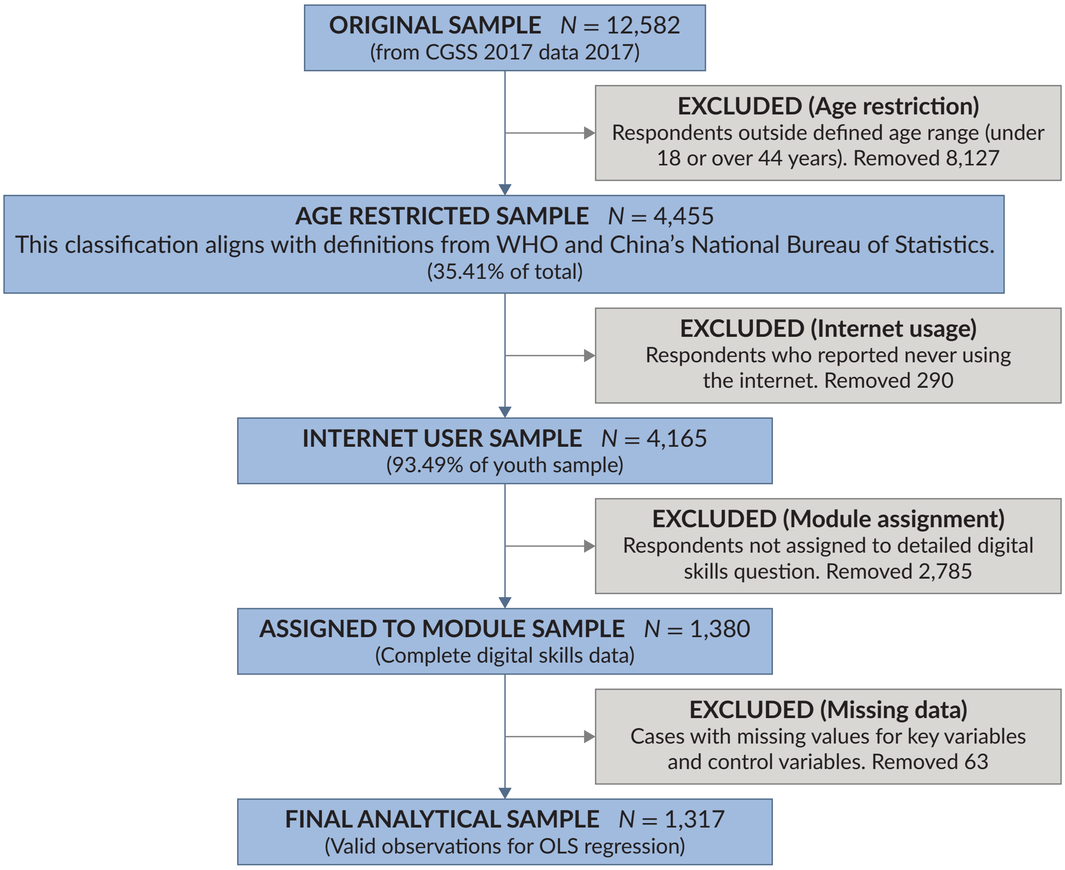

Figure 1. Sample selection and attrition flow diagram.

4.2.2. Independent Variable

In this study, digital skills (henceforth: DS) were assessed using a six-item scale in which the respondents rated their proficiency in the following areas:

1. Opening websites on a computer;
2. Downloading and installing applications on smartphones;
3. Finding information online;
4. Verifying important news shared on social media platforms such as WeChat and microblogging sites before believing it;
5. Knowing how to express personal thoughts in an online setting;
6. Assessing the security of an environment before making online payments or transactions.

Each item was rated on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

First, the DSL was measured as the average score of the six-item scale, with a higher score indicating a higher level of digital skills (M = 4.302, SD = 0.741). The Cronbach's alpha was 0.871, which showed satisfactory reliability.

The 5-point scale items across the six digital skill dimensions were subsequently recoded. Ratings from 1 (*strongly disagree*) to 3 (*not sure*) were recoded as 0, indicating the absence of digital skill in the respective skill type, whereas ratings of 4 (*agree*) and 5 (*strongly agree*) were recoded as 1, indicating the possession of the respective digital skills. Following the Bourdieusian digital capital framework (Calderón Gómez, 2020; Ragnedda, 2018), we operationalized digital skills not merely as technical tasks but only as embodied capital. We distinguished these skills based on their capital-enhancing potential within the social structure (Verwiebe & Hagemann, 2025). Accordingly, these six items were then grouped into two distinct dimensions:

1. Basic digital skills (BDS), which includes opening websites on a computer, downloading and installing applications on smartphones, and finding information online.
2. Advanced digital skills (ADS), which includes verifying important news shared on social media platforms such as WeChat and microblogging sites before believing it, expressing personal thoughts in an online setting, and assessing the security of an environment before making online payments or transactions.

This bipartite categorization is further validated by our empirical data. The descriptive statistics reveal a distinct gap in task difficulty where the nonpossession rates for advanced skills (i.e., 14.58%, 16.78%, 19.06%) are notably higher than are those for basic skills (i.e., 8.58%, 9.87%, 10.25%). Additionally, a confirmatory factor analysis supports treating these as two distinct latent constructs with excellent fit indices, including a comparative fit index of 0.978. The internal consistency was satisfactory, with Cronbach's α values of 0.870 for *BDS* and 0.764 for *ADS*.

Next, DS were further operationalized through multiple binary constructs. First, whether basic digital skills were acquired (*WBDS*) was coded as 1 if the respondents demonstrated skill (i.e., score = 1) in at least one of the *BDS* items; otherwise, *WBDS* = 0, indicating a complete absence of basic digital skills (M = 0.964, SD = 0.187). Similarly, we coded as a binary variable whether advanced digital skills were acquired (*WADS*): 1 for respondents with any advanced digital skills and 0 for those with no advanced digital skills (M = 0.951, SD = 0.217). Afterward, whether any digital skills were acquired (*WDS*) was coded as 0 if both *WBDS* and *WADS* were 0; otherwise, it received a code of 1 (M = 0.983, SD = 0.131).

Finally, the respondents were classified into three distinct categories according to their acquired digital skills: (1) individuals who possessed only basic digital skills (*WBDS* = 1, *WADS* = 0), (2) those who possessed both basic and advanced digital skills (*WBDS* = 1, *WADS* = 1), and (3) those who reported having only advanced digital skills (*WBDS* = 0, *WADS* = 1). Because of the rarity in practice and theoretical inconsistency of possessing advanced skills without foundational knowledge (e.g., van Laar et al., 2019), the third category was excluded. The final classification assigned the respondents with only basic digital skills to the DU, which was coded as 1, and those proficient in both basic and advanced digital skills were coded as 0 (M = 0.033, SD = 0.179).

4.2.3. Control Variables

Some demographic and socioeconomic variables were selected as control variables to account for potential confounding factors, considering previous studies on social mobility (H. Chen et al., 2018; Cojocaru, 2014; Du et al., 2021; C. Liu et al., 2023); these variables were marital status (unmarried = 0, married = 1; M = 0.678, SD = 0.467), age (M = 31.961, SD = 7.384), education (1 = elementary and below, 2 = middle school, 3 = high school, and 4 = college and above; *M* = 2.994, *SD* = 1.008), gender (female = 0, male = 1; *M* = 0.487, *SD* = 0.500), and hukou (urban = 0, rural = 1; *M* = 0.508, *SD* = 0.500). To assess health status (*M* = 4.007, *SD* = 0.905), the respondents were asked to evaluate their current physical condition on a scale from 1 (*very unhealthy*) to 5 (*very healthy*).

4.2.4. Moderating Variable

Following previous studies (e.g., C. Liu et al., 2023), SES was measured using a 5-point scale, where the participants indicated their perceived placement within society (*M* = 2.310, *SD* = 0.842), ranging from 1 (*lower level*) to 5 (*upper level*). A description of the variables is shown in Table 1.

Table 1. Variable description.

Variable	*N*	Mean	*SD*	Min.	Max.
Dependent variable					
PFM	1317	1.391	1.406	−5	9
Independent variable					
DS					
DSL	1317	4.301	0.741	1	5
WDS	1317	0.983	0.131	0	1
WBDS	1317	0.964	0.187	0	1
WADS	1317	0.951	0.217	0	1
DU	1269	0.033	0.179	0	1
Moderating variable					
SES	1317	2.311	0.842	1	5
Control variables					
MS	1317	0.678	0.467	0	1
Age	1317	31.961	7.384	18	44
Education	1317	2.994	1.008	1	4
Gender	1317	0.487	0.500	0	1
Hukou	1317	0.508	0.500	0	1
Health	1317	4.007	0.905	1	5

Notes: SD represents the standard deviation, DSL is the digital skills level, WDS indicates whether any digital skills were acquired, WBDS denotes whether basic digital skills were acquired, WADS signifies whether advanced digital skills were acquired, DU represents that only basic digital skills were acquired, SES is socioeconomic status, and MS is marital status.

5. Data Analysis

To explore the link between digital skills and PFM among Chinese young adults, the following empirical models were established:

$$PFM_i = \alpha_0 + \alpha_1 DSL_i + \alpha_2 Controls + \mu_i \tag{1}$$

$$PFM_i = \beta_0 + \beta_1 WDS_i + \beta_2 Controls + \varepsilon_i \tag{2}$$

$$PFM_i = \theta_0 + \theta_1 WBDS_i + \theta_2 WADS + \theta_3 Controls + \kappa_i \quad (3)$$

$$PFM_i = \gamma_0 + \gamma_1 DU_i + \gamma_2 Controls + \eta_i \quad (4)$$

where i represents individual i; PFM_i indicates the PFM of individual i; DSL_i denotes the digital skills level of individual i; WDS_i signifies whether individual i acquires any digital skills; $WBDS_i$ indicates whether individual i acquires basic digital skills; $WADS_i$ identifies whether individual i acquires advanced digital skills; DU_i points to whether individual i acquires only basic digital skills; $Controls_i$ denotes the control variables mentioned above for individual i; α_0, β_0, θ_0 and γ_0 symbolize constant terms; and μ_i, ε_i, κ_i and η_i are the random interference terms.

6. Results

6.1. Baseline Results

Table 2 presents the findings regarding the association between digital skills and PFM among young adults in China. M1 and M2 indicate that neither the DSL nor the WDS is related significantly to young people's PFM. These results fail to support H1. M3 differentiates among the skill types and reveals that the mastery of advanced digital skills is positively correlated with mobility expectations at the 10% significance level, whereas the association with basic digital skills remains statistically insignificant. These findings confirm H2a. M4 indicates that young people who possess only basic digital skills exhibit more pessimistic perceptions about future mobility than those who possess both basic and advanced digital skills do. H2b is therefore supported. The mean variance inflation factors (VIFs) for models 1, 2, 3, and 4 are 1.42, 1.55, 1.55, and 1.53, respectively, indicating that no multicollinearity issues exist across all of the models.

Table 2. Baseline results.

Predict variables	M1	M2	M3	M4
DSL	0.060 (1.00)			
WDS (None = 0)		−0.187 (−0.64)		
WBDS (None = 0)			−0.256 (−1.15)	
WADS (None = 0)			0.353* (1.85)	
DU				−0.507** (−2.34)
SES	−0.134*** (−2.90)	−0.104** (−2.24)	−0.106** (−2.27)	−0.110** (−2.32)
MS (Unmarried = 0)	−0.037 (−0.36)	−0.053 (−0.52)	−0.057 (−0.56)	−0.051 (−0.50)
Age	−0.042*** (−6.20)	−0.043*** (−6.35)	−0.042*** (−6.19)	−0.044*** (−6.38)
Education	−0.017 (−0.35)	−0.035 (−0.72)	−0.043 (−0.87)	−0.056 (−1.13)

Table 2. (Cont.) Baseline results.

Predict variables	M1	M2	M3	M4
Gender (Female = 0)	0.112 (1.47)	0.117 (1.55)	0.117 (1.55)	0.090 (1.17)
Health	0.036 (0.83)	0.051 (1.16)	0.049 (1.11)	0.048 (1.07)
Hukou	−0.144 (−1.60)	−0.104 (−1.15)	0.104 (−1.15)	−0.117 (−1.28)
Constant	2.747*** (7.14)	2.841*** (6.16)	2.570*** (6.02)	2.745*** (7.34)
Observations	1317	1317	1317	1269
R^2	0.075	0.121	0.123	0.132
Mean VIF	1.42	1.55	1.55	1.53

Notes: t statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$; DSL is the digital skills level, WDS indicates whether any digital skills were acquired, WBDS denotes whether basic digital skills were acquired, WADS signifies whether advanced digital skills were acquired, DU represents those only basic digital skills that were acquired, SES is socioeconomic status, MS is marital status.

6.2. Robustness Checks

To conduct the robustness checks, following the methodological approach of C. Liu et al. (2023), we respecified the dependent variable as the percentage of maximum possible change. Specifically, an alternative specification of the dependent variable is $PFM = (SS_2 - SS_1)/(10 - SS_1)$, if $SS_2 > SS_1$, and $PFM = (SS_2 - SS_1)/SS_1$, if $SS_2 < SS_1$. This dependent variable measures the percentage of the gap that the respondents with the highest (lowest) level of social optimism hope to bridge (expect to increase) in 10 years, both measured from the respondents' current levels. We then reestimated our models. The results of this alternative specification are entirely consistent with our primary analysis (Table 3).

Table 3. Robustness checks results.

Predict variables	M5	M6	M7	M8
DSL	0.009 (0.83)			
WDS (None = 0)		−0.017 (−0.31)		
WBDS (None = 0)			−0.048 (−1.19)	
WADS (None = 0)			0.063* (1.81)	
DU				−0.079** (−1.99)
SES	0.026*** (3.08)	0.027*** (3.20)	0.026*** (3.17)	0.027*** (3.22)
MS (Unmarried = 0)	−0.013 (−0.71)	−0.012 (−0.66)	−0.013 (−0.67)	−0.010 (−0.53)
Age	−0.007*** (−5.51)	−0.007*** (−5.82)	−0.007*** (−5.72)	−0.007*** (−5.87)

Table 3. (Cont.) Robustness checks results.

Predict variables	M5	M6	M7	M8
Education	0.004 (0.49)	0.007 (0.81)	0.006 (0.66)	0.004 (0.47)
Gender (Female = 0)	0.015 (1.11)	0.016 (1.19)	0.016 (1.19)	0.013 (0.92)
Health	0.014* (1.82)	0.015* (1.92)	0.015* (1.91)	0.016** (1.97)
Hukou	−0.029* (−1.79)	−0.028* (−1.70)	−0.028* (−1.70)	−0.030* (−1.82)
Constant	0.321*** (4.59)	0.370*** (4.91)	0.342*** (5.04)	0.366*** (6.30)
Observations	1317	1317	1317	1269
R^2	0.071	0.071	0.074	0.077
Mean VIF	1.42	1.34	1.35	1.32

Notes: *t* statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$; DSL is the digital skills level, WDS indicates whether any digital skills were acquired, WBDS denotes whether basic digital skills were acquired, WADS signifies whether advanced digital skills were acquired, DU represents those only basic digital skills that were acquired, SES is socioeconomic status, MS is marital status.

6.3. Moderating Results

Table 4 displays the results of the moderating analysis. M9 suggests that the interaction between DSL and SES is significantly negative at the 5% significance level. SES is measured as subjective SES, which overlaps conceptually with the dependent variable (perception-based mobility), raising bias concerns. We estimated a conditional change model in M10. This stringent specification removes potential structural bias by regressing the expected absolute SS2 directly on the predictors while strictly controlling for SS1. The results show that the interaction term remains significantly negative. Moreover, Figure 2 visually represents the negative interactive association between SES and DSL regarding PFM. These results confirm H3b, but H3a is not supported.

Table 4. Moderating results.

Predict variables	M9	M10
DSL	0.037 (0.61)	0.043 (0.71)
DSL × SES	−0.131** (−2.28)	−0.123** (−2.16)
SS_1		0.847*** (27.69)
SES	−0.139*** (−3.00)	0.037 (0.64)
MS (Unmarried = 0)	−0.045 (−0.43)	−0.062 (−0.61)
Age	−0.042*** (−6.09)	−0.040*** (−5.93)

Table 4. (Cont.) Moderating results.

Predict variables	M9	M10
Education	−0.020 (−0.41)	0.010 (0.21)
Gender (Female = 0)	0.105 (1.39)	0.085 (1.13)
Health	0.037 (0.84)	0.052 (1.21)
Hukou	−0.141 (−1.57)	−0.163* (−1.83)
Constant	2.699*** (8.60)	3.198*** (9.79)
Observations	1,317	1,317
R^2	0.078	0.530
Mean VIF	1.38	1.49

Notes: *t* statistics are in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$; *DSL* is the digital skills level, *SES* is socioeconomic status, *MS* is marital status, SS_1 indicates current social status.

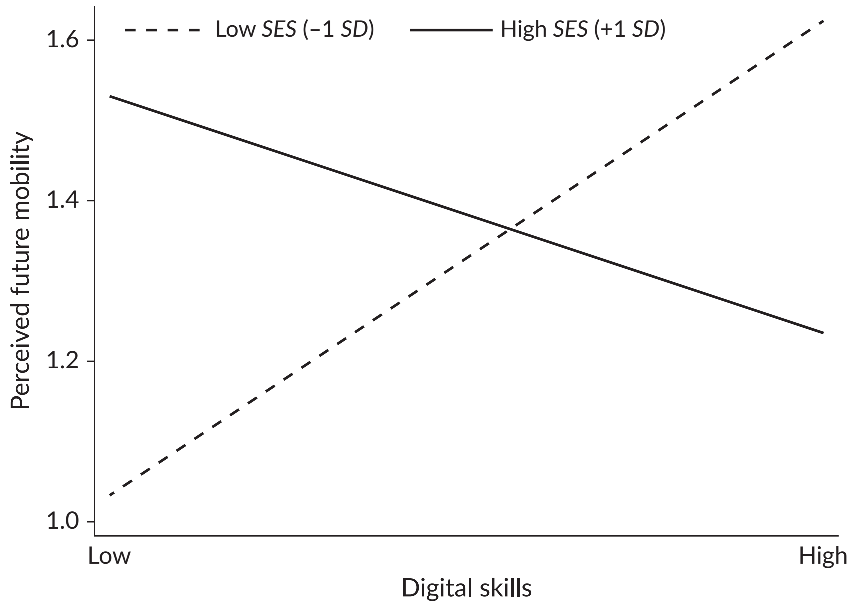

Figure 2. The interactive association between SES and DSL regarding PFM.

7. Discussion

This study determines that DSL is not correlated significantly with PFM. These findings challenge the optimistic utopian views of technological determinism theory (Bell, 1973), which generally argue that the mastery of technology can help individuals achieve social development. Examining the third level of the digital divide and the bidirectional feedback between socioeconomic and digital inequalities may help to understand why this purely optimistic approach fails in reality (Helsper, 2021; van Deursen & Helsper, 2015). Real-world social stratification constrains the extent to which individuals can leverage general digital skills for tangible offline benefits (Robinson et al., 2020). Consequently, disadvantaged youth face entrenched structural barriers that prevent them from converting basic computer skills into actual upward social mobility (Ragnedda & Ruiu, 2020). Therefore, this nonsignificant direct association should not be interpreted simply as evidence of the irrelevance of digital skills or the ineffectiveness of digital upskilling programs. Instead, this study reveals a stratified reality in which not all digital skills hold equal value. The benefit of these digital skills depends on their potential for capital conversion (Ragnedda, 2018).

This research further finds a significant negative interaction between SES and DSL regarding PFM. This finding of the negative moderating role of SES challenges Helsper's (2012) corresponding fields model, which posited that offline privileges are amplified in the digital domain, reinforcing the Matthew effect. Instead, this result provides empirical support for the resource substitution hypothesis (Ross & Mirowsky, 2006), suggesting that digital skills can function as crucial compensatory resources for the socially disadvantaged. Although Ragnedda (2017) emphasized that the conversion rates of digital capital are higher among wealthy people, the finding demonstrates that the personal resources of digital skills are associated with PFM positively and more strongly for low-SES youth than they are for their privileged peers. This result is also consistent with that of Wang (2025) who indicated that digital literacy is correlated more strongly with upward income mobility for disadvantaged people.

This study shows that there is no significant relationship between the acquisition of basic digital skills and *PFM*. This conclusion contradicts earlier research on the digital divide, which posits that basic internet accessibility naturally leads to improved life opportunities (DiMaggio et al., 2004). However, this result aligns with the argument of van Deursen and van Dijk (2014) that states that because operational skills have become relatively common, they no longer confer the same competitive advantage, and the locus of inequality is shifted to how the internet is capital-enhancing or recreationally used. Ragnedda (2017, 2018) noted that both the distinguishing value of a resource and the exchange value as a form of capital decrease as a resource becomes ubiquitous. Therefore, as basic digital skills become relatively widespread (CNNIC, 2025), these skills may no longer constitute a competitive advantage in capital accumulation for enhancing the social status of Chinese youth.

This study also determines that the acquisition of advanced digital skills is associated positively with PFM at a 10% significance level, which is relatively weak but important (Wooldridge, 2016). This result aligns with the theory of the third-level digital divide that emphasizes the disparity in tangible outcomes (van Deursen & Helsper, 2015). Previous research on the digital divide has distinguished internet use into capital-enhancing or noncapital-enhancing uses (van Deursen & van Dijk, 2014). These studies have reported that users with high skills are more likely to use the internet for capital-enhancing activities, while users with low skills tend to use the internet mainly for recreation. Correa (2016) found that high-skill users engage in content creation, whereas low-skill users are limited to passive consumption. Following this logic, this study identified a similar role for basic and advanced digital skills. As Verwiebe and Hagemann (2025) asserted, real digital capital belongs to the people who control the data and engage in creative production rather than the people engaged in prosumption. Thus, advanced skills, including strategic skills, are more beneficial for young people to acquire as true digital capital that can be converted into tangible benefits. The results also confirm Ragnedda's (2017) assertion that only specific high-value digital forms of capital can be effectively exchanged for offline benefits.

This research further identifies the critical finding that there is a disadvantaged group regarding digital skills who are likely to be left behind. This conclusion demonstrates that individuals with only basic digital skills are more pessimistic about their future than individuals with both basic and advanced digital skills are. This result provides empirical evidence that supports and enriches the concept of the DU (Ragnedda, 2020). Individuals with basic digital skills are not disconnected but are adversely embodied (Helsper, 2021). They may invest significant time in the digital world but lack the power to extract value from it. This structural characteristic aligns with the relative deprivation framework applied to digital inequality (Helsper, 2017), as users witness the digital dividends accumulating for others while remaining unable to benefit from them because of a lack of true digital capital conversion skills.

Overall, this nuanced understanding of digital skills aligns with the shift toward the third-level digital divide, where digital inequality moves from access toward the skills to translate digital engagement into tangible life outcomes (Scheerder et al., 2017; van Deursen, 2020). Through an exploratory design, our study responds to Merisalo and Makkonen's (2022) call for an enhanced discussion of the role of digital capital within the third-level digital divide. Moreover, this study demonstrates that without the potential for the conversion of digital capital (Ragnedda, 2018), being technically connected may also correlate with the emergence of a DU (Ragnedda, 2020), whose members are equipped with basic digital skills but risk being left behind. Finally, the findings provide empirical support for the resource substitution hypothesis and digital capital theory in the context of a developing economy.

8. Conclusion

This study explored how digital skills relate to the PFM of young adults in China. Drawing on socio-digital stratification theory, we found that simply acquiring basic digital skills is not associated significantly with higher PFM. Instead, advanced digital skills are linked positively to PFM. Notably, compared with young adults who have acquired both basic and advanced skills, those who possess only basic digital skills are more likely to exhibit pessimistic perceptions of future mobility. Furthermore, this study found strong empirical support for the resource substitution hypothesis. Interestingly, while the overall level of general digital skills does not associate significantly with PFM, this association varies significantly across different levels of SES. Specifically, for disadvantaged youth with a lower SES, higher overall DSLs are strongly and positively related to PFM.

These findings offer practical implications for digital inequality. As basic internet access becomes nearly universal under national initiatives such as "Broadband China," the policy focus needs to shift. Rather than merely expanding basic connectivity, intervention programs could aim to cultivate advanced information and strategic skills. Supporting disadvantaged youth to acquire these advanced competencies may provide them with better resources to navigate a highly competitive society and pursue upward social mobility.

However, several limitations must be noted to contextualize our exploratory findings. First, this study uses cross-sectional data from the CGSS 2017. This dataset predates recent technological advancements such as artificial intelligence, and its cross-sectional design inherently limits our ability to establish any causal direction. Although specific digital tools change rapidly, we argue that the underlying social processes of digital stratification likely remain stable. Future studies should explore these associations using updated measures of artificial intelligence awareness and advanced digital practices. Furthermore, our operationalization of advanced skills, such as expressing thoughts online, serves as a proxy for active engagement rather than a perfect measure of complex capital-enhancing strategies. Future research should utilize indicators that are more precise to measure high-level algorithmic control. Third, digital skills were assessed through self-reporting. Since young people sometimes overestimate their digital fluency, future research would benefit from using objective performance tests to capture actual skills more accurately. Fourth, we must clarify the exploratory nature of our findings regarding the DU. The subgroup of respondents who possess only basic skills was relatively small in our sample. Although the negative association with their PFM is statistically significant, this specific finding should be interpreted cautiously. Future research should verify these patterns through targeted sampling of marginalized populations. Additionally, the explanatory power of our models is relatively low, with an R^2 value of approximately 0.07. Although this indicates a modest explained variance, such values are typical and acceptable in studies analyzing subjective perceptions through large-scale micro-level survey data, as individual expectations are shaped by numerous unobservable idiosyncratic factors (Wooldridge, 2016). Comparable R^2 values are frequently reported in similar sociological and economic literature (e.g., Naito & Yamamoto, 2022; Oswald et al., 2015; Shi, 2023). Despite these limitations, we hope this study serves as a transparent starting point for understanding socio-digital stratification among young people.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The data that support the findings of this study are available from the Chinese General Social Survey (http://cgss.ruc.edu.cn).

References

Anderson, L. R. (2018). Adolescent mental health and behavioural problems, and intergenerational social mobility: A decomposition of health selection effects. *Social Science & Medicine*, *197*, 153–160. https://doi.org/10.1016/j.socscimed.2017.11.026

Au, A. (2024). Digitalization in China: Who's left behind? *Information, Communication & Society*, *27*(6), 1247–1265. https://doi.org/10.1080/1369118X.2023.2245871

Bell, D. (1973). *The coming of post-industrial society: A venture in social forecasting*. Basic Books.

Bian, Y. (2002). Chinese social stratification and social mobility. *Annual Review of Sociology*, *28*(1), 91–116. https://doi.org/10.1146/annurev.soc.28.110601.140823

Bourdieu, P. (1986). The forms of capital. In J. Richardson (Ed.), *Handbook of theory and research for the sociology of education* (pp. 241–258). Greenwood.

Calderón Gómez, D. (2020). Technological socialization and digital inclusion: Understanding digital literacy biographies among young people in Madrid. *Social Inclusion*, *8*(2), 222–232. https://doi.org/10.17645/si.v8i2.2601

Chen, C., & Qin, B. (2014). The emergence of China's middle class: Social mobility in a rapidly urbanizing economy. *Habitat International*, *44*, 528–535. https://doi.org/10.1016/j.habitatint.2014.10.007

Chen, H., Wang, X., Chen, G., & Li, Z. (2018). Upward social mobility in China: Do cities and neighbourhoods matter? *Habitat International*, *82*, 94–103. https://doi.org/10.1016/j.habitatint.2018.10.003

Cheng, S., & Wen, F. (2019). Americans overestimate the intergenerational persistence in income ranks. *Proceedings of the National Academy of Sciences*, *116*(28), 13909–13914. https://doi.org/10.1073/pnas.1814688116

CNNIC. (2025). *The 56th China statistical report on internet development*. https://www.cnnic.net.cn/NMediaFile/2025/0730/MAIN1753846666507QEK67ZS9DH.pdf

Correa, T. (2016). Digital skills and social media use: How Internet skills are related to different types of Facebook use among 'digital natives.' *Information, Communication & Society*, *19(8)*, 1095–1107. https://doi.org/10.1080/1369118X.2015.1084023

DiMaggio, P., & Bonikowski, B. (2008). Make money surfing the web? The impact of internet use on the earnings of US workers. *American Sociological Review*, *73*(2), 227–250. https://doi.org/10.1177/000312240807300203

DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital inequality: From unequal access to differentiated use. In K. M. Neckerman (Ed.), *Social inequality* (pp. 355–400). Russell Sage Foundation.

Du, H., Liang, Y., Chi, P., & King, R. B. (2021). Chinese perceive upward social mobility: How future mobility is influenced, but not limited by past mobility. *International Journal of Psychology*, *56*(6), 951–960. https://doi.org/10.1002/ijop.12771

Falck, O., Heimisch-Roecker, A., & Wiederhold, S. (2021). Returns to ICT skills. *Research Policy*, *50*(7), Article 104064. https://doi.org/10.1016/j.respol.2020.104064

Gugushvili, A., & Zelinska, O. (2023). What are the trends and explanations of perceived social mobility in Poland? *Applied Research in Quality of Life*, *18*(2), 811–832. https://doi.org/10.1007/s11482-022-10105-4

Hao, M., & Ke, X. (2024). Personal networks and grassroots election participation in China: Findings from the Chinese General Social Survey. *Journal of Chinese Political Science*, *29*(1), 159–184. https://doi.org/10.1007/s11366-023-09861-3

Hargittai, E. (2010). Digital na(t)ives? Variation in internet skills and uses among members of the "net generation." *Sociological Inquiry*, *80*(1), 92–113. https://doi.org/10.1111/j.1475-682X.2009.00317.x

Hargittai, E. (2021). *Handbook of digital inequality*. Edward Elgar Publishing. https://doi.org/10.4337/9781788116572

Helsper, E. (2012). A corresponding fields model for the links between social and digital exclusion. *Communication Theory*, *22*(4), 403–426. https://doi.org/10.1111/j.1468-2885.2012.01416.x

Helsper, E. (2017). The social relativity of digital exclusion: Applying relative deprivation theory to digital inequalities. *Communication Theory*, *27*(3), 223–242. https://doi.org/10.1111/comt.12110

Helsper, E. (2021). *The digital disconnect: The social causes and consequences of digital inequalities*. Sage Publications.

Hout, M. (2014). A summary of what we know about social mobility. *The ANNALS of the American Academy of Political and Social Science*, *657*(1), 27–36. https://doi.org/10.1177/0002716214547174

Huang, X. (2020). The Chinese dream: *Hukou*, social mobility, and trust in government. *Social Science Quarterly*, *101*(5), 2052–2070. https://doi.org/10.1111/ssqu.12847

Huhe, N. (2014). Understanding the multilevel foundation of social trust in rural China: Evidence from the China General Social Survey. *Social Science Quarterly*, *95*(2), 581–597. https://doi.org/10.1111/ssqu.12049

Ignatow, G., & Robinson, L. (2017). Pierre Bourdieu: Theorizing the digital. *Information, Communication & Society*, *20*(7), 950–966. https://doi.org/10.1080/1369118X.2017.1301519

Iivari, N., Sharma, S., & Ventä-Olkkonen, L. (2020). Digital transformation of everyday life—How COVID-19 pandemic transformed the basic education of the young generation and why information management research should care? *International Journal of Information Management*, *55*, Article 102183. https://doi.org/10.1016/j.ijinfomgt.2020.102183

ITU. (2020). *Measuring digital development: Facts and figures 2020*. https://www.itu.int/en/ITU-D/Statistics/Pages/facts/default.aspx

Jackson, B., Kubzansky, L. D., Cohen, S., Jacobs, D. R., Jr., & Wright, R. J. (2007). Does harboring hostility hurt? Associations between hostility and pulmonary function in the coronary artery risk development in (young) adults (CARDIA) study. *Health Psychology*, *26*(3), 333–340. https://doi.org/10.1037/0278-6133.26.3.333

Jackson, M., Goldthorpe, J. H., & Mills, C. (2005). Education, employers and class mobility. *Research in Social Stratification and Mobility*, *23*, 3–33. https://doi.org/10.1016/S0276-5624(05)23001-9

Liu, C. (2012). The myth of informatization in rural areas: The case of China's Sichuan province. *Government Information Quarterly*, *29*(1), 85–97. https://doi.org/10.1016/j.giq.2011.06.002

Liu, C., Liu, H., Zhang, H., & Yuan, Q. (2023). The impact of internet use on the perceptions of class boundaries and life trajectories: A report from a representative survey in China. *Telecommunications Policy*, *47*(10), Article 102663. https://doi.org/10.1016/j.telpol.2023.102663

Liu, C., & Wang, L. (2021). Who is left behind? Exploring the characteristics of China's broadband non-adopting families. *Telecommunications Policy*, *45*(9), Article 102187. https://doi.org/10.1016/j.telpol.2021.102187

Liu, G. L. (2025). Digital empowerment for rural migrant students in China: Identity, investment, and digital literacies beyond the classroom. *ReCALL*, *37*(2), 215–231. https://doi.org/10.1017/S0958344024000302

Lutz, C. (2019). Digital inequalities in the age of artificial intelligence and big data. *Human Behavior and Emerging Technologies*, *1*(2), 141–148. https://doi.org/10.1002/hbe2.140

Merisalo, M., & Makkonen, T. (2022). Bourdieusian e-capital perspective enhancing digital capital discussion in the realm of third level digital divide. *Information Technology & People*, *35*(8), 231–252. https://doi.org/10.1108/ITP-08-2021-0594

Mok, K. H., & Wu, A. M. (2016). Higher education, changing labour market and social mobility in the era of massification in China. *Journal of Education and Work*, *29*(1), 77–97. https://doi.org/10.1080/13639080.2015.1049028

Naito, H., & Yamamoto, S. (2022). Is better access to mobile networks associated with increased mobile money adoption? Evidence from the micro-data of six developing countries. *Telecommunications Policy*, *46*(6), Article 102314. https://doi.org/10.1016/j.telpol.2022.102314

OECD. (2019). *OECD skills outlook 2019: Thriving in a digital world*. OECD Publishing. https://doi.org/10.1787/df80bc12-en

Oswald, A. J., Proto, E., & Sgroi, D. (2015). Happiness and productivity. *Journal of Labor Economics*, *33*(4), 789–822. https://doi.org/10.1086/681096

Park, S. (2017). *Digital capital*. Palgrave Macmillan.

Qin, C., Zhu, Y., Li, D., & Liu, C. (2024). The impact of digital skills on health: Evidence from the China General Social Survey. *Digital Health*, *10*. https://doi.org/10.1177/20552076241304592

Qin, G., & Li, X. (2024). The political identity of China's emerging youth. *Social Science Quarterly*, *105*(7), 2122–2136. https://doi.org/10.1111/ssqu.13455

Qiu, J. L. (2009). *Working-class network society: Communication technology and the information have-less in urban China*. MIT Press. https://doi.org/10.7551/mitpress/9780262170062.001.0001

Ragnedda, M. (2017). *The third digital divide: A Weberian approach to digital inequalities* (1st ed.). Routledge.

Ragnedda, M. (2018). Conceptualizing digital capital. *Telematics and Informatics*, *35*(8), 2366–2375. https://doi.org/10.1016/j.tele.2018.10.006

Ragnedda, M. (2020). *Enhancing digital equity: Connecting the digital underclass*. Palgrave Macmillan. https://doi.org/10.1007/978-3-030-49079-9

Ragnedda, M., & Ruiu, M. L. (2017). Social capital and the three levels of digital divide. In M. Ragnedda & G. W. Muschert (Eds.), *Theorizing digital divides* (pp. 21–34). Routledge. https://doi.org/10.4324/9781315455334-3

Ragnedda, M., & Ruiu, M. L. (2020). *Digital capital: A Bourdieusian perspective on the digital divide*. Emerald Publishing.

Robinson, L., Cotten, S. R., Ono, H., Quan-Haase, A., Mesch, G., Chen, W., Schulz, J., Hale, T. M., & Stern, M. J. (2015). Digital inequalities and why they matter. *Information, Communication & Society*, *18*(5), 569–582. https://doi.org/10.1080/1369118X.2015.1012532

Robinson, L., Schulz, J., Blank, G., Ragnedda, M., Ono, H., Hogan, B., Mesch, G., Cotten, S., Kretchmer, S., Hale, T., Drabowicz, T., Yan, P., Wellman, B., Harper, M.-G., Quan-Haase, A., Dunn, H., Casilli, A., Tubaro, P., Carvath, R., . . . Khilnani, A. (2020). Digital inequalities 2.0: Legacy inequalities in the information age. *First Monday*, *25*(7). https://doi.org/10.5210/fm.v25i7.10842

Rodríguez-Camacho, J. A., Linder, M., Jütte, D., & Hennig-Thurau, T. (2024). Digital capital: Importance for social status in contemporary society and antecedents of its accumulation. *Computers in Human Behavior*, *159*, Article 108316. https://doi.org/10.1016/j.chb.2024.108316

Ross, C. E., & Mirowsky, J. (2006). Sex differences in the effect of education on depression: Resource multiplication or resource substitution? *Social Science & Medicine*, *63*(5), 1400–1413. https://doi.org/10.1016/j.socscimed.2006.03.013

Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics and Informatics*, *34*(8), 1607–1624. https://doi.org/10.1016/j.tele.2017.07.007

Shi, Z. (2023). The impact of regional ICT development on job quality of the employee in China. *Telecommunications Policy*, *47*(6), Article 102567. https://doi.org/10.1016/j.telpol.2023.102567

Song, L. (2024). Does social trust shape the perceived intergenerational social mobility? *Cities*, *150*, Article 105071. https://doi.org/10.1016/j.cities.2024.105071

Su, Z., Cao, Y., He, J., & Huang, W. (2015). Perceived social mobility and political trust in China. *African and Asian Studies*, *14*(4), 315–336. https://doi.org/10.1163/15692108-12341347

Tiffin, P. A., Pearce, M. S., & Parker, L. (2005). Social mobility over the lifecourse and self reported mental health at age 50: Prospective cohort study. *Journal of Epidemiology and Community Health*, *59*(10), 870–872. https://doi.org/10.1136/jech.2005.035246

Tooth, L., & Mishra, G. (2013). Intergenerational educational mobility on general mental health and depressive symptoms in young women. *Quality of Life Research*, *22*(7), 1589–1602. https://doi.org/10.1007/s11136-012-0310-8

Torche, F. (2014). Analyses of intergenerational mobility: An interdisciplinary review. *The ANNALS of the American Academy of Political and Social Science*, *657*(1), 37–62. https://doi.org/10.1177/0002716214547476

UNESCO. (2018). *A global framework of reference on digital literacy skills for indicator 4.4.2*.

van Deursen, A. J. (2020). Digital inequality during a pandemic: Quantitative study of differences in COVID-19-related internet uses and outcomes among the general population. *Journal of Medical Internet Research*, *22*(8), Article 20073. https://doi.org/10.2196/20073

van Deursen, A. J., Courtois, C., & van Dijk, J. A. G. M. (2014). Internet skills, sources of support, and benefiting from internet use. *International Journal of Human–Computer Interaction*, *30*(4), 278–290. https://doi.org/10.1080/10447318.2013.858458

van Deursen, A. J., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. *New Media & Society*, *16*(3), 507–526. https://doi.org/10.1177/1461444813487959

van Deursen, A. J., & Helsper, E. J. (2015). The third-level digital divide: Who benefits most from being online? In *Communication and Information Technologies Annual* (Vol. 10, pp. 29–52). Emerald Group Publishing. https://doi.org/10.1108/S2050-206020150000010002

van Deursen, A. J., Helsper, E., Eynon, R., & van Dijk, J. A. (2017). The compoundness and sequentiality of digital inequality. *International Journal of Communication*, *11*, 452–473. https://ijoc.org/index.php/ijoc/article/view/5739

van Dijk, J. A. G. M., & van Deursen, A. J. A. M. (2014). *Digital skills: Unlocking the information society*. Palgrave Macmillan.

van Laar, E., van Deursen, A. J., van Dijk, J. A., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, *72*, 577–588. https://doi.org/10.1016/j.chb.2017.03.010

van Laar, E., van Deursen, A. J., van Dijk, J. A., & de Haan, J. (2018, May 24–28). *Determinants of 21st-century digital skills: A systematic literature review* [Paper presentation]. 68th Annual International Communication Association Conference 2018, Prague, Czech Republic.

van Laar, E., van Deursen, A. J., van Dijk, J. A., & de Haan, J. (2019). The sequential and conditional nature of 21st-century digital skills. *International Journal of Communication*, *13*, 3462–3487.

Verwiebe, R., & Hagemann, S. (2025). Bourdieu revisited: New forms of digital capital—Emergence, reproduction, inequality of distribution. *Information, Communication & Society*, *28*(11), 1861–1883. https://doi.org/10.1080/1369118X.2024.2358170

Vuorikari, R., Kluzer, S., & Punie, Y. (2022). *DigComp 2.2: The Digital competence framework for citizens. With new examples of knowledge, skills and attitudes*. Publications Office of the European Union. https://doi.org/10.2760/115376

Wang, J. (2025). Can digital literacy improve income mobility? Evidence from China. *Telecommunications Policy*, *49*(6), Article 102960. https://doi.org/10.1016/j.telpol.2025.102960

Whyte, M. (2010). *Myth of the social volcano: Perceptions of inequality and distributive injustice in contemporary China*. Stanford University Press.

Wooldridge, J. M. (2016). *Introductory econometrics: A modern approach* (6th ed.). Cengage Learning.

Wu, X. (2019). Inequality and social stratification in postsocialist China. *Annual Review of Sociology*, *45*, 363–382. https://doi.org/10.1146/annurev-soc-073018-022516

Xia, J. (2010). Linking ICTs to rural development: China's rural information policy. *Government Information Quarterly*, *27*(2), 187–195. https://doi.org/10.1016/j.giq.2009.10.005

Xia, J. (2022). Juggling ecumenical wisdoms and xenophobic institutions: Framing and modelling China's telecommunications universal service and rural digitalization initiatives and policies. *Telecommunications Policy*, *46*(2), Article 102258. https://doi.org/10.1016/j.telpol.2021.102258

Xiong, B., & Yu, B. (2024). The impact of internet development on youth's job quality in the digital economy era: Transmission mechanism and empirical test. *Social Indicators Research*, *175*(1), 269–294. https://doi.org/10.1007/s11205-024-03439-z

Zhang, Y., & Jiang, J. (2019). Social capital and health in China: Evidence from the Chinese General Social Survey 2010. *Social Indicators Research*, *142*(1), 411–430. https://doi.org/10.1007/s11205-018-1907-2
Zhou, D., Zha, F., Qiu, W., & Zhang, X. (2024). Does digital literacy reduce the risk of returning to poverty? Evidence from China. *Telecommunications Policy*, *48*(6), Article 102768. https://doi.org/10.1016/j.telpol.2024.102768
Zhu, Z., Ma, W., Sousa-Poza, A., & Leng, C. (2020). The effect of internet usage on perceptions of social fairness: Evidence from rural China. *China Economic Review*, *62*, Article 101508. https://doi.org/10.1016/j.chieco.2020.101508
Zuiderveen Borgesius, F. J., Trilling, D., Möller, J., Bodó, B., De Vreese, C. H., & Helberger, N. (2016). Should we worry about filter bubbles? *Internet Policy Review*, *5*(1). https://doi.org/10.14763/2016.1.401

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