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The COVID-19 pandemic and deepening digital inequalities in China

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ABSTRACT

As Internet usage reshapes our societies, digital inequalities have increased over the past few decades. During the COVID-19 pandemic, many countries accelerated their digital transformation processes, and it is widely believed the COVID-19 pandemic has deepened existing inequalities in the digital realm. Yet, few studies have empirically examined whether digital inequalities in the labor market increased during the pandemic. This analysis studies how the COVID-19 pandemic affected Chinese workers' Internet usage and how this influence varied across socioeconomic groups. By using the ordered probit model and leveraging the most recent data from the China Family Panel Studies and the Johns Hopkins Coronavirus Resource Center, we find that the pandemic significantly increased the overall level of Internet usage in the country, and the mediating effects of the perceived importance of the Internet and access to the Internet are confirmed. As Internet usage increased, digital inequalities in China's labor market deepened, especially among young and wealthy workers with high social status in urban areas, while older and poorer workers in rural areas benefited less from this new 'digital wave.' Moreover, during the pandemic, Internet usage increased among employees working in state-owned enterprises (SOEs), which suggests a growing digital inequality gap between SOEs and other sectors. Following a series of robustness tests, our research findings remain valid. We propose a policy redesign that embodies a comprehensive long-term vision and guarantees raising the levels of Internet usage for socially and economically disadvantaged groups in China.

1. Introduction

Reducing inequalities is the target of Goal 10 of the United Nations Sustainable Development Goals, which aims to offer equal opportunities to the general population, irrespective of age, sex, disability, race, ethnicity, origin, economic conditions, or any other status. However, the UN reports that the recent pandemic has deepened existing inequalities (UN, 2022), including digital inequalities (.). The COVID-19 crisis has further expanded the already existing unequal distribution of social and economic resources (Deaton, 2021; Martínez-Domínguez & Fierros-González, 2022), which hits the most vulnerable communities the hardest. Vulnerable communities include, in particular, those who have no or little ability to access digital devices or do not have enough digital skills or willingness to use digital technologies (Sommerlad & David, 2022). In addition, many COVID-19 pandemic control measures have forced the public to transfer their work and life online, with many new online activities continuing even after the pandemic. While the overall level of Internet usage has increased, initial studies highlight that this transformation process was not equally distributed as the

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pandemic likely deepened digital inequalities (Van Dijk, 2005).

By using China as a case study, this research examines how digital inequalities in the labor market changed at the height of the COVID-19 pandemic (here, the period in February and March 2020). As the second-largest digital economy in the world and with a high Internet penetration rate of 75.6% in 2022 (NBS, 2023), China boasts Internet usage that is very high and widespread. At the same time, digital inequalities are also significant (H. Liu et al., 2017), and the COVID-19 crisis likely had quite a different impact depending on the socioeconomic group. China's pandemic control policies (e.g., border closures, social distancing, and local and national lockdowns with zero-COVID tolerance) further increased the importance of information and communications technology (ICT). ICT became not just a means of disseminating information and performing contact tracing but also the only remaining vector for social interactions. During the pandemic, the public quickly adapted to the new opportunities facilitated by the digital transformation, including a surging demand for online services (Mansell, 2021), improved intelligence in public health (David et al., 2022; Dron et al., 2022; Kostka & Habich-Sobiegalla, 2022), and faster digital e-governance (Addo & Senyo, 2021; Kloppenburg et al., 2022).

Existing studies on digital inequalities for China's labor market have shown that, for instance, those who are younger and better-educated and have a higher income tend to have higher Internet usage rates than older, less-educated, and poorer individuals (Guo & Wan, 2022; Li & Ranieri, 2013; Mo et al., 2013; Wang, Zhou, & Wang, 2021). Such inequalities for the socially and economically disadvantaged groups may be exacerbated by unequal access to the Internet or having connected devices during the crisis and the digital skills necessary to effectively move much of everyday life into the online sphere (Beaunoyer et al., 2020). While digital inequalities have existed for a long time in China, this research looks at how the COVID-19 crisis influenced such ICT-related social inequalities and whether it exacerbated them – something that has not yet received the attention it deserves. This is a particularly timely topic as digital inequalities can also put already disadvantaged groups at greater risk during public health crises like COVID-19 (Beaunoyer et al., 2020; Sommerlad & David, 2022; Zheng & Walsham, 2021).

This analysis adopts an ordered probit model and uses the most recent 2020 Chinese individual survey data sourced from the China Family Panel Studies (CFPS) (CFPS, 2021) and health statistics from the Johns Hopkins Coronavirus Resource Center (JHU, 2022). The following two questions are at the core of this study: (1) If and how did the general Internet usage levels in China increase during the COVID-19 pandemic? (2) And how were digital inequalities in China's labor market affected during the COVID-19 pandemic in different socioeconomic groups (i.e., variation across regions, age groups, income levels, and job categories)?

This paper makes numerous contributions based on prior literature on digital inequalities (Ciarli et al., 2021; Hargittai & Hinnant, 2008; Van Deursen et al., 2021; Zheng & Walsham, 2021). First, to the best of our knowledge, this is the first study to empirically examine changing Internet usage in China's labor market during the COVID-19 pandemic. The theoretical basis is enriched by using the perceived importance of the Internet and access to the Internet as mediating variables to explain Internet usage rates for workers during the pandemic. Second, by using the latest CFPS individual data, which has seldom been used in existing literature, and combining it with health statistics from the Johns Hopkins Coronavirus Resource Center, this research introduces a novel and integrated dataset. Third, from an empirical standpoint, this study examines different socioeconomic groups during the pandemic, adding to the current labor literature that digital inequalities affect older and poorer workers in rural areas, particularly during a health crisis. Finally, our results show that digital inequalities vary according to employment status: Those who work for state-owned enterprises (SOEs) experienced a higher digital improvement during the pandemic than those working for other public institutions and private sectors.

The remainder of the paper is organized as follows. Section 2 reviews the broader literature and outlines our theoretical framework. The data, variables, and models are explained in section 3 before our empirical results are presented in section 4. Section 5 discusses the findings, and section 6 concludes the paper with a summary of the key findings and several policy recommendations.

2. Theoretical framework

Social distancing and lockdown policies during the COVID-19 pandemic forced people to increase their rate of Internet usage. Internet usage rates are generally influenced by overall perceived technology importance and acceptance or 'motivation attitude' and actual 'physical access' to the Internet (Van Dijk, 2017). The socially and economically vulnerable groups are obviously at a disadvantage in this process with limited access to the Internet, technical support, and help. These limitations can exacerbate potential digital inequalities in the labor market. While local political and economic institutions shape Internet usage, which is also embedded in distinctive cultural practices, patterns of interpersonal communication are increasingly converging around the world, especially among younger demographics (Ørmen et al., 2021). This convergence allows us to incorporate evidence from beyond China to support our hypotheses.

Specifically, subsection 2.1 delves into the literature regarding pandemic-induced Internet usage rates, with a special focus on telecommuting work. Subsections 2.2 and 2.3 shed light on the moderating roles of the perceived importance of the Internet and access to it in relation to the COVID-19 impact on the Internet usage rate. These three subsections address the first research question. Aligned with the second research question, subsection 2.4 explores digital inequalities in the labor market across various socioeconomic groups. We formulate hypotheses based on the literature reviews in each subsection.

2.1. Internet usage rates during the COVID-19 pandemic

The Internet plays a central role in modern society as a key source of information and market space (Derksen et al., 2022). There is a consensus that in many countries, the COVID-19 pandemic has accelerated digitalization processes across society (Amankwah-Amoah et al., 2021; Gabryelczyk, 2020). Amid social distancing and strict zero-tolerance COVID-19 policies in China, consumers had to suddenly turn toward online shopping (Yang & Kwon, 2022). Governments and enterprises, especially small and medium-sized ones, felt compelled to expedite their digital transformation (Bai et al., 2021; Sonobe et al., 2021). A recent report by the International Monetary Fund (Jaumotte et al., 2023) posits that while the COVID-19 crisis may bolster longer-term productivity, it could also widen the gap between digital and non-digital workers in the labor market. The report underscores how COVID-19 has reinforced the importance of not only communications infrastructures and services but also access to and robust governance of data. These new trends all contribute to the increasing use of the Internet and wider use of digital services, and thus, the overall expansion of a country's level of digitalization. As China began to relax its zero-COVID policy from December 2022 onward, digitalization is expected to experience a surge in its growth trajectory in the post-pandemic era. In light of this, we propose Hypothesis 1.

H1. Internet usage rate in China increased significantly during the COVID-19 pandemic.

2.2. Mediating effect of perceived importance of the internet

According to Rogers (2003), the public's attitude toward new technology is a critical intervening variable in the innovation adoption process. Social distancing policies relating to COVID-19 greatly altered public attitudes toward remote working and living, including consumers' acceptance of Internet shopping (Faqih, 2022; Shen et al., 2022), students' perceptions of online learning (Laksana, 2021), and patients' perceptions of telemedicine (Budd et al., 2020). Recent studies show that workers' satisfaction with home office was high (Bellmann & Hübler, 2020), and the productivity of U.S. employees increased by an estimated average of 5% during the pandemic (Robinson, 2022). With a wider range of experiences with the Internet, we propose that the perceived *importance* of the Internet increased during the COVID-19 pandemic (Hypothesis 2.1).

In addition, a recent study shows that the perception of the Internet's importance positively affects the development of digitalization in China (Wang et al., 2022), since users consider the Internet useful to finish their job tasks and easier to use over time (Porter & Donthu, 2006; Teo et al., 1999). According to the technology acceptance literature, perceived usefulness and perceived ease of use have a very positive influence on public attitudes toward new technologies (e.g., Davis, 1989; Davis et al., 1989). Therefore, we assume the perceived importance of the Internet is positively associated with Internet usage rates (Hypothesis 2.2). On the whole, we propose the perceived importance of the Internet is a mediating variable for the COVID-19 pandemic's impact on Internet usage in China (Hypothesis 2.3).

H2.1. The perceived importance of the Internet has increased during the COVID-19 pandemic.

H2.2. This increase in the perceived importance of the Internet improves the overall Internet usage rate.

H2.3. The perceived importance of the Internet is the mediating variable in the COVID-19 pandemic's impact on the overall Internet usage rate.

2.3. Mediating effect of access to the internet

The COVID-19 pandemic has drastically increased the reliance on the Internet. People needed to shop online from home and use the Internet to work remotely, and many basic government services shifted from paper-based to electronic-based (Amankwah-Amoah et al., 2021), all of which required people to spend more time online and, thus, made it much more necessary for them to have access to the Internet. Within the education sector, for example, Internet access saw a significant enhancement among Chinese high-school students during the COVID-19 pandemic, both in terms of speed and coverage (Guo & Wan, 2022). In this light, we propose a positive association between the COVID-19 pandemic and access to the Internet (Hypothesis 3.1). Internet access is the primary driver of Internet usage rates in developing countries (Lopez-Sintas et al., 2020; Van Deursen, 2020). In addition, individuals with a greater array of technologies and devices for Internet access tend to be more frequent users (Busselle et al., 1999). This study tests whether access to the Internet is positively associated with Internet usage in China during the pandemic (Hypothesis 3.2). We propose that access to the Internet is the mediating variable in COVID-19's impact on Internet usage rates overall (Hypothesis 3.3).

H3.1. Access to the Internet has increased during the COVID-19 pandemic.

H3.2. This increased access to the Internet has improved Internet usage rates overall.

H3.3. Access to the Internet is the mediating variable in the COVID-19 pandemic's impact on Internet usage rates.

2.4. Digital inequalities across different socioeconomic groups

Considering the urban–rural digital inequalities in Internet access (de Clercq et al., 2023), European Union (EU) has established rural development programs to construct smart villages that bridge the digital gap between urban and rural areas (ENRD, 2020). By contrast, digital investments by central and local governments in China have heavily tilted toward larger cities. While many rural residents struggle to get stable access to the Internet, the issue in urban areas is more about having the digital skills to use the Internet effectively (Guo & Wan, 2022). Previous studies have shown that during the pandemic, inadequate and unreliable Internet services – particularly in rural areas and for the elder population (Wang, Zhou, & Wang, 2021) – lead to inequalities in medical services (Smith-East & Starks, 2021) and education (Korkmaz et al., 2022). Considering the well-developed existing digital infrastructure and preferential policies in Chinese cities, we propose Hypothesis 4.1, according to which the Internet usage rate has increased more in urban than in rural areas during the COVID-19 pandemic.

Digital inequality varies across different age groups (Zilian & Zilian, 2020), and recent research shows it has worsened for the older population because of the impact of the COVID-19 pandemic (Leukel et al., 2021; Morris et al., 2022). The vulnerable elders usually have difficulty mastering digital apps and QR codes, a skill that became essential for living and working during the COVID-19 crisis. In China, the widespread and sometimes mandatory e-governance platforms are not very user-friendly and frequently fail to take into account the needs and digital skill levels of Chinese elders (Guo et al., 2022). The elderly also often have difficulty learning how to use online medical services (Lolich et al., 2019). By contrast, young people tend to be better-educated and, thus, more receptive to new technologies, which is part of the reason why younger employees are more likely than middle-aged or older workers to work from home in European countries (Eurofound, 2020). Thus, Hypothesis 4.2 states that Internet usage has increased more for the young age group than the older population during the COVID-19 pandemic.

Research further shows that digitalization and Internet usage vary across income groups. A study in Russia found that low-income communities are among the most vulnerable groups in terms of digital inequality (Grishchenko, 2020). Moreover, digitalization in OECD countries benefits rich groups disproportionately due to the existence of 'winner-take-all' market structures (Guellec & Paunov, 2017). Rich communities also have higher competencies in mastering new digital skills than poor communities, illustrating structural inequalities of digitalization (Zilian & Zilian, 2020). A recent survey conducted in the Netherlands revealed that high-income communities have more positive attitudes toward digital devices and are usually the first to actually buy them, which implies that these economically advantaged groups have more of the required skills to acquire and engage in advanced technology and Internet usage (Van Deursen et al., 2021). In this light, Hypothesis 4.3 proposes that the Internet usage rate increased more significantly in the high-income group than in the middle- and low-income groups during the COVID-19 pandemic.

During the COVID-19 crisis, digital technologies dramatically reshaped business structures and models to adapt to market changes and business requirements (Li et al., 2022; Matt et al., 2022). Amid the pandemic, many enterprises have pushed for new investments in digital technologies, a clear vision of digital transformation, and greater knowledge sharing (Zangiacomi et al., 2020). The public sector has also adopted its structures, strategies, and official interactions with the general public in this new digital age (Lindgren et al., 2019; Ylipulli & Luusua, 2020). New research shows that SOEs in China perform better than private firms when it comes to financially benefiting from digitalization (Zeng et al., 2022). Prior studies have also discussed how ICTs have enhanced enterprises' environmental performance (Wen et al., 2021) or how Internet usage has had a positive impact on carbon mitigation (Awan et al., 2022). However, to date, no studies have analyzed the digital transformation of different types of enterprises' ownership during the COVID-19 pandemic. Therefore, Hypothesis 4.4 states that the Internet usage rate sees a sharper increase for SOE employees than for employees who worked at other public institutions, as well as private and foreign enterprises, during the pandemic.

H4.1. The Internet usage rate increased more sharply in urban areas than in rural areas during the COVID-19 pandemic.

H4.2. The Internet usage rate increased more among the young age group than the old age group during the pandemic.

H4.3. The Internet usage rate increased more among high-income groups than among middle- and low-income groups during the pandemic.

H4.4. The Internet usage rate increased more for employees in SOEs than for employees working in other public sectors, as well as private and foreign enterprises, during the pandemic.

Based on these hypotheses, this study proposes a theoretical framework as illustrated in Fig. 1. H1 hypothesizes a positive impact of the COVID-19 pandemic on Internet usage rates. H2.1 and H2.2 hypothesize a positive effect of the COVID-19 pandemic on the perceived importance of the Internet, and the effect of the perceived importance of the Internet on the Internet usage rate, respectively. Meanwhile, H2.3 combines these ideas and suggests the moderating role of the perceived importance of the Internet in influencing the impact of COVID-19 on the Internet usage rate. Similarly, H3.1 and H3.2 posit a positive influence of the COVID-19 pandemic on access to the Internet and a subsequent positive influence of access to the Internet on the Internet usage rate, respectively. H3.3 combines these concepts and proposes that Internet access moderates the impact of the COVID-19 pandemic on the Internet usage rate. Lastly, H4.1-4.4 propose varying effects of the COVID-19 pandemic on Internet usage rates across multiple socioeconomic groups, depending on factors such as urban/rural regions, ages, income levels, and job categories.

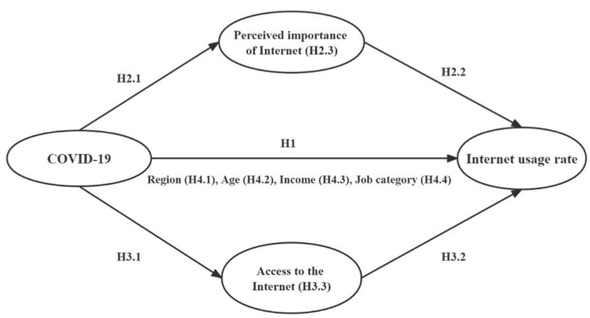

Fig. 1. Theoretical framework.

3. Data and method

3.1. Data

Data on the COVID-19 cases and incidence rate was extracted from the Johns Hopkins Coronavirus Resource Center (JHU, 2022). The center provides regularly updated coronavirus data and expert guidance, including cases, deaths, tests, hospitalizations, and vaccines, to inform the public, policymakers, and healthcare professionals around the world. All other data used in this study was sourced from the China Family Panel Studies (CFPS, 2021). The CFPS is the most comprehensive large-scale multidisciplinary social survey launched by Peking University and followed up every two years since 2010, covering all regions and representing the entire population of mainland China. By tracking individuals, families, and communities over time, the CFPS provides high-quality longitudinal data for academic investigation and policy research in important areas such as Chinese society, economy, population, education, and health. We use the most recently released dataset, which was collected in 2020. This round of the survey has a nationally representative sample in 31 provinces, municipalities, and autonomous regions of mainland China. The CFPS dataset holds substantial recognition within academia and has found widespread application in studies published in esteemed journals like Nature Energy (Wang et al., 2023), Applied Energy (Lin & Zhu, 2021), Chinese Sociological Review (Zhang, 2020), China Economic Review (Nie et al., 2023), and Telecommunications Policy (Liu & Wang, 2021; Lu et al., 2023; Shi, 2023).

Data cleaning followed a three-step approach. First, we deleted the respondents' data marked 'missing value' in the *Province* and *Region* variables (i.e., the information of respondents with unknown provenance was deleted). Second, values of 'Not Applicable,' 'Decline to Answer,' and 'Don't Know' were removed. Third, we converted the literal variables into numeric variables. In so doing, about 25.66% of the observations were removed, resulting in a final sample of 26,158 valid responses. [1]

In a broader sense, digitalization is defined as 'the use of digital technologies and data as well as interconnection that results in new or changes to existing activities.' (OECD, 2019). We follow other studies by selecting the Internet usage rate as our dependent variable. Prior studies discussed different topics that occurred in digital transformation based on this definition. For instance, Wang et al. (2022) use the time spent on the Internet per week to represent 'Internet usage' and analyze the digitalization divide. Sonobe et al. (2021) use digital wallets/online payments and mobile payments to represent 'digital payment,' and they discuss the digitalization responses of the micro, small, and medium enterprises. For our dependent variable, we use the work mode type during the peak of the pandemic in February and March 2020 as a proxy indicator for estimating the Internet usage rate, which signifies the extent of digitalization in China's labor market. The data is sourced from Question COVID5 of the CFPS Individual dataset (CFPS, 2021). After a short description of the practice of telework, defined as the practice of working from home, making use of the Internet and e-mail, the main question asks respondents: "What was your work mode at the height of the pandemic in February and March 2020?" Respondents were provided with four options from 1 to 4 (1 = 'No Internet telecommuting'; 2 = 'Occasional use of Internet telecommuting'; 3 = 'Frequently use of Internet telecommuting'; 4 = 'Full use of Internet telecommuting'). Since Internet usage is the primary measurement of the digital divide (see, for instance, Van Dijk (2017)), different Internet usage rates in the given group can be regarded as digital inequality.

We examine the mediating effects of the perceived importance of the Internet and access to the Internet to understand the variation in Internet usage rates during the pandemic. We assume the strict lockdown measures during the pandemic kept people away from their offices as they had to work from home, which improved their perceptions of the importance of the Internet and increased their dependence on access to information via the Internet, resulting in greater Internet usage. By drawing on Liou et al. (2022) and Wang et al. (2022), we use a five-point Likert scale to specify respondents' self-rated importance of access to information on the Internet from very unimportant to very important. In line with Shen and Chiou (2010) and Chiou and Ting (2011), we use the time spent on mobile devices and computers/laptops per day to represent access to the Internet, which is more accurate than grouping people into several time ranges (Marciano et al., 2022; Wang et al., 2022) or simply employing a binary variable that represents the use (or not) of the Internet (He et al., 2022; Wan et al., 2022).

Following Zong et al. (2021) and Song et al. (2022), we use COVID-19 cases as an independent variable and replace the incidence rate in the robustness tests in line with Lee et al. (2022). We use the COVID-19 cases and incidence rate data for February and March 2020 because, in China, the COVID-19 pandemic was at its most severe during these two months. It was concentrated in Wuhan, where the official lockdown started on 23 January and ended on April 8, 2020. After that, the pandemic was confined to certain Chinese cities and on a much smaller scale (JHU, 2022). Thus, we believe that using the two months of data could accurately reflect different Internet usage opportunities as a response to the COVID-19 pandemic (i.e., the higher the COVID-19 cases, the more likely a person is to work from home). The number of COVID-19 cases denotes the cumulative cases of coronavirus infections, using persons as the unit of measurement (Song et al., 2022; Zong et al., 2021), while the incidence rate denotes the cumulative cases as a percentage of the local population, measured per 10,000 people (JHU, 2022). Detailed information on the COVID-19 pandemic distribution in China is illustrated in Figure A1 in the Appendix.

Sociodemographic factors sourced from the CFPS individual dataset include age, gender, marital status, agricultural/non-agricultural job, education, income, and social status. *Hukou* and *Bianzhi* are unique to the Chinese systems and are included in our models due to the important role they play in defining a person's social status in China. *Hukou* is a tool for population registration to control internal migration, manage social protection, and preserve social stability (Gersovitz, 2016). *Hukou* is not only an identity in China but also entitles the person to certain social welfare benefits in light of the scarce community resources (e.g., medical and

[1] For more details on the sampling method of CFPS, please refer to: http://www.isss.pku.edu.cn/cfps/docs/20230629171546061292.pdf.

education resources) serving China's huge population. As the distribution of resources is very unequal in the present *Hukou* system (Afridi et al., 2015) and drawing from Shi (2023), we assume that whether a respondent has an urban or a rural *Hukou* affects their Internet usage while working from home during the COVID-19 pandemic. Consequently, we incorporate *Hukou* into our models. *Bianzhi* refers to the number of posts with certain civil service benefits, which mainly exist in government and Party sectors (e.g., SOEs controlled by the government) and in public institutions such as education, medicine, and research. *Bianzhi* is basically "an entitlement device that people used to establish their identities in order to receive benefits" (Han, 1999, p. 358). Those whose posts are within the *Bianzhi* system receive civil service benefits and are said to 'eat imperial grain.' They are, therefore, unlikely to be unemployed and can live a more stable life. Therefore, we also incorporate *Bianzhi* into our models. Table 1 provides an overview of all the variables' characteristics, while survey questions and variable measurements are shown in Table A1 in the Appendix.

3.2. Method

This study uses the ordered probit model to examine digital inequalities in China's labor market. The model was proposed by McKelvey and Zavoina (1975) to analyze categorical, non-quantitative choices. The ordered probit model is suitable for this study (Angrist & Pischke, 2009; Wooldridge, 2010) because the dependent variable (i.e., self-rated Internet usage rate) is ordinal data ranging from 1 to 4, and the higher the value, the higher the Internet usage level. The ordinal data is intended to facilitate marginal effect analysis and discussion. The cross-sectional data structure also enables the ordered probit model as a suitable research method. More importantly, the ordered probit model takes into account unobserved heterogeneity while using the full information of the data (Rudolf, 2014). As both the ordered probit model and the ordered logit model are commonly employed to analyze such ordinal data, we prefer to apply the former to the main regressions since it is more widely used in Internet usage–related pieces of literature (Shi, 2023; Zhong et al., 2022; Zhu et al., 2020), while the ordered logit model is also employed to test robustness in this study. The basic equation of the ordered probit model is:

$$y_i^* = \beta_i X_i + \varepsilon_i \tag{1}$$

where y_i stands for the dependent variables, and y_i^* are the latent variables. Latent variables are not directly observed but rather

Table 1
Sample – Characteristics of all key variables (n = 26,158).

Characteristics	Percentage (n)	Mean	Characteristics	Percentage (n)	Mean
Digitalization		1.7581	Middle school	30.76% (3884)	3
No Internet telecommuting	58.58% (3254)	1	High school	19.43% (2453)	4
Occasional use of Internet telecommuting	18.31% (1017)	2	Senior college	11.38% (1436)	5
Frequently use of Internet telecommuting	11.85% (658)	3	Undergraduate	10.70% (1351)	6
Full use of Internet telecommuting	11.26% (626)	4	Postgraduate	1.01% (127)	7
COVID-19 cases	100% (26,113)	0.1280	Doctor of Philosophy	0.07% (9)	8
Incidence rate	100% (26,113)	0.2464	Income	100% (8269)	4.2712
Perceived importance of Internet		3.4011	Non-agricultural		0.5873
Very unimportant	21.35% (5123)	1	Agricultural job	41.27% (7597)	0
Unimportant	6.04% (1449)	2	Non-agricultural job	58.73% (10,809)	1
Fairly important	17.73% (4255)	3	Job category		3.7012
Important	20.93% (5022)	4	Government departments/Party offices/mass organization	6.30% (572)	1
Very important	33.95% (8150)	5	Public institutions	9.13% (829)	2
Access to the Internet	100% (15,672)	0.2224	State-owned enterprises	12.59% (1143)	3
Age	100% (26,113)	44.9964	Private companies/individually owned business	61.66% (5599)	4
Hukou		0.2839	Foreign/Hong Kong–Macao–Taiwan enterprises	2.47% (224)	5
Non-agricultural *Hukou* & residence *Hukou*	71.61% (15,696)	0	Individual/family	6.15% (559)	6
Agricultural *Hukou*	28.39% (6222)	1	Private non-enterprise organizations	1.70% (154)	7
Gender		0.5046	*Bianzhi*		0.4699
Male	49.53% (12,935)	0	No	53.01% (1330)	0
Female	50.47% (13,178)	1	Yes	46.99% (1179)	1
Marital status		0.8492	Social status		3.0660
Single	15.08% (3100)	0	Very low	8.25% (1809)	1
Married	84.92% (17,463)	1	Low	16.06% (3520)	2
Education		3.4127	Moderate	47.92% (10,505)	3
Illiterate/semi-illiterate	10.77% (1359)	1	High	16.40% (3595)	4
Primary school	15.88% (2004)	2	Very high	11.37% (2495)	5

Sources: China Family Panel Studies (CFPS, 2021), Johns Hopkins Coronavirus Resource Center (JHU, 2022).

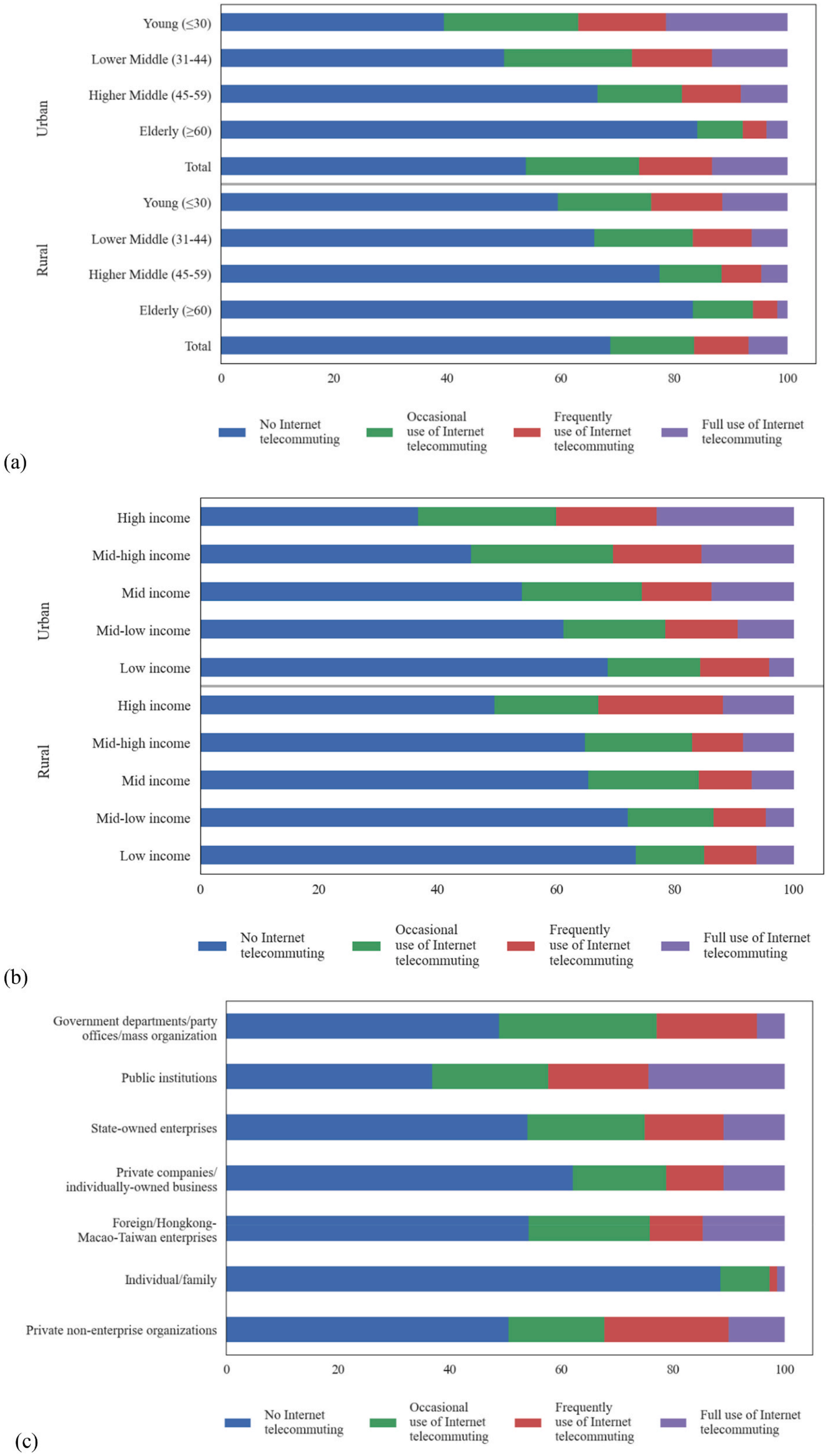

Fig. 2. China's Internet usage patterns during the pandemic. **Notes**: This figure shows China's Internet usage patterns at the height of the COVID-19 pandemic in February and March 2020. Fig. 2(a) and (b) show the Internet usage rates among the four age groups and the five income levels, while

the Internet usage rates among the seven job categories are shown in Fig. 2(c).
Source: China Family Panel Studies (CFPS, 2021).

inferred through a mathematical model from other variables that are observed (refer to Everitt (1984) and Ronning and Kukuk (1996)). In this study, the observable dependent variables are the Internet usage rates (on a scale from 1 to 4), and the latent variables are the coded four levels of Internet usage. X_i is a vector of explanatory variables assessing the attribution of Internet usage, and β_i is the coefficient of X_i, a vector of estimated parameters to be projected, representing the impact magnitude of the independent variable on the dependent variable. Finally, ε_i is an unobserved white-noise disturbance, with $E(\varepsilon_i) = 0$.

To examine the marginal effects of the ordinal four levels of Internet usage, we assume that α_1, α_2, and α_3 are thresholds to be projected, and $\alpha_1 < \alpha_2 < \alpha_3$. Based on Eq. (1), we generate the following Eq. (2):

$$y_i = \begin{cases} 1 & y_i^* \leq \alpha_1 \\ 2 & \alpha_1 < y_i^* \leq \alpha_2 \\ 3 & \alpha_2 < y_i^* \leq \alpha_3 \\ 4 & y_i^* > \alpha_3 \end{cases} \tag{2}$$

According to Long (1997), the formulas for the probabilities with four observed outcomes of Internet usage will be:

$$\begin{cases} P(y=1|X) = P(y^* \leq \alpha_1|X) = 1 - \Phi(\alpha_1 - X_i\beta_i) \\ P(y=2|X) = P(\alpha_1 < y^* \leq \alpha_2|X) = \Phi(\alpha_2 - X_i\beta_i) - \Phi(\alpha_1 - X_i\beta_i) \\ P(y=3|X) = P(\alpha_2 < y^* \leq \alpha_3|X) = \Phi(\alpha_3 - X_i\beta_i) - \Phi(\alpha_2 - X_i\beta_i) \\ P(y=4|X) = P(y^* > \alpha_3|X) = 1 - \Phi(\alpha_3 - X_i\beta_i) \end{cases} \tag{3}$$

The parameters of the model specified in Eq. (3) are estimated by using the maximum likelihood method. However, the coefficients of the models cannot reveal the effects of the regressors, so a marginal effect analysis is necessary to examine the effects of independent variables on the probability of each of the four different levels of Internet usage rates.

To test the mediating effects of the perceived importance of the Internet and access to the Internet on Internet usage rates during the pandemic, we employ the classical causal steps approach that was developed by Baron and Kenny (1986) and has been widely used as the method of mediation testing in social science research (Shao, 2022b; Zhu, Ma, et al., 2020).

$$Internet\_use_i = \alpha_1 COVID - 19_i + \sum Individual_i + \mu_i \tag{4}$$

$$Internet\_Perception_i = \alpha_2 COVID - 19_i + \sum Individual_i + \mu_i \tag{5}$$

$$Access\_to\_Internet_i = \alpha_3 COVID - 19_i + \sum Individual_i + \mu_i \tag{6}$$

$$Internet\_use_i = \alpha_4 COVID - 19_i + \beta Internet\_Perception_i + \sum Individual_i + \mu_i \tag{7}$$

$$Internet\_use_i = \alpha_5 COVID - 19_i + \gamma Access\_to\_Internet_i + \sum Individual_i + \mu_i \tag{8}$$

where $\boldsymbol{Internet\_use_i}$ refers to the four levels of Internet usage reported by individual $\boldsymbol{i}$, $\boldsymbol{COVID - 19_i}$ is the published COVID-19 cases in different regions of China. $\boldsymbol{Internet\_Perception_i}$ and $\boldsymbol{Access\_to\_Internet_i}$ denote the two mediating variables of perceived importance of the Internet and access to the Internet, respectively. $\sum \boldsymbol{Individual_i}$ is the vector of respondents' characteristics, and μ_i is an error term. Eq. (4) is the basic regression that directly examines the impact of COVID-19 on Internet usage rates, Eq. (5) checks the impact of COVID-19 on the perceived importance of the Internet, and Eq. (7) measures the mediating effect of the perceived importance of the Internet between COVID-19 and the Internet usage rate. The same applies to Eq. (6) and Eq. (8). Since data regarding access to the Internet is not ordinal, we use fixed ordinary least square instead (refer to Wang et al. (2022)) to control the effects of each province's unique characteristics, which do not change over time, on the dependent variable. It is worth noting that the results are presented in forest plots to be visually friendly, in line with Becker and Kennedy (1992), Lechner and Okasa (2020), Kostka et al. (2021), and Shao (2022a).

4. Empirical results

4.1. Internet usage patterns in China during the COVID-19 pandemic

This section presents the Internet usage patterns in different socioeconomic groups (including region, age, income, and job category) in China at the peak of the pandemic in February and March 2020. According to Fig. 2(a), Internet usage rates differ substantially across age groups in China, which is consistent with the findings of Cheshmehzangi et al. (2022) and Shen et al. (2022). Specifically, the Internet usage rate in urban areas is generally higher than in the rural parts of the country; and the younger the people, the higher the rate. The proportion of Internet users (occasional, frequent, and full use of Internet telecommuting) gradually decreases as age increases, and the elder population becomes the new vulnerable group when it comes to using digital tools in this crisis (Beaunoyer et al., 2020; Guo et al., 2022). On the whole, urban residents hold a 46% Internet usage rate compared with the value of 31% for their rural counterparts in our sample, implying a digital gap in urban and rural areas, aligning with the findings of Wang, Zhou, and Wang (2021). A similar situation applies to income groups (see Fig. 2(b)) as the share of Internet users gradually increases as incomes grow, and the Internet usage rate is generally higher in an urban area than in a rural area, which is consistent with the viewpoints of Grishchenko (2020) and Jamil (2021), who argue that poor rural communities in developing countries are usually at a disadvantage when it comes to benefiting from the digital transformation.

Regarding Fig. 2(c), the proportion of Internet users employed by public institutions, one of the seven job categories in our analysis, is among the highest at 63%. In this group, the share of those who make full use of Internet telecommuting is also among the highest, with a value of 24%. In line with our expectations, the proportion of employees from the government departments, Party offices, and the mass organization follows with a value of 51%, since these sectors, as well as public institutions, are Chinese public utility units that pursue an e-governance transformation and, thus, widely employ digital technologies (Li & Shang, 2020; Liang et al., 2019). By contrast, Internet usage rates for self-employed individuals and families, who often run small stands and street vendor shops, are among the lowest with a value of 12%, as they usually have no contract, work on a small scale, and in most cases do not need to work online. Therefore, we infer that the Internet usage rate for public sector employees is generally higher than for their private and foreign counterparts.

4.2. *Internet usage during the COVID-19 pandemic and the influencing mechanisms*

Our hypotheses presented in section 2 generated a range of predictor variables related to the mediating effects of the perceived importance of the Internet (H2.1–2.3) and access to the Internet (H3.1–3.3). To examine how these variables are associated with Internet usage in China, we undertook an ordered probit regression summarized in Fig. 3. We find that COVID-19 cases have a positive impact on Internet usage at the 5% significance level; the more COVID-19 cases, the higher the Internet usage rate. Unlike prior studies (Amankwah-Amoah et al., 2021; Faraj et al., 2021), we empirically confirmed the significant and positive effect of the COVID-19 pandemic on the Internet usage rate in China. Thus, H1 is supported. The Chinese government implemented a strict nationwide home quarantine policy during the Wuhan outbreak, which forced the public to transfer their work pattern and lifestyle online. Marginal effects of the COVID-19 impact on Internet usage rate are presented in Fig. 4, while the comprehensive results are available in Table A2 in the Appendix. The marginal effects denote the probability of changes in the dependent variables of no use, occasional use, frequently use, and full use of Internet telecommuting. In line with our expectations, COVID-19 cases show a significantly negative sign for non-Internet users but positive for Internet users, and the effect gradually increases as the Internet usage rate increases. Marginal effects on the probability of adopting the Internet telecommuting work mode are reported in percentage points (Hantzsche, 2022; Mendonça et al., 2015). It is estimated that a one percentage point increase in COVID-19 cases would result in a 0.0336 percent reduction in the probability of not using Internet telecommuting and, conversely, an increase in the probability of occasional use, frequently use, and full use of Internet telecommuting by 0.0024, 0.0105, and 0.0206 percentage points, respectively.

Concerning explanatory variables, our analysis finds that marital status, age, and agricultural/non-agricultural jobs show no significant signs. This suggests that the digital inequalities among married and single individuals, various age brackets, and agricultural versus non-agricultural job categories do not appear to be notably exacerbated. Gender has a positive and significant association

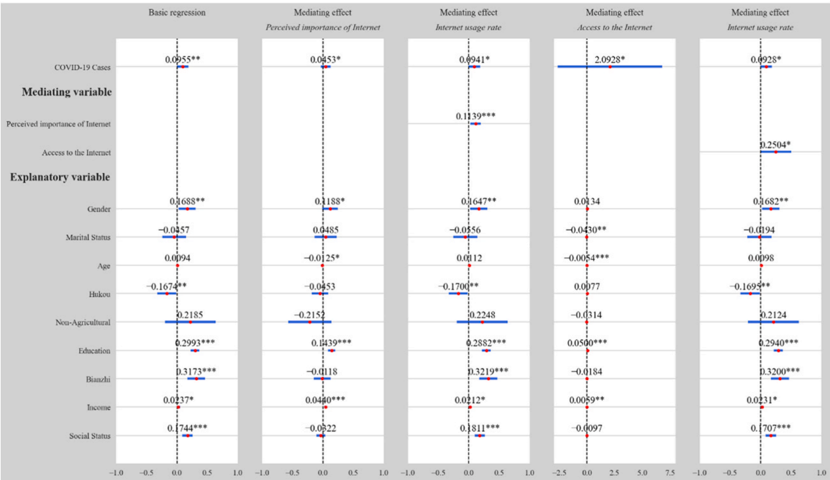

Fig. 3. COVID-19's impact on the Internet usage rate in China and the mediating effects of the perceived importance of the Internet and access to the Internet. **Notes**: (1) We use a forest plot to show the results. The red dot denotes the coefficient of the variables, and the blue line denotes the 95% confidence interval. *, **, and *** denote significant p-values at the 10%, 5%, and 1% levels, respectively. The same applies to the following figures. (2) The first column shows the basic regression result of COVID-19's impact on Internet usage rate, the second and third columns illustrate the mediating effect of the perceived importance of the Internet, and the fourth and fifth columns illustrate the mediating effect of access to the Internet. We use the fixed ordinary least square technique in the fourth column since the dependent variable of access to the Internet is not ordinal data (see the explanation in the final part of the Method section).

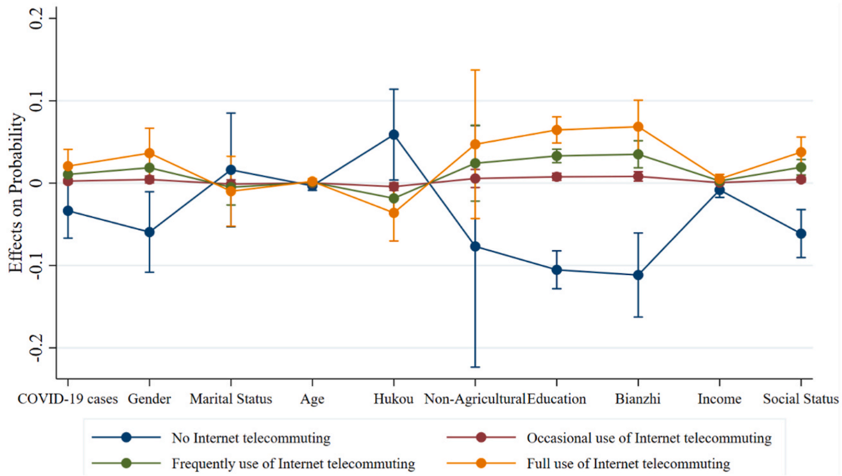

Fig. 4. Average marginal effects with 95% confidence intervals. **Note**: This graph is generated based on the basic regression (in the first column of Fig. 3). The comprehensive results of the marginal effect regression are provided in Table A2 in the Appendix.

with the Internet usage rate. Therefore, the growth rate of female Internet users outpaces that of their male counterparts during the pandemic. This divergence can be attributed to the fact that female users, more than their male Internet users, tend to rely on the Internet for online shopping and to stay up-to-date on the latest news, particularly under lockdown conditions (Huang et al., 2021; Yang et al., 2023). Income is positively associated with the dependent variable at a 10% significance level. Higher income levels lead to a greater inclination to intensify Internet usage frequency at the peak of the pandemic, although the effect is small. This finding underscores a deepening digital gap between the rich and the poor in China. Having a *Hukou* status shows a negative association with the dependent variable indicating that the increase in Internet usage frequency among urban workers surpasses that among rural workers. This corresponds to our finding in section 4.1 that the Internet usage rate in urban China is generally higher than in the rural parts of the country. Following Zilian and Zilian (2020), van Deursen et al. (2021), and Velicu et al. (2022), our findings show that education is positively associated with the Internet usage rate at the 1% significance level. This suggests that individuals with higher levels of education rely more heavily on the Internet than those with lower educational attainment, particularly in times of confinement. This outcome implies a widening digital gap, possibly due to well-educated individuals having greater access to digital devices and being likely to accept new technologies and acquire digital skills. Respondents in the *Bianzhi* system use the Internet more frequently than those employed outside of the system. This is in line with the remarkable surge in online education, e-governance, and online medical services during the two-month lockdown period. This corresponds to our finding in section 4.1 that public sector employees usually have a higher Internet usage rate. In line with our expectations, respondents with higher social statuses tend to use digital devices more extensively, while respondents who self-rate their social status as lower are not necessarily reliant on Internet usage.

The mediating effects of the perceived importance of the Internet and access to the Internet during the COVID-19 period are shown in the last four columns of Fig. 3. COVID-19 cases are the determinant factor of the perceived importance of the Internet (the second column), and both the COVID-19 cases and the perceived importance of the Internet are positively and significantly associated with the Internet usage rate (the third column). By referring to Zhu, Ma, et al. (2020) and Wang et al. (2022), we conclude that the perceived importance of the Internet mediates between COVID-19 cases and the Internet usage rate. Thus, H2.1–2.3 are supported. The same applies to access to the Internet, which was affected by COVID-19 cases (the fourth column), and both of them are positively and significantly associated with the Internet usage rate (the fifth column). Access to the Internet is supported to be the mediating variable for COVID-19's impact on the Internet usage rate, supporting H3.1–3.3. In addition, marginal effects for the mediating models are illustrated in Figure A2 in the Appendix, while the robustness checks for COVID-19's impact on the Internet usage rate and the mediating effects are shown in Figure A3 in the Appendix.

4.3. Deepening of digital inequalities during the peak of COVID-19 pandemic in China's labor market for different socioeconomic groups

In this section, we examine COVID-19's impact on Internet usage rates and illustrate digital inequalities in different socioeconomic groups, including region, age, income, and job category. Digital inequalities between urban and rural areas (Guo & Wan, 2022; Korkmaz et al., 2022), young and old (Leukel et al., 2021; Smith-East & Starks, 2021), and rich and poor (Grishchenko, 2020; Van Deursen, 2020) during the pandemic have been discussed in prior studies. Here we verify the correlation in the China scenario and also test COVID-19's impact on Internet usage rates for different job categories in China for the first time. We do not include other sociodemographic factors because *Bianzhi* and *Hukou* are special systems confined to China and without academic implications for non-China studies; gender, marital status, education levels, agricultural/non-agricultural job, and social status have usually been deployed as explanatory variables (see Leukel et al. (2021), Battisti et al. (2022), and Wang et al. (2022)).

As shown in Fig. 5, we find that COVID-19 cases in urban areas are positively associated with the Internet usage rate at a 5% significance level, while no significant sign occurs in rural areas. Therefore, H4.1 is supported. Section 4.1 indicated that Internet usage rates in urban China are generally higher than in rural parts of the country. The association is positive among the young group aged under 30, albeit only reaching a significance level of 10%, while no significant signs occur in other groups, implying that the youngest group saw a relatively substantial improvement in their Internet usage rate during the COVID-19 period, aligning with the results of section 4.2. Therefore, H4.2 is supported. Similarly, the association is only positively significant for the high-income group, which supports H4.3, indicating that only the richest communities have experienced an obvious 'digital upgrade' as a result of the pandemic. In addition, a digital transformation is more likely to occur in SOEs than in other sectors, which is consistent with the arguments of Zeng et al. (2022) that SOEs are the biggest financial beneficiaries of digital transformation in China. Thus, H4.4 is supported. Robustness checks for different socioeconomic groups are shown in Figure A4 in the Appendix.

5. Discussion

Lockdown policies and social distancing measures have greatly altered the public's attitudes toward digital devices and ICT. Working from home and having social contact online have switched from being an amenity to being an absolute necessity. The crisis has made the public aware of the importance of the Internet and, where circumstances permit, increased the time they spend online. However, digital inequalities in various Chinese socioeconomic groups have been further aggravated during this rapid digital transformation. For example, people with low incomes or who live in rural areas are unable to buy or update digital devices, and the elderly who lack the right digital skills get lost in virtual spaces. Such an exacerbation of inequality deserves to be taken seriously by the government and the public.

5.1. COVID-19 pandemic moves people's work and life online

The COVID-19 pandemic has profoundly affected people's life and work patterns. At the peak of the pandemic, about 60% of urban young people (aged under 30) in China needed the Internet for social interaction and work, and more than 21% relied completely on the Internet – a level comparable to that of the richest one-fifth of urban residents (23%). In addition, more than half of the employees of public institutions and the government and Party institutions use the Internet to work and thus are digitalized. Unsurprisingly, this pandemic-triggered digital transformation has also played out in Europe. According to a survey in April 2020 b y Eurofound (2020), 39% of employees in the 27 member states of the EU indicated they worked from home during the COVID-19 crisis, and this share rapidly increased to 48% by July 2020. The share is especially high for computer-based office jobs: For example, about 90% of Morgan Stanley's employees worked remotely during the pandemic, a sharp increase over the pre-pandemic level (Amankwah-Amoah et al., 2021).

Given the enduring impact of COVID-19, allowing a certain proportion of the workforce to work from home is necessary to prevent job losses and retain economic vitality. A recent McKinsey report (Lund et al., 2021) estimates that between 20% and 25% of workers in advanced economies and about 10% in emerging economies will work from home for more than three days a week in the post-pandemic era, which is four to five times the pre-crisis level. Therefore, despite existing societal digital inequalities with the

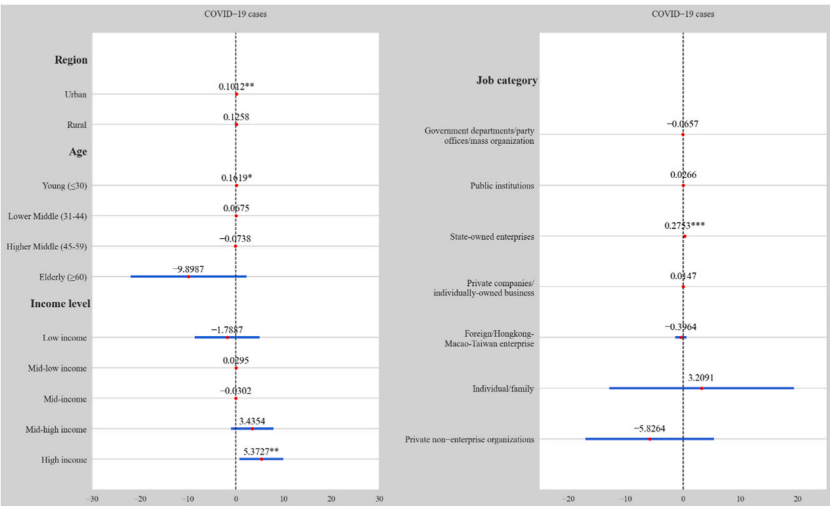

Fig. 5. Empirical results for COVID-19's impact on Internet usage rate in different Chinese socioeconomic groups. **Note**: Regression results for explanatory variables are omitted.

younger, well-educated, and higher-income groups having more digital skills and Internet access, the pandemic has actually evolved into a kind of 'catalyst' to transform the whole society in terms of business models, work patterns, consumer behaviors, as well as lifestyle (Amankwah-Amoah et al., 2021), many of which are likely to endure into the post-pandemic era.

5.2. Mediating effects of perceived importance of the internet and access to the internet

Considering the mediating effects of the perceived importance of the Internet and access to the Internet for Internet usage during the pandemic, we propose two possible pathways to the crisis that have exacerbated digital inequality. On the one hand, before the pandemic, Internet usage was not necessarily a priority in daily routines, work, and life could be carried out smoothly for non-Internet users, and Internet users mostly did not have to rely exclusively on virtual spaces for social interaction and business activities. This changed quickly with the onset of the pandemic when social distancing measures made the virtual space a basic precondition for social interaction, and using digital technologies became not only an amenity but a necessity (Beaunoyer et al., 2020). In this light, people increasingly perceived the Internet as an essential part of their personal and professional lives, but this changed attitude toward ICT can only increase Internet usage for those who actually have the digital skills to use digital devices or can learn the skills from their neighbors, for example. As a result, the gap of digital inequality has widened with digital skills and those who are socially and economically disadvantaged.

Thus, our findings support research arguing that the pandemic has widened the gap between the rich and the poor (Deaton, 2021) as access to the Internet remains unequal in China (Loo & Ngan, 2012). Digital improvement is highly dependent on infrastructure investment (Ofori et al., 2022), but COVID-19 lockdown measures placed a hold on digital infrastructure investments (Gosens & Jotzo, 2020) and made it impossible for enterprises to carry out normal business activities (Jiang et al., 2021). In the future, government agencies might also have to reduce investments due to the decline in tax revenue and the fiscal deficit (Ai et al., 2022), which will likely plunge vulnerable groups further into digital poverty (Seah, 2020). On the whole, the pandemic promoted general Internet usage in China's labor market through the perceived importance of the Internet and access to the Internet, but digital inequalities have also been exacerbated in the process.

5.3. Digital inequalities among different socioeconomic groups

Our results show digital inequalities of China's labor market have deepened during the pandemic. Specifically, the significant correlation in the urban sample reflects the deepening of the urban–rural gap in digitalization (Molero-Simarro, 2017; Tian et al., 2021). The gap is manifested in the recently released *China Internet Development Statistics Report 2022*; CNNIC, 2022), which shows the Internet penetration rate in rural areas was only 59% by June 2022, compared with 90% in urban areas. The urban–rural digital gap is mainly attributed to the unequal distribution of digital investments, which may impede Internet users' access to information (Yan & Schroeder, 2020) and create new forms of marginalization among poor rural households (Haenssgen, 2018).

Our findings show that the elder population's unfavorable position in using the Internet was exacerbated during this health crisis. Elder adults are generally less involved and skilled at using digital tools than their younger counterparts, which is often referred to as the 'grey divide' (Huxhold et al., 2020; Quan-Haase et al., 2018). An online survey from the Tencent Research Institute revealed that about 85% of Chinese elders can socially interact through WeChat, but the proportion reduced to 65% when it comes to accessing information, and only 50% can use the Internet for online payments (TRI, 2018). Moreover, the elderly usually have lower budgets to use the Internet, and they also lack people to help them use digital devices (Lee et al., 2011). Therefore, the elderly may be marginalized by the information society due to their weak ability to accept and skillfully use rapidly updated digital technologies. These barriers cause numerous inconveniences, including people not being able to effectively use China's contact-tracing app, Health Code, and will inevitably reduce their life satisfaction (Zheng & Walsham, 2021).

Our study further highlights regional economic disparities as the main driving force of digital inequality. This finding supports previous studies (Hilbert, 2010) showing that unequal economic development of ICT directly leads to digital inequality and high-income groups tend to develop ICT skills and further advance in the current digital era, while those unable to participate will be marginalized, thereby deepening the inequalities of digitalization (Van Deursen et al., 2021). During the COVID-19 pandemic, the wealth gap has widened (Deaton, 2021), which is likely to further exacerbate inequalities regarding Internet usage.

Internet usage was affected by the COVID-19 pandemic and significantly increased among well-educated Chinese individuals with high social status. There are mainly two pathways in which differences in educational attainment can lead to digital inequality because of COVID-19. On the one hand, the more educated an individual is, the greater exposure they have to ICT and the more easily they can master ICT skills to obtain COVID-19 information (Mo et al., 2013; Sommerlad & David, 2022), thus enabling them to be in a favorable position to adapt to this health crisis. On the other hand, since China's COVID-19 cases were mainly concentrated in cities, urban residents with higher levels of education were more likely and could more conveniently use the Internet than rural residents. The better ICT infrastructure in urban areas also stimulated such digital inequalities. Similar situations apply to social status since it is positively correlated with education and income.

In terms of gender dynamics, we find that Internet usage has risen noticeably among Chinese females, as evidenced by the results in Fig. 3. This trend aligns with the conclusions drawn by Yang et al. (2023). The online-to-offline food delivery industry experienced explosive growth during the COVID-19 pandemic as people were confined to their homes, and female members of the household have tended to be responsible for buying household necessities through mobile apps like Meituan (Choi et al., 2021) and Ele. me (Kim et al., 2021). This is a big change compared with the pre-pandemic era, when men were the main frequent users of the Internet (Fatehkia et al., 2018), despite the limited gender dividend yielded by the digital economy. The latter phenomenon accentuates the growing labor demand for female-preference occupations (Lu et al., 2023) and an enhancement in the overall job quality for women (Shi, 2023). Although the crisis has inadvertently given Chinese women a boost in Internet usage rates and narrowed the gender digital gap, this is likely to be temporary because online shopping is no longer mandatory after the strict lockdown. The COVID-19 pandemic is basically a disaster for women: A recent survey from Peking University (Cai et al., 2021) revealed that 7.4% of Chinese women were unemployed, and 10% had dropped out of the labor market by November 2020, while the figures are only 2.4% and 5.7% for men. Moreover, in the first half of 2020, the proportion of women working from home was 25%–35% higher than men.

Interestingly, our analysis also shows digital inequalities based on where one is employed in China. We find the Internet usage rate is significantly positively associated with employment status in SOEs, implying that the workers employed by SOEs were more likely to use the Internet at the peak of COVID-19. This is consistent with the reality that the public services in China are mostly monopolized by SOEs, including medical services, the banking system, post and telecommunications, electricity, and gas and water supply. Such public services were the basic necessities of a functioning society and had to continue at the peak of COVID-19 via the Internet, which promoted the digital transformation in SOEs. Statistics confirm this viewpoint as, by March 2020, more than 90% of the central and local SOEs had resumed work online (Zhu, 2020). In addition, public institutions like schools and universities were notified they had to switch from offline lessons to online courses, which enhanced students' and teachers' use of the Internet (Guo & Wan, 2022). By contrast, we find the Internet usage rate in the private sector shows no significant improvement. *The China Private Enterprises Digital Transformation Research Report 2022*; TRI, 2022) reveals that about 39% of private enterprises are still in the early stage of digital transformation, and less than 2% believe they have sufficiently applied digital technologies. Therefore, the pandemic-triggered digital transformation of SOEs is faster than that of private enterprises.

On the whole, COVID-19 was not only a short-term economic shock but also a profound change in all aspects of the whole society. The COVID-19 pandemic has greatly changed Chinese people's way of life. China's digital inequalities in the labor market became very apparent and made the advantaged groups receive greater dividends while the disadvantaged groups could not equally enjoy the development opportunities brought by the ICT revolution, leading to further marginalization that may lead to a crisis if left unaddressed.

6. Conclusion

Based on the most recent CFPS individual dataset and the Johns Hopkins Coronavirus Resource Center dataset in 2020, we used the ordered probit model to examine Internet usage rates at the peak of COVID-19, as well as the influencing mechanisms. Our study offers the following three main findings. First, the Internet usage rate increased when the COVID-19 pandemic in China was at its peak. The perceived importance of the Internet and access to the Internet play essential roles in mediating COVID-19's impact on Internet usage rates. Second, Internet usage rates improved especially among Chinese females, the well-educated, and people with a high social status and with *Bianzhi* or non-agricultural/residence *Hukou*. COVID-19's impact on Internet usage rates is positively significant in urban areas and among young populations and wealthy communities, revealing the deepening of digital inequalities among different socioeconomic groups. Third, the Internet usage rate is especially high among employees working for SOEs, which suggests an increase in digital inequality between SOEs and other sectors.

The study is constrained by several research limitations. The use of a one-wave cross-sectional dataset restricts our ability to capture fluctuations in the Internet usage rate over time. Thus, we know little about China's digitalization process after the end of the zero-tolerance COVID-19 policies in December 2022. A comparative analysis before and after COVID-19 is needed, which would require at least two waves of survey data, as highlighted in Drews et al. (2022). Furthermore, as our analysis is based on data from Chinese workers in the labor market, it cannot reveal changes in online behavior during the pandemic for non-workers, including children, teenagers, household spouses, and retirees. Thus, the study omits significant segments of society, which hold vital relevance for the holistic success of digital transformation.

Numerous avenues for future research emerge from our study. First, considering the study's focus on Internet usage rate data during the pandemic's peak over a two-month period, future research could illuminate the shifts in the digitalization process in China's labor market after the suspension of zero-COVID-19 measures. This could involve examining whether and to what extent telecommuting work modes have persisted within certain socioeconomic groups and exploring the underlying factors. Second, the pandemic's influence on issues like work efficiency, work flexibility, work–life balance, team engagement, and self-reported job/life satisfaction has also triggered changes in Internet usage patterns during the post-COVID-19 era. These are important topics that warrant further research attention.

Declaration of competing interest

The authors declare no conflict of financial and non-financial interest.

Data availability

Data will be made available on request.

Acknowledgements

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APPENDIX

Appendix 1. *Distribution of COVID-19 cases and the incidence rate in China (February & March 2020)*

The geographic distribution of COVID-19 cases and the incidence rate in China is depicted in Figures A1(a) and A1(b). Since Wuhan (the capital city of Hubei province) had the vast majority of cases and formed the epicenter of the outbreak (Yang et al., 2020), Hubei is far ahead with 67,801 accumulated cases and an incidence rate of about 12 per 10,000 people. The most heavily affected areas are in Hubei's neighboring provinces (i.e., Henan and Hunan) or areas with close economic ties (i.e., Guangdong and Shanghai). The underlying reason is that the coronavirus spreads more easily through human migration between geographically and economically adjacent areas. However, regions with fewer accumulated cases do not necessarily have a better incidence rate. Beijing ranks 10th with 580 accumulated cases as of March but with an incidence rate of 0.26 per 10.000 people, second only to Hubei. Considering this difference, we will replace the independent variable from COVID-19 cases with the incidence rate to check the robustness of our empirical results.

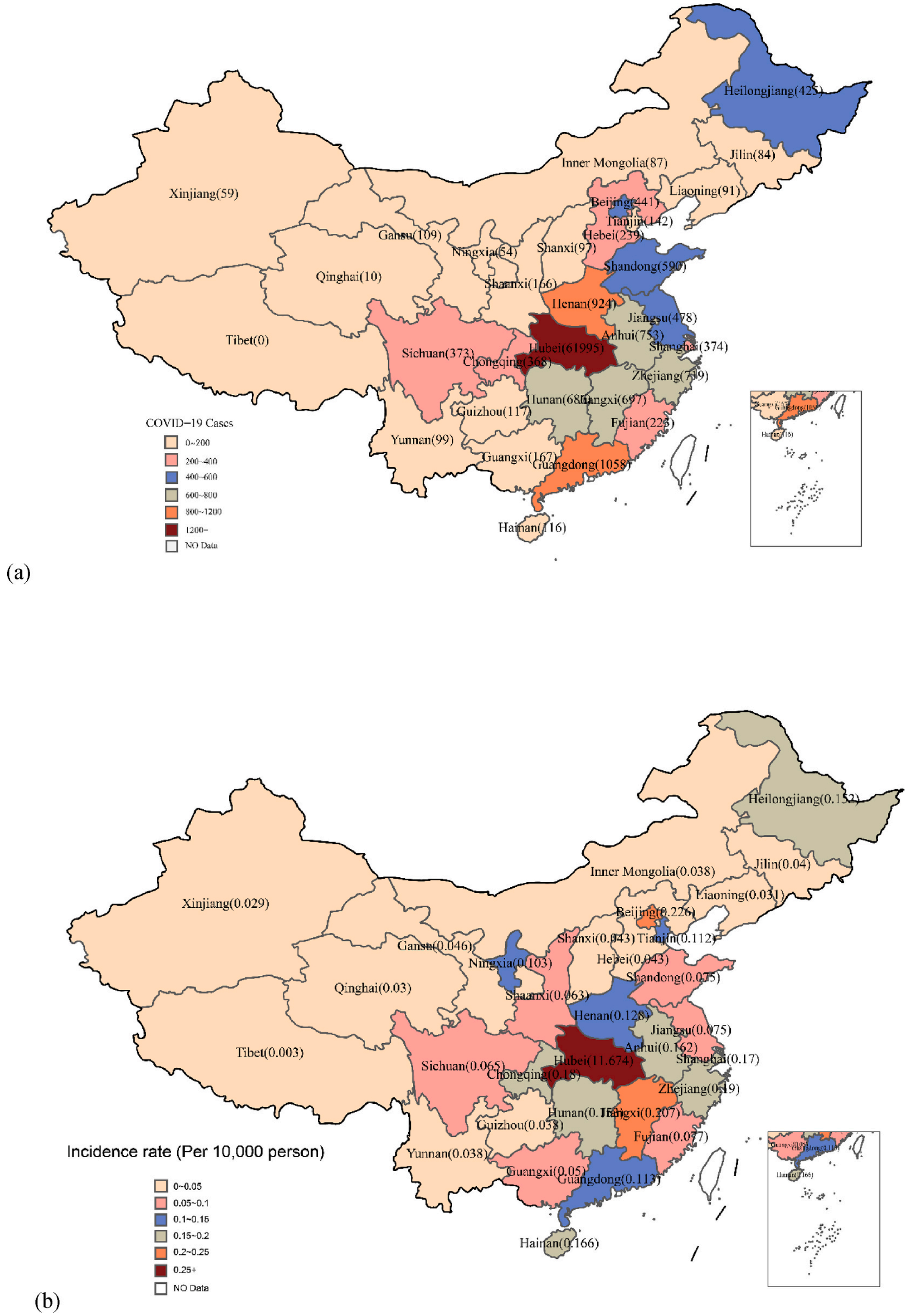

Fig. A1. The distribution of the COVID-19 pandemic in China. **Note**: (a) and (b) represent the geographical distributions of China's COVID-19 cases and incidence rates in February and March 2020, respectively. **Source**: Johns Hopkins Coronavirus Resource Center (JHU, 2022).

Appendix 2*. Survey questions and measurements of all the variables in this study*

Table A1 presents the survey questions and measurements for all the variables in this study.

Table A1
Survey questions and measurements of all the variables in this study.

Variable	Question	Measurement
Dependent variable		
Internet usage rate	COVID5: Many employers have adopted web/teleconferencing, online working, online sales, and other telecommuting modes/working from home due to the impact of the COVID-19 pandemic. What was your work mode at the height of the pandemic in February and March 2020?	'No Internet telecommuting' = 1 'Occasional use of Internet telecommuting' = 2 'Frequently use of Internet telecommuting' = 3 'Full use of Internet telecommuting' = 4
Independent variables		
COVID-19 cases	The cumulative cases of infection with the COVID-19 virus by March 2020 for each province, municipality, and autonomous region in China.	Actual figures in provincial-level total numbers. Unit in 10,000 people.
Incidence rate	The cumulative COVID-19 cases as a percentage of the local population by March 2020 for each province, municipality, and autonomous region in China.	Actual figures in provincial-level percentage. Unit in per 10,000 people.
Mediating variables		
Perceived importance of Internet	U802: How important is the Internet to your access to information?	'Very unimportant' = 1; 'Unimportant' = 2; 'Fairly important' = 3 'Important' = 4; 'Very important' = 5
Access to the Internet	U201A: Generally speaking, how much time do you spend surfing the Internet on your mobile device (mobile phone, tablet, etc.) per day? U202A: Generally speaking, how much time do you spend surfing the Internet on your computer/laptop per day?	Enter time spent on a mobile device and computer/laptop per day for each respondent. Unit in 1000 min.
Explanatory variables		
Age	A001B: What is your age?	Respondents' actual age in 2020, calculated by birth year.
Gender	A002: What is your gender?	'Male' = 0; 'Female' = 1
Marital status	EA0: What is your current marital status?	'Single' = 0; 'Married' = 1
Education	W01: What is your highest educational background?	'Illiterate/Semi-illiterate' = 1; 'Primary school' = 2; 'Middle school' = 3 'High school' = 4; 'Senior college' = 5; 'Undergraduate' = 6 'Postgraduate' = 7; 'Doctor of Philosophy' = 8
Income	G11: What is your typical monthly salary for the past 12 months, taking into account salary, bonus, cash benefits, and in-kind allowances, excluding tax, the five insurances, and the housing fund?	Real monthly net income (in RMB)
Non-agricultural	G101: Is your job agriculture-related or not?	'Agricultural job' = 0; 'Non-agricultural job' = 1
Job category	G2: Which category does your employer belong to?	'Government departments/party offices/mass organization' = 1 'Public institutions' = 2; 'State-owned enterprises' = 3 'Private companies/individually owned business' = 4 'Foreign/Hong Kong–Macao–Taiwan enterprises' = 5 'Individual/family' = 6; 'Private non-enterprise organizations' = 7
Hukou	A301: What is your current situation in *Hukou*?	'Non-Agricultural *Hukou*' & 'Residence *Hukou*' = 0 'Agricultural *Hukou*' = 1
Bianzhi	G2032: Do you have *Bianzhi*?	'No' = 0; 'Yes' = 1
Social status	N8012: What is your self-reported social status?	'Very Low' = 1; 'Low' = 2; 'Moderate' = 3; 'High' = 4; 'Very High' = 5

Notes: (1) Independent variables are derived from the Johns Hopkins Coronavirus Resource Center (JHU, 2022), while other variables are obtained from CFPS (CFPS, 2021).
(2) Regarding the *Internet usage rate* variable, responses in the questionnaire are in reverse order (with 1 denoting *'Full use of Internet telecommuting,'* for example). We adjusted the order to facilitate the explication of the regression results.
(3) The variable indicating respondents' regions (i.e., urban or rural areas) is not a survey question but rather a pre-setting of the investigators. We assigned 'Urban' as 1 and 'Rural' as 0.
(4) Based on the *Opinions on Further Advancing the Reform of the Household Registration System* (SC, 2014), certain provinces have amalgamated agricultural and non-agricultural *Hukou* into residence *Hukou*, while others have not. Therefore, we designate 'Agriculture *Hukou*' as 0 and 'Non--agriculture *Hukou*' and 'Residence *Hukou*' as 1. In addition, we excluded responses indicating 'No *Hukou*' (signifying that respondents have no *Hukou* either in China or in other countries) and 'Not appliable' (indicating respondents are foreigners).
(5) We excluded data where respondents reported being 'Divorced,' a 'Widow/Widower,' or a 'Cohabitee,' while retaining data for those categorized as 'Single' or 'Married.' This selection was made to more accurately gauge whether the "Married" and "Single" respondents experienced deepening digital inequalities during the pandemic, instead of the blurry "Married" and "Others" in the case that we combine "Single," "Divorced," "Widow/Widower," and "Cohabitee" together. Additionally, respondents designated as "Divorced," "Widow/Widower," or "Cohabitee" constituted only a marginal percentage and would not bias the outcome (with only 85 respondents cohabitating with a partner, 397 respondents being divorced, and 1329 respondents having experienced the death of their (most recent) spouses).
(6) For the *Education* variable, we grouped the response 'Never attended school' under 'Illiterate/semi-illiterate,' resulting in a value of 1.
(7) *Job category* is omitted as a control variable in the regression due to its nominal nature, rather than ordinal. However, we maintain this classification for empirical analyses.

Sources: China Family Panel Studies (CFPS, 2021) and Johns Hopkins Coronavirus Resource Center (JHU, 2022).

Appendix 3. *Marginal effect results from baseline regression*

Aligned with the baseline regression depicted in Fig. 4 in the main text, we present the empirical results in Table A2 below.

Table A2
Marginal effect results.

Variable	Baseline regression	Marginal effects			
		No Internet telecommuting	Occasional use of Internet telecommuting	Frequently use of Internet telecommuting	Full use of Internet telecommuting
COVID-19 Cases	0.0955** (0.048)	−0.0336** (0.017)	0.0024* (0.001)	0.0105** (0.005)	0.0206** (0.010)
Explanatory variable					
Gender	0.1688** (0.071)	−0.0594** (0.025)	0.0043** (0.002)	0.0186** (0.008)	0.0364** (0.015)
Marital Status	−0.0457 (0.100)	0.0161 (0.035)	−0.0012 (0.003)	−0.0050 (0.011)	−0.0099 (0.022)
Age	0.0094 (0.008)	−0.0033 (0.003)	0.0002 (0.000)	0.0010 (0.001)	0.0020 (0.002)
Hukou	−0.1674** (0.080)	0.0588** (0.028)	−0.0043* (0.002)	−0.0185** (0.009)	−0.0361** (0.017)
Non-agricultural Job	0.2185 (0.213)	−0.0768 (0.075)	0.0056 (0.006)	0.0241 (0.024)	0.0472 (0.046)
Education	0.2993*** (0.036)	−0.1052*** (0.012)	0.0076*** (0.002)	0.0330*** (0.004)	0.0646*** (0.008)
Bianzhi	0.3173*** (0.075)	−0.1116*** (0.026)	0.0081*** (0.003)	0.0350*** (0.008)	0.0685*** (0.016)
Income	0.0237* (0.013)	−0.0083* (0.005)	0.0006 (0.000)	0.0026* (0.001)	0.0051* (0.003)
Social Status	0.1744*** (0.043)	−0.0613*** (0.015)	0.0044*** (0.002)	0.0192*** (0.005)	0.0376*** (0.009)

Note: Standard errors in parentheses; *, **, and *** denote significant p-values at 10%, 5%, and 1% levels, respectively.

Appendix 4. *Results for the marginal effects of the mediating models*

Figure A2 below presents the marginal effects of the mediating models in Fig. 3.

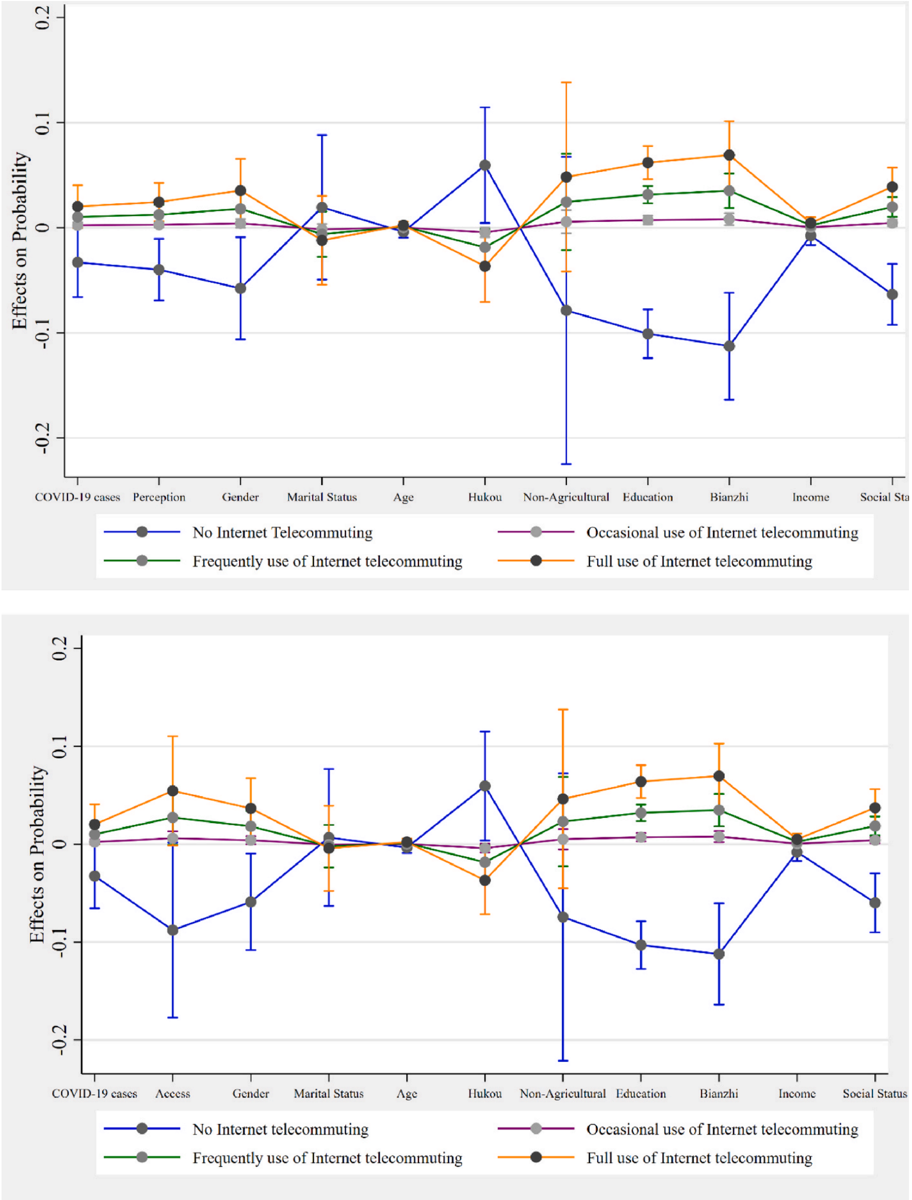

Fig. A2. Average marginal effects with 95% confidence intervals. Note: In the context of this figure, 'Perception' refers to the mediating variable 'Perceived importance of Internet,' and 'Access' pertains to the mediating variable 'Access to the Internet.'

Appendix 5. *Robustness checks for COVID-19's impact on the Internet usage rate and the mediating effects*

Figure A3 presents the robustness of empirical results for COVID-19's impact on the Internet usage rate and the mediating effects by replacing the research method from the ordered probit model with the ordered logit model and replacing the independent variable from COVID-19 cases with the incidence rate. After conducting ordered logit models, we perform a Brant test. The insignificant test statistics provide evidence that the parallel regression assumptions are met. As can be seen, the results shown in Figure A3 are very similar to Fig. 3 in the main text, thus strengthening the reliability of our findings.

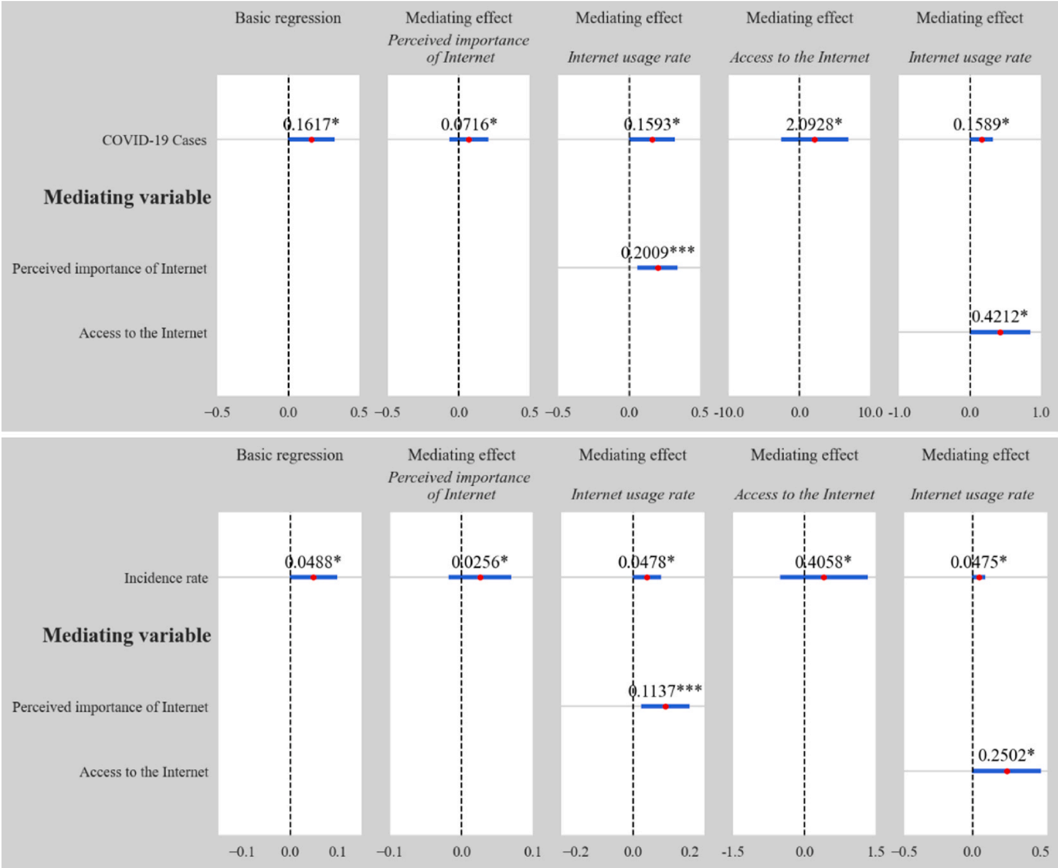

Fig. A3. Robustness checks for COVID-19's impact on the Internet usage rate and the mediating effects. **Notes**: (1) Regression results for explanatory variables are omitted since they are not the focal points of this section. (2) Brant tests conducted on the ordered probit models yield insignificant statistics, suggesting that the parallel regression assumption has not been violated.

Appendix 6. *Robustness checks for different socioeconomic groups*

Figure A4 presents the robustness of empirical results for different socioeconomic groups. As can be seen, the results shown in Figure A4 are very similar to Fig. 5 in the main text, thus strengthening the reliability of our findings.

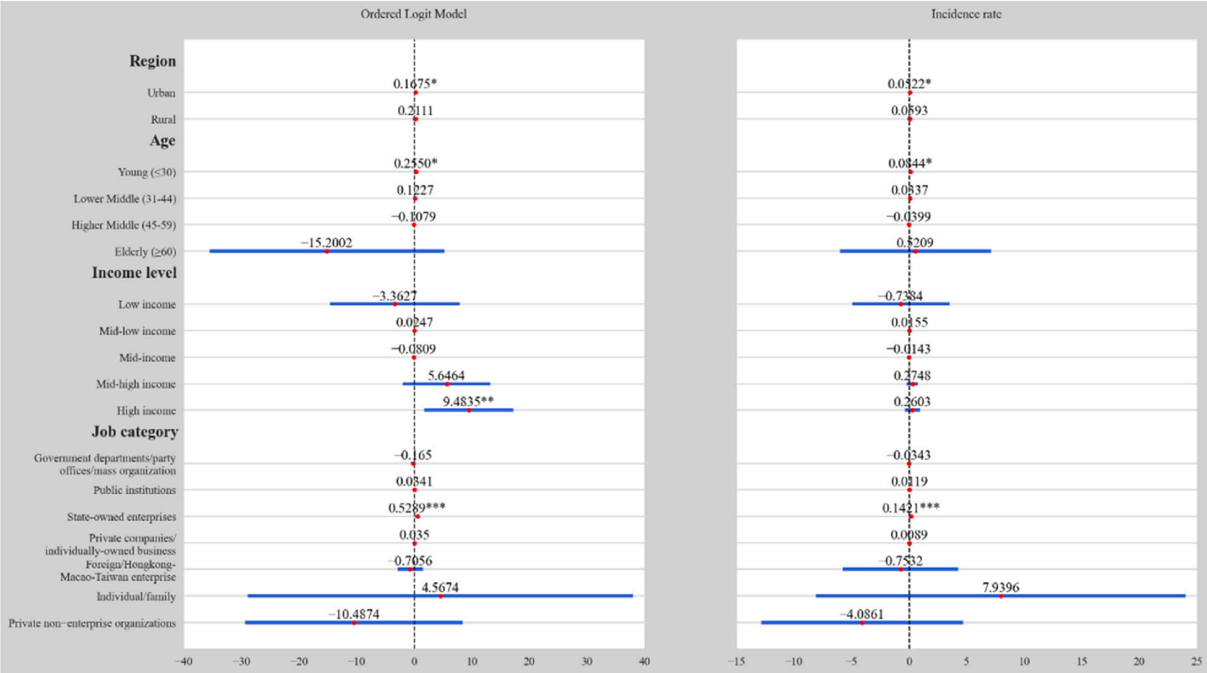

Fig. A4. Robustness checks for different socioeconomic groups. **Notes**: Regression results for explanatory variables are omitted.

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