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Determinants of the digital outcome divide in E-learning between rural and urban students: Empirical evidence from the COVID-19 pandemic based on capital theory

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ARTICLE INFO

Keywords:

Digital divide
E-learning
Capital theory
Cultural capital
Social capital

ABSTRACT

Digital outcome divide, the inequality of the outcomes of exploiting and benefitting from the ICT access and usage, has been raised as a severe concern of the e-learning practices during the COVID-19 pandemic. This study drew on capital theory and related literature and conducted a survey of 492 Chinese middle school students to explore: (1) whether a digital outcome divide exists between rural and urban students under the e-learning condition during the COVID-19 pandemic; (2) if it does, how does students' every form of capital impact the digital outcome divide. Our results revealed several important findings. First, we confirmed the existence of the digital outcome divide between rural and urban students, as rural students reported lower levels of behavioral engagement in e-learning courses compared to their urban peers. Second, we found that differences exist between rural and urban students in habitus (i.e., intrinsic motivation) and forms of capital, including cultural (i.e., e-learning self-efficacy) and social capital (i.e., parental support and teacher support), which are the main causes of the digital outcome divide. Third, a Blinder-Oaxaca decomposition analysis further confirmed that those factors could explain the major parts of the digital outcome divide between urban and rural students and that e-learning self-efficacy, intrinsic motivation, and parental support were the most dominant factors contributing to the rural-urban digital outcome divide in the e-learning context. Our study provides several important theoretical and managerial implications for researchers and educators.

1. Introduction

E-learning, an integration of education and technology, is a powerful medium for learning, offering tremendous advantages in terms of liberating the interactions between learners and instructors from the limitations of time and space (Al-Fraihat et al., 2020; Sun et al., 2008). During the COVID-19 pandemic outbreak when schools experienced temporary closures, e-learning was widely adopted to maintain continuity in education for many primary and middle schools (Dhawan, 2020). A survey conducted by UNESCO, UNICEF, and the World Bank reveals that 149 countries take education response to COVID-19, and e-learning has been provided as a solution in all high-income countries (UNESCO et al., 2020). Take China for instance, nearly 200 million students participated in e-learning classes during the pandemic (MOEC, 2020b). The number of visits on the e-learning platforms of primary and middle school students reached 1.711 billion (MOEC, 2020c). Though

e-learning served as an effective response to the pandemic, unequal outcomes are also observed from such emergent and large-scale practice. For instance, according to a research on Chinese students and parents, 55.3% of respondents thought the outcome of e-learning was worse than studying in school (iiMedia Research, 2020). Such inequality of e-learning outcomes is more salient in comparison between students of rural and urban areas, and how to facilitate equal benefit from e-learning during and after COVID-19 has become a major concern for many countries (Beaunoyer et al. 2020; China Youth Daily, 2020; UNESCO et al., 2020).

According to the literature, the inequality of e-learning outcomes can be referred to as the digital outcome divide (Scheerder et al., 2017; Wei et al., 2011). In the three-stage digital divide framework, it is the third-level digital divide (Wei et al., 2011), which refers to the inequality of the outcomes (e.g., learning and productivity) of exploiting and benefitting from the ICT access and usage (Ragnedda, 2017, p. 5; Wei et al., 2011, p.

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<https://doi.org/10.1016/j.chb.2021.107177>

Received 13 August 2021; Received in revised form 23 December 2021; Accepted 29 December 2021

Available online 31 December 2021

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170). Correspondingly, the first and second-level digital divide refers to *inequality of access to ICT and capability to use ICTs* respectively (Riggins & Dewan, 2005, p. 300). Though some scholars point out that the digital outcome divide has become a primary social crisis in the COVID-19 and post-COVID-19 era (Azubuiké et al., 2020; Beaunoyer et al., 2020; Dhawan, 2020), previous empirical studies primarily focused on the first and second-level digital divide (Scheerder et al., 2017), neglecting the digital outcome divide (third-level digital divide) (Scheerder et al., 2017; Song et al., 2020; Wei et al., 2011). The reason might be that the inequality of access or capability is much easier to observe and measure, but the measurement of digital outcome divide varies with research contexts. However, digital outcome divide is likely to lead to profound consequences, not least in the reinforcement of existing social inequalities (Scheerder et al., 2017). Thus, empirical studies are needed to determine who benefits the most (or least) from e-learning and why.

Among a few studies that have explored the digital outcome divide, the primary attention has been paid to the demographic (e.g., gender) and socio-economic factors (e.g., family socioeconomic backgrounds). For instance, existing research findings indicate that people with higher income (Eynon & Malmberg, 2021; Song et al., 2020) or educational level (Scheerder et al., 2019) are more likely to benefit from the use of ICTs. Though such findings help in understanding the various manifestations and causes of the phenomenon (i.e., digital outcome divide) in the long term, they might not be sufficient in terms of providing practical measures on how to alleviate such inequalities in the education context. On the one hand, such factors as demographic conditions (e.g., age, gender) or socio-economic backgrounds (i.e., family income or parental education) are difficult to change in the short term. On the other hand, these factors might be overly generalized as a basis to provide practical implications for specific contexts. Thus, empirical studies

focusing on contextual factors are needed. In the current context, there is a lack of a structured environment (i.e., school) and students' e-learning outcomes are more likely to be determined by contextual factors, such as distractions and oversight (Loeb, 2020). That is to say, away from the learning atmosphere of schools, the influence of students' characteristics and their family environment became more prominent (iiMedia Research, 2020; Singh et al., 2021), especially when e-learning is imperative rather than an alternative pathway during the pandemic (Charles Hodges et al., 2020; Locke, 2021). Thus, more empirical studies focusing on the individual-level contextual factors are needed to understand the phenomenon in a more subtle way, which would make the intervention easier (Singh et al., 2021).

Driven by these gaps, we aim to address the following research questions: (1) *Does a digital outcome divide exist between Chinese rural and urban students under e-learning conditions during the COVID-19 pandemic?* (2) *If it does, what specific factors contribute to it?*

To examine the first research question, we manifested the digital outcome divide in e-learning as differences in behavioral engagement between rural and urban students, which reflects students' effort spent in e-learning (Sun et al., 2019, 2020). It is closely related to students' satisfaction and achievement in e-learning (Chiu, 2021; Fredricks et al., 2004). In addition, to investigate how individual-level contextual factors contribute to the potential digital outcome divide, we adopt Bourdieu's capital theory (Bourdieu, 1986). Since the digital divide is deeply embedded in social, economic, and cultural contexts (Beaunoyer et al., 2020), this perspective is suitable for theorizing the connection between individuals' schemes for actions and the social structure and the environment in which they are embedded (Calderón Gómez, 2020, pp. 1–20). Moreover, this sociological lens facilitates the investigation into unequal access to other types of resources above and beyond those

Table 1
Summary of empirical studies on digital divide related to education.

Level of Digital Divide Focused	Author/Year	Level of Analysis	Method	Main Findings
First-level	Azubuiké et al. (2020)	Individual	Survey	This study found significant differences between students in government schools and their private school counterparts in access to remote learning opportunities and learning tools during the pandemic.
	González-Betancor (2021)	Regional	Secondary data	This study revealed that for most European countries, access to ICT at home is influenced to a great extent by the family's SES.
Second-level	Li and Ranieri (2013)	Individual	Survey	This study found that students from rural or migrant schools score lower on all the Internet inequality indicators (digital access, autonomy of use, social support, Internet use, and self-efficacy) and are therefore more disadvantaged in Internet usage status than their urban peers.
	Drabowicz (2014)	Regional	Survey	This study found that in all countries investigated, boys reported using computers and the Internet for educational purposes more often than girls.
	Hohlfeld et al. (2017)	Individual	Secondary survey data	Students with low socioeconomic status generally use software more for computer-directed activities such as drill and practice or remedial work, while their high-SES counterparts are using software more for student-controlled activities such as creating with or communicating through technology.
	Gameel and Wilkins (2019)	Individual	Survey	This study found that some of the learners have significantly higher skills than learners in other regions.
	Ren et al. (2022)	Individual	Survey	The results showed that home environment and resources were significant predictors of adolescents' general digital skill, creative skill, and educational use of Internet.
	Liao et al. (2016)	Individual	Secondary survey data	The results show that the students' characteristics, autonomy of use, family background, and resource inputs account for 35% of rural-urban digital inequality (i.e., digital self-efficacy).
Third-level	Goncalves et al. (2018)	Individual	Survey	This study found that ICT use is mainly influenced by habit, ICT skills, and benevolence.
	Wei et al. (2011)	Individual	Survey	The first-level digital divide can affect the second-level digital divide which in turn can influence the third-level digital divide.
	van Deursen and Helsper (2015)	Individual	Survey	The Internet remains more beneficial for those with higher social status, in terms of what they achieve as a result of this use for several important domains.
	Scheerder et al. (2019)	Household	Qualitative Interview	Highly educated people demonstrated a critical view toward the Internet, resulting in considered use and redefinition. While the less-educated members are less likely to benefit from ICT use.
	Song et al. (2020)	Regional	Secondary Data and Spatial analysis	The leading determinants of the digital divide are socio-economic problems such as income.
	Eynon and Malmberg (2021)	Individual	Survey	A person's demographic (e.g., age and gender) and socio-economic status (family income) influence their level of digital skills and level of engagement with learning online. Moreover, engagement in e-learning is a strong predictor of people's learning online, both personally and in ways that may be capital enhancing.

relating to economic status (Hsieh et al., 2011). In the next section, we will detail the theoretical background and hypotheses.

2. Theoretical background and hypotheses development

2.1. Previous studies: from digital access and capability to the digital outcome

Most previous studies acknowledged that there are at least two levels of the digital divide, namely, the digital access divide (the first-level) and the digital capability divide (the second-level) (DiMaggio et al., 2004; DiMaggio & Hargittai, 2001, pp. 1–23). The digital access divide represents “the inequality of access to information and communication technologies (ICTs)” (Riggins & Dewan, 2005, p. 300), which emphasizes the inequality between the “haves” and the “have-nots”, differentiated by dichotomous measures of access to new technologies (DiMaggio et al., 2004). Influenced by the digital access divide and other contextual factors (Wei et al., 2011), the digital capability divide refers to the inequality of IT capability or “the ability to use the technology” (Riggins & Dewan, 2005, p. 300). In addition, other scholars emphasized the third level of the digital divide to investigate the outcomes of IT investment and implementation. Arising from the first and second level of the digital divide and other contextual factors (Wei et al., 2011), the digital outcome divide (the third-level) is defined as *the inequality of the outcomes (e.g., learning and productivity) of exploiting and benefitting from the ICT access and usage* (Ragnedda, 2017, p. 5; Wei et al., 2011, p. 170).

The literature on the digital divide has grown tremendously in the past decade and generates many insights. We divide these studies into three research streams according to the level of the digital divide they focused on. First, one major stream of research focuses on the digital access divide among students of different school types (e.g., Azubuike et al., 2020) or socio-economic backgrounds (e.g., González-Betancor, 2021). For instance, Azubuike et al. (2020) found that private school students were more likely to access to e-learning opportunities than their government school counterparts during the COVID-19 pandemic. The second research stream includes studies that focused on the digital capability divide. These studies found that students or adults of different socio-economic backgrounds (e.g., Hohlfeld et al., 2017; Liao et al., 2016) or gender (e.g., Drabowicz, 2014; Gameel & Wilkins, 2019) experienced inequality in their ICT-related skills or abilities. For example, students with higher socioeconomic status were found to have greater control ability over ICT-related activities than their peers of low socioeconomic status (Hohlfeld et al., 2017).

Third, a small number of studies investigated the third-level digital divide (Scheerder et al., 2017), which constitutes the second research stream. The main focus and findings of these studies are summarized in Table 1 (Eynon & Malmberg, 2021; Scheerder et al., 2019; Song et al., 2020; van Deursen & Helsper, 2015; Wei et al., 2011). In brief, the previous studies involved multiple subjects or contexts, including school students (Wei et al., 2011), adult education (Eynon & Malmberg, 2021), and people’s routine use of ICTs (Scheerder et al., 2019; van Deursen & Helsper, 2015). In terms of the findings, these studies were largely focused on the demographic or socio-economic aspects of the individuals (Eynon & Malmberg, 2021; Scheerder et al., 2019; van Deursen & Helsper, 2015) or a region (Song et al., 2020), including age (Eynon & Malmberg, 2021), gender (Eynon & Malmberg, 2021), education level (Scheerder et al., 2019; Song et al., 2020), and income (Eynon & Malmberg, 2021; Song et al., 2020; van Deursen & Helsper, 2015). As for the quantitative studies in this research stream, the measurement of digital outcome or the digital outcome divide varies with the research contexts. For instance, Wei et al. (2011) measured the digital outcome as knowledge outcome and skills outcome. While the study of Eynon and Malmberg (2021) focused on the education context and measured students’ outcomes as personal learning outcomes and capital-enhancing outcomes.

Taken together, previous studies have found that students of

different backgrounds (e.g., rural and urban) are unequal in their digital access and capability (e.g., Azubuike et al., 2020; Liao et al., 2016). However, we have limited knowledge on whether the digital outcome divide also exists between students of different backgrounds. This might be because the inequality of access or capability is easier to observe and measure, while the measurement for the digital outcome divide is not sufficiently nuanced (Eynon & Malmberg, 2021). Besides, the known determinants of the digital outcome divide were either inherent to individuals since birth or highly economically dependent, which is difficult to change in the short term. Thus, empirical studies are needed to identify the specific factors contributing to the digital outcome divide between rural and urban students (van Deursen & Helsper, 2015). Against these gaps, this study aims to investigate the large-scale e-learning practices in China during the COVID-19 pandemic, when Chinese rural and urban students were both arranged to study through the Internet, to examine their e-learning outcome differences (i.e., digital outcome divide).

2.2. Current study: digital outcome divide and engagement in e-learning

As mentioned, this study focuses on the digital outcome divide, which is becoming increasingly salient in recent times. First, inequality in access might no longer be the major concern for many countries or areas, because it is gradually bridged between advantaged and disadvantaged groups in these areas. For instance, Internet access is near-universal for most developed countries, such as the Netherlands. Even in China, for the primary target of this study, namely, Chinese students, the Internet penetration rate was 95.0% and 94.7% for Chinese urban and rural students by 2020, respectively (CNNIC, 2021, p. 1). The difference in the Internet penetration rate between urban and rural students was only 0.3%, decreasing from the rate difference of 3.6% in 2019 (CNNIC, 2020, pp. 2, 2021, p. 1). Second, the three levels of the digital divide do not occur independently but are interrelated through the chain effects from the first through to the third level (Wei et al., 2011). Thus, the pre-existing differences in the access to and capability of exploiting ICTs are expected to have amplified the digital outcome divide when large-scale online education was implemented (Beaunoyer et al., 2020).

To examine the digital outcome divide through empirical evidence, we manifested it as the different levels of behavioral engagement in e-learning between rural and urban students. Behavioral engagement refers to “the behavioral effort that learners expend in e-learning to participate in academic activities, master the knowledge, and pursuit high-quality performance” (Sun et al., 2019, pp. 3158, 2020, p. 2). Behavioral engagement is classified as a dimension of engagement (Fredricks, 2011; Sun et al., 2019, 2020). Since the other dimension, psychological engagement, is a strong predictor of it (Fang et al., 2017), behavioral engagement is also often studied as a single dependent variable in previous studies (Fang et al., 2019; Sun et al., 2019). Consistent with our research target stressing the effort students devoted to e-learning during the COVID-19 pandemic, we focus on the behavioral aspect of the engagement.

Engagement (e.g., behavioral engagement) is one of the most commonly used indicators of students’ learning outcomes (Christenson et al., 2012). It is closely related to students’ persistence in and satisfaction with e-learning (Chiu, 2021; Fredricks et al., 2004). At the same time, it is a strong predictor of students’ academic achievement and well-being in e-learning (Chiu, 2021; Christenson et al., 2012). Notably, engagement (e.g., behavioral engagement) can also be considered as a process (Christenson et al., 2012), mediating the contextual facilitators and later learning outcomes (e.g., academic performance) (e.g., Eynon & Malmberg, 2021). Here, in the e-learning context, we consider engagement as an outcome rather than a process, because the focus of this study is students’ outcome of exploiting from e-learning (i.e., digital outcome) rather than their later outcomes (e.g., academic performance). In the current study, behavioral engagement reflects students’ active

participation, efforts, and attendance in the e-learning class and is measured by such items as “I am an active student in online learning.” (Gunuc & Kuzu, 2015).

In summary, although the first and second-level digital divide seems to be decreasing or even disappearing in some areas in the world, the influences they have made might continue in the form of the digital outcome divide. Moreover, urban students have more experience and resources in using ICTs than their rural peers (Li & Ranieri, 2013), which are the important conditions for effective e-learning outcomes (Wei et al., 2011). Therefore, we expected that the digital outcome divide exists between Chinese rural and urban middle school students under the e-learning condition during COVID-19. As such, we propose the following Hypothesis:

Hypothesis 1. (H1): Rural students show a lower level of behavioral engagement in e-learning during COVID-19 than their urban peers.

2.3. Forms of capital underlying digital outcome divide

As mentioned, quantitative empirical studies are especially needed to understand the specific facilitators translating ICT use into specific offline outcomes (van Deursen & Helsper, 2015). Against this backdrop and following our first Hypothesis, this study further aims to explore how individual-level contextual factors lead to the digital outcome divide between Chinese rural and urban students. To achieve this goal, we proposed our research model by drawing from the capital theory and related literature. We will detail the capital theory and our research hypotheses as follows.

Bourdieu's capital theory, unlike conventional economic theories, recognizes that capital need not be strictly economic and that it also implies other factors, including cultural capital and social capital (Bourdieu, 1986). Bourdieu also identified the concept of habitus, which emphasizes the internal part of a person converted from ones' accumulated capital and wealth. Previous studies have employed this theory to explain individuals' ICT usage patterns (Hsieh et al., 2011) as well as the offline outcomes of ICT use (Calderón Gómez, 2020, pp. 1–20).

Based on the assumption that the outcome of ICT usage, like many other human life outcomes, is constrained by individuals' social structure or environment (Calderón Gómez, 2020, pp. 1–20; Hsieh et al., 2011), we propose that students' behavioral engagement in e-learning is mainly affected by their habitus, cultural capital and social capital (Bourdieu, 1986). Fig. 1 demonstrates the research model of this study. First, as mentioned, we investigate whether the digital outcome divide (i.e., behavioral engagement difference) exists between Chinese rural and urban students in addressing the first research question. Second, to explore the specific factors of the digital outcome divide and address the second research question, we propose that (1) factors such as habitus, cultural capital, and social capital are significantly related to students' behavioral engagement; and (2) there are differences between rural and urban students regarding the above factors, which explain the digital outcome divide between these two groups. In the following sections, we will illustrate how habitus and forms of capital influence students' e-learning outcomes and are possessed unequally by rural and urban students.

2.3.1. Habitus

Prior studies have found that individual motivation or orientation toward using an ICT exerts a significant effect on their actual behavior (Hsieh et al., 2011). In previous studies on ICTs, habitus is defined as an individual's disposition, attitude, and expected benefits towards ICT (e.g., using ICT for learning propose) (Hsieh et al., 2011; Kvasny & Keil, 2006). For instance, students are initially motivated to attend e-learning classes by the desire to use ICT for learning purposes. Habitus serves as one of the individual psychological resources and is critical to individual behavior (Henry, 2004; Hsieh et al., 2011).

To capture this psychological capital, Hsieh et al. (2011) suggested

that intrinsic motivation and extrinsic motivation are the constituent properties of habitus in the ICT adoption context. However, in the current e-learning context, students were arranged to attend the e-learning classes, that is, they are faced with the similar external force to adopt the ICT (e-learning class). As such, students' habitus toward e-learning under the COVID-19 condition might be largely reflected as their internal perception of this arrangement, that is, the intrinsic motivation. Therefore, this study manifests students' habitus as their intrinsic motivation to attend e-learning classes, that is, “doing an activity for the inherent satisfaction of the activity itself” (Ryan & Deci, 2000, p. 71). For example, when a student attends e-learning classes because they find it interesting and satisfying to study online, they are driven by intrinsic motivation (Ryan & Deci, 2000; Vallerand et al., 1992). As e-learning during the pandemic is usually compulsory and emergent, it is expected that students with stronger intrinsic motivation will get used to the new learning environment sooner and put more effort into it, as intrinsic motivation is highly correlated with persistence in the academic challenge (Boyd, 2002; Walker et al., 2006). Empirical studies also reveal that intrinsic motivations are important mental factors in facilitating ICT engagement (Haan, 2004), and continuous intention to use an online learning platform (Luo et al., 2019). Thus, we hypothesize the following:

Hypothesis 2. (H2): Students' intrinsic motivation (habitus) positively influence their behavioral engagement in e-learning during COVID-19.

Habitus is also a product of experience, specifically relating to unconscious family socialization, and it evolves with the individual's encounters with the world (DiMaggio, 1979). In other words, habitus “is not a destiny” (Bourdieu & Nice, 2004); instead, it generates a schema that intensifies specific actions by someone (Belland, 2009). We propose that rural and urban students may have different levels of intrinsic motivation towards e-learning under the condition of COVID-19. First, before the pandemic, e-learning courses based on voluntary participation are more popular among students who live in big cities (iResearch, 2020), thus urban students are more familiar with e-learning because they have more experience in learning through ICTs (Hollingworth et al., 2011). By contrast, rural students with less e-learning experience must suddenly adapt to new skills and behaviors. According to cognitive load theory, the barrier to converting learning styles can cause more cognitive load for rural students (Chen & Wu, 2015; Sweller et al., 1998) and damage their interest and enjoyment (i.e., intrinsic motivation). Second, people can learn and adapt through experience (Hatch & Dyer, 2004), and urban students with more e-learning experience are likely to be better off at learning online than their rural counterparts. Like Loeb (2020) points out, students who struggle in offline learning will likely struggle more online due to their learning habits and experience. Thus, satisfaction with competence can lead to higher intrinsic motivation among urban students (Ryan & Deci, 2000). As such, we hypothesize that:

Hypothesis 3. (H3): Rural students had a lower level of intrinsic motivation to attend e-learning classes during COVID-19 than urban students.

2.3.2. Cultural capital

Cultural capital is an important cognitive resource related to ICT usage that influences individuals' behaviors (Hsieh et al., 2011). It has been identified as existing in three states: (1) the embodied state, within one's mind and body, which reflects the internal competencies needed to appropriate, understand, and use cultural artifacts; (2) the institutionalized state, a form of objectification such as educational qualifications; (3) and the objectified state, in forms of cultural goods such as artifacts, books, and paintings (Bourdieu, 1986; Hsieh et al., 2011). Previous studies in education have mainly focused on objectified forms of cultural capital such as books at home (Scherer & Siddiq, 2019), with few studies examining the embodied and institutionalized state of

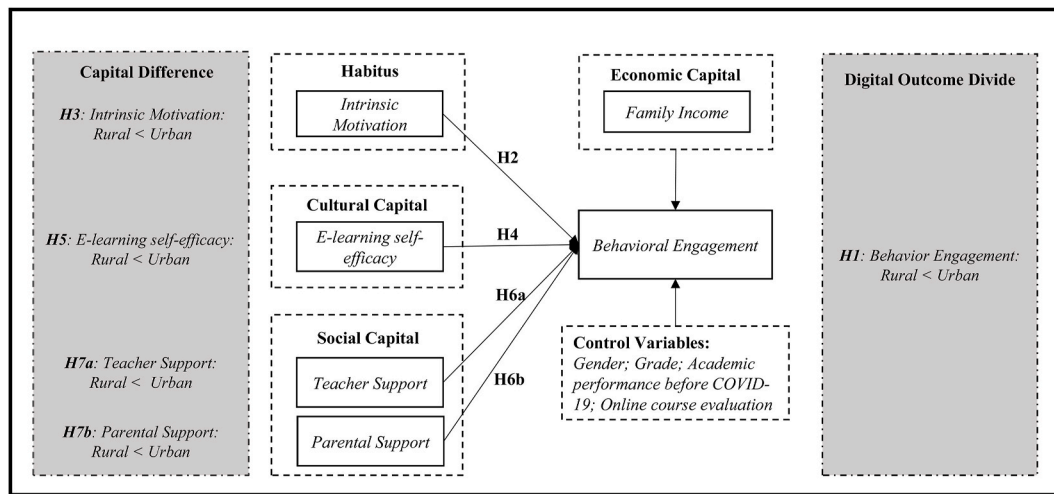


Fig. 1. Research model.

cultural capital. Besides, institutionalized cultural capital, such as educational qualifications, is not suitable for middle school students since they are still in education. Therefore, we focus on the embodied cultural capital of middle school students, which has begun to accumulate from early childhood (Reay, 2004). Adopted from a previous study, this study manifests embodied cultural capital as self-efficacy in e-learning (Hsieh et al., 2011). Specifically, e-learning self-efficacy refers to one's beliefs about their capabilities in performing a behavior aimed at meeting situational (i.e., online learning situation) demands (Bandura, 1986).

In the current context, e-learning self-efficacy may positively influence students' behavioral engagement in e-learning for several reasons. First, students with higher e-learning self-efficacy exhibit stronger confidence in their ability to utilize ICTs to accomplish required learning tasks, and they are less likely to be affected by occasional IT failures (Teo et al., 2002). Second, higher e-learning self-efficacy can predict greater satisfaction with e-learning (Hamdan et al., 2021), further leading to better learning outcomes (Al-Fraihat et al., 2020). Thus, students with higher e-learning self-efficacy may be more active in engaging in online courses because of higher perceived satisfaction with online learning arrangements during the pandemic. Third, students with higher e-learning self-efficacy are more likely to seek challenges and set higher goals for themselves, leading to better behavioral engagement (Walker et al., 2006; Wood & Bandura, 1989). Thus, we hypothesize as follows:

Hypothesis 4. (H4): E-learning self-efficacy (cultural capital) positively influenced students' behavioral engagement in e-learning during COVID-19.

In the e-learning context, there may be several explanations for the differences between rural and urban students in e-learning self-efficacy. First, inequality in e-learning self-efficacy can result from the difference in general Internet self-efficacy, as per a study by Hamdan et al. (2021), which found that higher perceived Internet self-efficacy could predict higher confidence in completing online courses during COVID-19. Compared with urban students, rural students were reported to have lower general digital/computer self-efficacy, reflecting their judgment of their ability to use computers, software, and digital applications to execute certain tasks (Liao et al., 2016; Teo et al., 2002). Since students had to accomplish online courses at home, those from rural areas were more likely to suffer from unstable connections and device barriers (Rahiem, 2020). As such, the differences in Internet connectivity and device accessibility at home could be one reason for the difference in digital self-efficacy between rural and urban students.

Second, differences in e-learning self-efficacy can also be caused by inequalities in self-efficacy of using ICT for learning propose. Typical

devices for online activities, including e-learning, are personal computers, tablets, televisions, and smartphones. Among these devices, personal computers are found to be especially beneficial for self-efficacy and self-directed learning (Teo et al., 2002). Smartphones are less suitable for work or education purposes compared to personal computers or tablets since their smaller screen size and greater scrolling requirements can result in increased cognitive burden for users (Murphy et al., 2016; Pearce & Rice, 2013; Scheerder et al., 2019). Rural students in China are less likely to have personal computers or tablets, leading to lower e-learning self-efficacy compared with urban students (CNNIC, 2020, p. 6). Furthermore, students' cultural capital (i.e., e-learning self-efficacy) can be shaped by their family environment (Reay, 2004). Students from families of low socioeconomic status have been found to have fewer opportunities and experiences to develop ICT competencies, especially for educational use, which leads to fewer positive e-learning self-efficacy beliefs (Vekiri, 2010). By contrast, parents of urban students are better educated (Liao et al., 2016) and are more used to working or learning through the Internet (Scheerder et al., 2019). Middle-class parents' positive experience of technologies enables them to engage with their children's learning using technology (Hollingworth et al., 2011), thus enhancing the children's judgment of self-ability to study online. Thus, we hypothesize as follows:

Hypothesis 5. (H5): Rural students had a lower level of e-learning self-efficacy during the COVID-19 pandemic than urban students.

2.3.3. Social capital

Social capital refers to the instrumental benefits that one can attain from the social network (Bourdieu, 1984). Previous studies have demonstrated that the social resources accessed from acquaintances who can offer advice or support in one's social network are instrumental for ICT use (Haan, 2004; Hsieh et al., 2011). In the context of e-learning under the COVID-19 condition, most students around the world, including Chinese students, were in isolation and unable to participate in normal social activities. These challenging circumstances (i.e., the COVID-19 pandemic) brought unprecedented disruption to social activities, since social capital is mainly established, maintained, and realized through social interaction (Zheng et al., 2020). Thus, students' social capital was limited to social resources from the home or through the Internet in the current context. For instance, when taking e-learning classes, students are embedded in their immediate physical environment, including family life and the surrounding resources, to advance e-learning outcomes (Singh et al., 2021). Although there might be many forms of social capital, this study focuses on the two social capital factors that appear to be especially relevant to the home-based e-learning

context—parental and teacher support—as the outcomes of the child-parent and student-teacher interactions, respectively.

Social capital can positively influence students' behavioral engagement in e-learning in several ways. First, support from teachers and parents can be instrumental to solving technical problems related to learning online (Haan, 2004), thus creating a better IT environment to facilitate students' engagement in courses. Second, social support can alleviate students' negative emotions (e.g., loneliness), influenced by the isolated learning environment, without face-to-face interaction with teachers or classmates (Bareket-Bojmel et al., 2021; Wang & Zhang, 2020). Third, students are required to be engaged in the class over a longer period than in other online activities, such as playing games (Singh et al., 2021). As such, it is especially demanding for them to keep themselves engaged on screen since they are easily distracted by physical surroundings, including other family members, social chats, or games on a device (Xie & Siau, 2020). Thus, support from family members can create a household environment conducive to home learning, which can encourage dedication and efficient learning behaviors (Gao et al., 2021). Thus, we hypothesize as follows:

Hypothesis 6a. (H6a): The teacher support dimension of social capital positively influenced students' behavioral engagement in e-learning during COVID-19.

Hypothesis 6b. (H6b): The parental support dimension of social capital positively influenced students' behavioral engagement in e-learning during COVID-19.

Although people with greater socio-economic advantage (i.e., urban students) tend to have more social resources, this assumption must be adopted with caution depending on the context (Hsieh et al., 2011). As for teacher support, two tensions coexist to influence the inequality of teacher support between rural and urban students. On one hand, rural students may have received more support from teachers, since educators were required by the Chinese government to provide additional support for students from socioeconomically disadvantaged areas such as rural and remote mountainous regions (MOEC, 2020a). On the other hand, studies found that rural schools lacked superior faculty members who were capable of teaching remotely (Guo et al., 2020). In all, we conclude that although certain needs exist that teachers should provide additional support to rural students, rural schools and teachers struggled to meet this demand. Thus, we hypothesize as follows:

Hypothesis 7a. (H7a): Rural students received less e-learning teacher support during COVID-19 than urban students.

Regarding parental support, several factors explain the difference between rural and urban students. First, urban parents are more familiar with learning online and capable of accessing online learning resources (Bacher-Hicks et al., 2021; Bonal & Gonzalez, 2020). By contrast, rural parents have less experience with e-learning or the related knowledge to assist their children (Guo et al., 2020). Second, parents and/or other caregivers cared for children while unable to work or attempting to work remotely during the COVID-19 pandemic. Rural parents were confronted with higher economic uncertainty to maintain family income than urban parents (Engzell et al., 2021). Thus, rural students may have received less parental support while their parents were overwhelmed by activities and sought to cope with the situation.

Hypothesis 7b. (H7b): Rural students received less parental support in e-learning during COVID-19 than urban students.

2.3.4. Economic capital

Economic capital reflects one's ability to acquire and gain access to ICTs (Hsieh et al., 2011; Kvasny & Keil, 2006). Consistent with previous studies, students' economic capital is represented as family income in this study (Zhang, 2016). Economic capital serves as the most basic determinant of the digital divide in terms of imposing material barriers to access (Calderón Gómez, 2020, pp. 1–20). To eliminate economic

capital as a determinant in ICT access, the Chinese government and educators provided free online courses to students nationwide and television courses for students from remote and poor areas (MOEC, 2020a). Moreover, to account for the effects of any family-based monetary resources (e.g., devices and Internet) in accessing e-learning systems, we specified economic capital as our control variable.

3. Methodology

3.1. Instrument measurement

All the measurement items were adapted from previous studies. Since the original instruments were in English, we adopted the back-translation method to ensure the accuracy of the instrument. First, a bilingual researcher translated the original items into Chinese. Thereafter, two other researchers were invited to translate the Chinese versions into English. We compared the two versions with the original items and found that they were mostly consistent. Finally, we invited 20 researchers to check the wording and format of the questionnaires to ensure content validity. The final questionnaire items are shown in Table 2.

We conducted a pretest before the formal survey. We created our questionnaire on Wenjuanxing (<https://www.wjx.cn/>). In December 2020, the second author and the corresponding author of this paper invited the middle school students they know to participate in the survey. The attention check items were distributed throughout the questionnaire to identify and screen responses from those who did not pay attention or were not engaged. For instance, one of the attention check items was "Please select 'Agree' on this question". Besides, we interviewed some participants through telephone after they completed the questionnaire to improve the questionnaire according to their feedbacks. We gave each respondent six yuan as a reward and collected 57 valid questionnaires. We conducted reliability and validity analyses. The results showed that Cronbach's alpha of each construct was greater than 0.7 and that the average variance explained (AVE) of each construct was greater than 0.5, indicating acceptable reliability and validity. All the constructs, the corresponding measurement items, and the sources are listed in Table 2. We adopted 7-point Likert scales, with 1 representing "quite disagree," 4 representing "neutrality," <http://dict.youdao.com/w/neutrality/-%20keyfrom=E2Ctranslation> and 7 representing "quite agree."

3.2. Data collection

After the pretest, we distributed the updated electronic questionnaire to more students. The formal data were obtained through two waves of the data collection process. The first wave of data collection was conducted during January 2021 by using the snowballing technique (Patton, 1990). Specifically, we invited the middle school students of the pretest to send the questionnaire URL to their schoolmates through social networking services (i.e., Tencent QQ). Students who have participated in the survey were rewarded with monetary pay. Since our data collection period was within the winter vacation of Chinese students, students who had participated in our survey were active online and positively forwarded our survey link. To validate that all participants were middle school students, we asked them to fill in the school's name and their class and check whether their answers were the same as some of the other participants. After the first wave of data collection, we received 349 responses with different IP addresses. To increase the sample size and diversity, we conducted the second wave data collection during May 2021 by cooperating with two middle schools in a region of middle China. All middle schools in the region had employed e-learning during COVID-19 for at least two months. To study the difference between rural and urban students, two schools were chosen after careful comparison of the geographic location of all middle schools in the region. Specifically, a school located in the relatively remote area in the

Table 2
Instrument measurement.

Construct	Items	Source
Intrinsic Motivation (IM)	Learning through the internet is pleasant.	Vallerand et al. (1992)
	Learning through the internet is enjoyable.	
Parental Support (PS)	Learning through the internet is fun.	Fantuzzo et al. (2000); Wang and Salle (2019)
	My parents help me with homework when I study through the Internet at home.	
	My parents prepare learning materials for me when I study through the Internet at home.	
Teacher Support (TS)	My parents review my homework when I study through the Internet at home.	Swan et al. (2008)
	My teacher provides clear instructions on how to participate in online learning activities.	
	My teacher tells us how we can plan to meet our goals for online learning.	
E-learning Self-efficacy (ESE)	My teacher is helpful in guiding the class towards understanding course topics in a way that helps me clarify my thinking.	Dierdorff et al. (2010)
	I am confident in my abilities to master new materials in online learning situations.	
	I am confident in my abilities to complete related homework after taking online lessons.	
Behavioral Engagement (BE)	I am confident that I can completely adapt to online learning.	Gunuc and Kuzu (2015)
	I follow the rules in online learning.	
Online Course Evaluation (OCE)	I am an active student in online learning.	Eom and Ashill (2016)
	I do my homework in time.	
	The course objectives and procedures are clearly communicated.	
	The course material is organized into logical and understandable components.	
	The instructor inspires interest in the subject matter of this course.	

region was chosen to cover more rural students, while another school located in a relatively central location of the region was chosen as a supplement data source. We distributed the questionnaire to students through the assistance of IT (Information Technology) teachers of these two schools. The students are asked by their teachers to complete our survey using the schools' computers at the IT classes. At last, we received 158 responses during the second wave of data collection.

Combining the two data sources, we obtained 507 responses. To validate the geographic location of students (rural or urban), all respondents were asked to fill in the school's name and choose their geographic location from the rural area, urban area, and unknown.¹ After removing questionnaires whose answer to the geographic area was "unknown" or whose attention check answers were wrong, the final sample includes 492 valid questionnaires. We cross-checked the students' self-reported geographic location with school location as well as IP address to determine the geographic location of students. The final sample profile is shown in Table 3. Rural students made up 46.75% and urban students made up 53.25%. Male and female students made up 65.24% and 34.76%, respectively. Ninety-six percent of the sample studied online for at least two months, and the main equipment used was the cellphone. The most frequently used e-learning system was Dingding (61.99%), and classes were mainly live.

¹ We designed this vague option in case some students feel uncomfortable revealing the sensitive information.

Table 3
Sample profile (N = 492).

Variable	Option	N	Percentage
Gender (GEN)	Female	171	34.76%
	Male	321	65.24%
Grade	JMS-First year	74	15.04%
	JMS-Second year	109	22.15%
	JMS-Third year	104	21.14%
	SMS-First year	52	10.57%
	SMS-Second year	96	19.51%
	SMS-Third year	57	11.59%
Geographic Location	Rural	230	46.75%
	Urban	262	53.25%
Length of E-learning	Less than one month	16	3.25%
	Two to three months	241	48.98%
	More than three months	235	47.76%
Equipment Type	Cellphone	380	77.24%
	Tablet	166	33.74%
	Laptop	117	23.78%
	Notebook	104	21.14%
	TV	20	4.07%
Forms of E-learning	Live class	449	91.26%
	Recorded lesson	191	38.82%
	Video	136	27.64%
E-learning System Used	Dingding	305	61.99%
	Tencent Class	123	25.00%
	Chaoxingxuexitong	77	15.65%
	Ketangpai	9	1.83%
	Tencent meeting	90	18.29%
	QQ	100	20.33%
	Kongzhongketang	82	16.67%

Note: JMS = junior middle school; SMS = senior middle school.

3.3. Data analysis

3.3.1. Common method bias

We examined common method bias (CMB) since our data were self-reported. Following the recommendations of Podsakoff et al. (2003), we separated the measurement items of the dependent and independent variables in the questionnaire. Statistically, we first applied Harmon's single-factor analysis. The first factor explained 20.8% of the total variance, which was below 50%. Therefore, no single factor explained most of the variance. We then used the marker variable technique to test CMB. The second smallest value (0.011) was selected from the correlation matrix as the conservative estimate of CMB, and an adjusted correlation matrix was produced (Lindell & Whitney, 2001). In Table A1 in the Appendix, we see that the significance of the correlations remained the same and that the differences between the adjusted and original correlations were no more than 0.07, further indicating that CMB was not a serious issue in our study.

3.3.2. Measurement model testing

To test the convergent and discriminant validity of each construct, we applied principal component analysis. The Kaiser-Meyer-Olkin (KMO) statistic was 0.930, and the P-value of Bartlett's test of sphericity was less than 0.05, indicating that the data were suitable for factor analysis (Kaiser, 1974). We extracted seven factors in total, which explained 80.9% of the total variance. Table 4 shows the rotated factor loadings of each factor. The factor loadings of each construct with its items were all above 0.5. Meanwhile, the factor loadings of each construct with other items were all below 0.5, indicating good convergent and discriminant validity (Chin, 1998).

We then evaluated the construct reliability, convergent validity, and discriminant validity by examining Cronbach's alpha, composite reliability (CR), and the average variance extracted (AVE). In Table 6, we see that the CR and Cronbach alpha values of each construct were all greater than 0.7, indicating good construct reliability (Nunnally, 1978). At the same time, the AVEs of each construct were greater than 0.5, and the loadings of each construct with its corresponding items were all

Table 4
Principal component factor analysis with varimax rotation.

	Intrinsic Motivation	Teacher Support	Parental Support	E-learning Self-efficacy	Online Course Evaluation	Behavioral Engagement
IM1	0.821	0.145	0.286	0.189	0.151	0.161
IM2	0.823	0.16	0.212	0.217	0.252	0.165
IM3	0.804	0.143	0.169	0.152	0.244	0.237
PS1	0.236	0.119	0.829	0.181	0.098	0.163
PS2	0.25	0.124	0.785	0.182	0.133	0.152
PS3	0.112	0.224	0.788	0.115	0.170	0.19
BE1	0.170	0.214	0.226	0.331	0.165	0.725
BE2	0.260	0.208	0.233	0.22	0.221	0.751
BE3	0.197	0.290	0.171	0.225	0.163	0.738
TS1	0.119	0.799	0.182	0.182	0.179	0.21
TS2	0.104	0.810	0.173	0.182	0.222	0.184
TS3	0.190	0.788	0.126	0.137	0.221	0.19
ESE1	0.139	0.164	0.235	0.818	0.189	0.241
ESE2	0.202	0.262	0.133	0.775	0.236	0.258
ESE3	0.319	0.176	0.213	0.688	0.231	0.255
OCE1	0.237	0.326	0.083	0.201	0.747	0.137
OCE2	0.221	0.238	0.136	0.184	0.798	0.183
OCE3	0.232	0.171	0.296	0.257	0.696	0.215

We then conducted a confirmatory factor analysis with AMOS 24. The overall indices were all acceptable, as depicted in Table 5 (Bentler & Bonett, 1980).

greater than 0.7, thereby indicating good convergent validity (Fornell & Larcker, 1981). Further, the square root AVEs of each construct were all greater than its correlation coefficients with other constructs, indicating good discriminant validity, as shown in Table 7 (Fornell & Larcker, 1981).

3.3.3. Hypotheses testing

After ensuring that all the constructs had good reliability and validity, we started testing the hypotheses. First, we applied ANOVA in SPSS to test the hypotheses on the differences in behavioral engagement, habitus, and forms of capital between rural and urban students (i.e., H1, H3, H5, H7a, and H7b). Then, we adopted the structural equation model (SEM) in AMOS 24 to test that how habitus and forms of capital impact students' e-learning outcomes (i.e., H2, H4, H6a, and H6b).

3.3.3.1. ANOVA testing. An ANOVA was used to test the hypotheses on the differences in behavioral engagement, habitus, and forms of capital between rural and urban students. Following Hsieh et al. (2011), we computed the means of all the items for each construct to determine the scores for the composite variables. We then specified the means of intrinsic motivation, e-learning self-efficacy, parental support, teacher support, and behavioral engagement as the dependent variables and the geographic location of students (i.e., rural vs. urban) as the independent variable.

The results of the ANOVA are shown in Table 8 and Fig. 2. There were significant differences regarding behavioral engagement, intrinsic motivation, e-learning self-efficacy, and parental support between rural and urban students, thus supporting H1, H3, H5, H7b, respectively. However, there were no significant differences in teacher support between rural and urban students. Thus, H7a is not supported.

3.3.3.2. Structural model testing. The structural model was tested with the maximum likelihood technique, which was used with AMOS 24. As shown in Table 9, all the fit indices of the structural model met the recommended values of each index, indicating an acceptable model fit.

The results of ANOVA and SEM are summarized in Fig. 3. The overall model had good predictive power since the explained variance of behavioral engagement was 71%. As for the significance of the hypothesized relationships, intrinsic motivation regarding habitus had a significantly positive effect on behavioral engagement ($b = 0.132$, $p <$

0.05), thus supporting H2. E-learning self-efficacy relating to cultural capital exerted a significant positive influence on behavioral engagement ($b = 0.429$, $p < 0.001$). In terms of social capital, parental support had a significant positive effect on behavioral engagement ($b = 0.235$, $p < 0.001$). Teacher support also had a significant positive effect on behavioral engagement ($b = 0.147$, $p < 0.01$). Furthermore, none of the control variables had a significant influence on behavioral engagement.

Taken together, the ANOVA results confirmed the digital outcome divide between rural and urban students during e-learning as well as the different levels of forms of capital. Besides, the SEM results confirmed the influence of forms of capital on students' outcomes in e-learning (i.e., behavioral engagement). The results of hypotheses testing are summarized in Fig. 3.

3.3.4. Decomposition of the digital outcome divide

Once the existence of the digital outcome divide and the influences of the capitals on students' outcomes in e-learning are confirmed, it becomes compelling to investigate the relative importance of those drivers for alleviating the digital outcome divide. Therefore, we applied the Blinder-Oaxaca decomposition method to unravel the extent to which habitus and the forms of capital lead to the difference between rural and urban students (Hsieh et al., 2011). This method is appropriate to study outcome differences of groups (e.g., race or geographic location), thus it has been widely employed by studies on gaps or divides in various research fields, such as wage gaps by sex or race (Blinder, 1973; Oaxaca, 1973), generational divide (Etezady et al., 2021) as well as digital divide (Liao et al., 2016). For instance, Liao et al. (2016) adopted this method and revealed that the factors observed (students' characteristics, autonomy of use, family backgrounds, and resource inputs) account for 35% of the rural-urban digital capability divide of schoolchildren (i.e., digital self-efficacy). Basically, by decomposing mean differences in log outcomes based on linear regression models, the Blinder-Oaxaca decomposition method explains the gap or divide (e.g., digital outcome divide) between two cohorts by distinguishing from: (1) effects due to the cohorts having different endowments (characteristics effect); (2) effects due to those endowments have different influences on the dependent variable (association effect) (Jann, 2008).

According to the method, the ordinary least squares (OLS) equation of the determinants for rural and urban students is expressed separately as:

Table 5
Fit indices of the measurement model.

Fit Indices	CMIN/DF	RMSEA	NFI	TLI	CFI	IFI
Recommended Value	<3	<0.08	>0.90	>0.90	>0.90	>0.90
Model Value	2.607	0.057	0.952	0.961	0.970	0.970

Table 6
Reliability and validity.

Construct	Items	Loadings	AVE	CR	Cronbach's Alpha
Intrinsic Motivation	IM1	0.883	0.788	0.916	0.916
	IM2	0.929			
	IM3	0.849			
E-learning Self-efficacy	ESE1	0.855	0.730	0.890	0.889
	ESE2	0.88			
	ESE3	0.828			
Teacher Support	TS1	0.838	0.694	0.720	0.871
	TS2	0.849			
	TS3	0.812			
Parental Support	PS1	0.861	0.674	0.861	0.859
	PS2	0.822			
	PS3	0.777			
Online Course Evaluation	OCE1	0.808	0.670	0.859	0.857
	OCE2	0.836			
	OCE3	0.812			
Behavioral Engagement	BE1	0.83	0.688	0.869	0.867
	BE2	0.862			
	BE3	0.795			

$$Y_{r,i} = X'_{r,i} \beta_r + \varepsilon_{r,i} \tag{1}$$

$$Y_{u,j} = X'_{u,j} \beta_u + \varepsilon_{u,j} \tag{2}$$

where $Y_{r,i}$ and $Y_{u,j}$ are the level of behavioral engagement (the mean score of the items for behavioral engagement) for rural student i and urban student j , respectively; X is a vector of the independent and control variables shown in the Hypothesis model; β_r and β_u are the estimated coefficients for rural and urban students, respectively; and $\varepsilon_{r,i}$ and $\varepsilon_{u,j}$ are the random errors. Thus, the difference in behavioral engagement between rural and urban students is expressed as:

$$\bar{Y}_r - \bar{Y}_u = \underbrace{[\hat{\beta}_r(\bar{X}_r - \bar{X}_u)]}_{\text{characteristics effect}} + \underbrace{[\bar{X}_u(\hat{\beta}_r - \hat{\beta}_u)]}_{\text{association effect}} \tag{3}$$

As shown in Equation (3), $\bar{Y}_r - \bar{Y}_u$ represents the observed difference in the average levels of behavioral engagement between rural and urban students. $\hat{\beta}_r$ and $\hat{\beta}_u$ are the vectors of the estimated coefficients from Equations (1) and (2). \bar{X}_r and \bar{X}_u are the vectors of the average values of the characteristics observed for rural and urban students, respectively. The difference in the rural and urban students' behavioral engagement can be decomposed into two components: the characteristic and association effects. The first term in the right side of Equation (3), $\hat{\beta}_r(\bar{X}_r - \bar{X}_u)$ represents the characteristic effect resulting from the group differences in the average values of the observed characteristics. Specifically, the characteristic effect arises because the rural and urban students have

Table 7
Discriminant validity.

	Intrinsic Motivation	Parental Support	Teacher Support	E-learning Self-Efficacy	Online Course Evaluation	Behavioral Engagement
IM	0.888	0.554	0.459	0.582	0.609	0.582
PS		0.821	0.462	0.533	0.495	0.557
TS			0.833	0.547	0.610	0.600
ESE				0.854	0.630	0.691
OCE					0.819	0.596
BE						0.829

different average qualifications (e.g., intrinsic motivation, e-learning self-efficacy, and parental support) when both groups receive the same treatment. The second term, $\bar{X}_u(\hat{\beta}_r - \hat{\beta}_u)$ signifies the association effect capturing the part of the disparity in behavioral engagement owing to the differences in the estimated coefficients in Equations (1) and (2). The association effect captures all the potential effects of the differences in the unobserved characteristics.

We conducted the twofold Blinder-Oaxaca decomposition in Stata 15 (Jann, 2008). The twofold decomposition method focuses on the characteristic effect and association effect while neglecting the simultaneous effect of differences in endowments and coefficients (Jann, 2008). The result is presented in Table 10. As shown, rural students scored lower than urban students on behavioral engagement by 0.393 points. Furthermore, as mentioned earlier, the behavioral engagement gap can be divided into two parts: the characteristic and association effects. On one hand, the characteristic effects represent the different levels of observed factors, including intrinsic motivation, e-learning self-efficacy, parental support, teacher support, and other control variables, accounted for 72.9% ($-0.287/(-0.393) = 72.9\%$) of the rural-urban digital outcome divide. In other words, this 72.9% of the digital outcome divide could be reduced if rural students had the same intrinsic motivation, e-learning self-efficacy, parental support, teacher support, and other student and family characteristics as their urban peers (Jann, 2008; Liao et al., 2016). On the other hand, the association effect, which was due to the differences in the unobserved parts between rural and urban students, accounted for 27.1% of the rural-urban digital outcome divide in e-learning.

To obtain the relative importance of the influencing factors, we analyzed the detailed characteristic effect and represented the decomposition results for each of the observed factors in Table 11. The last column of Table 11 shows the contribution of each factor regarding the explained part of the behavioral engagement difference between the rural and urban students (Jann, 2008), which represents the relative importance of each factor in explaining the difference in behavioral engagement between the rural and urban students. Specifically, e-learning self-efficacy, intrinsic motivation, and parental support were the most dominant factors contributing to the rural-urban digital outcome divide in the e-learning context. They explained 33.4%, 16.8%, and 19.5% of the digital outcome divide, respectively.

Table 8
ANOVA results for group differences in capital.

	Means	F-value	Sig.	Hypothesis Support
Behavioral engagement	5.604	5.977	14.449	0.000*** H1 Supported
Intrinsic motivation	5.187	5.564	10.146	0.002** H3 Supported
E-learning self-efficacy	5.313	5.597	6.525	0.011* H5 Supported
Teacher support	5.897	6.057	3.472	0.063 H7a Not Supported
Parental support	4.993	5.505	16.081	0.000*** H7b Supported

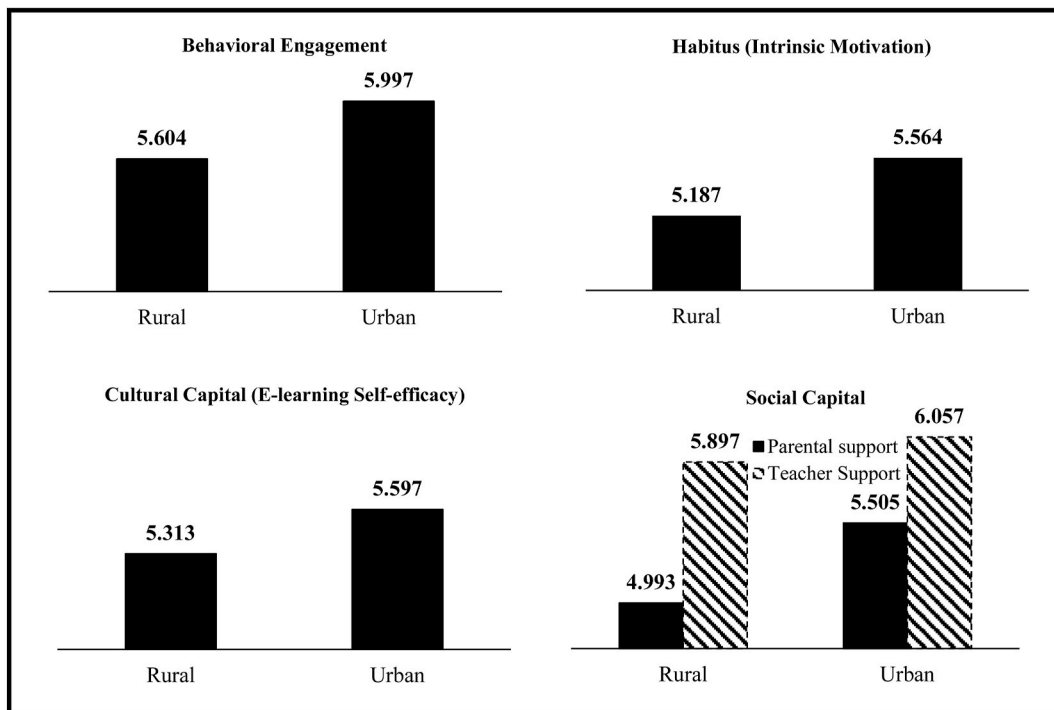


Fig. 2. Detailed comparison of means for rural and urban students.

Table 9
Fit indices of the structural model.

Fit Indices	CMIN/DF	RMSEA	NFI	TLI	CFI	IFI
Recommended Value	<3	<0.08	>0.90	>0.90	>0.90	>0.90
Model Value	2.078	0.047	0.948	0.962	0.972	0.972

4. Discussion

4.1. Summary of findings

This research yields several significant findings. First, empirical

evidence of this study indicated that rural students were less likely to benefit from learning through the Internet than their urban peers (supporting H1). This finding confirms the concern regarding the digital outcome divide implied by recent studies (Beaunoyer et al., 2020; Dwivedi et al., 2020). Second, this study revealed the underlying contextual factors of e-learning outcomes (i.e., behavioral engagement). Specifically, we found that habitus (i.e., intrinsic motivation), cultural (i.e., e-learning self-efficacy), and social capital (i.e., teacher support and parental support) positively influenced students’ behavioral engagement in e-learning (supporting H2, H4, H6a, and H6b). This finding confirmed that social environmental factors are important determinants for e-learning outcomes in current context (Singh et al., 2021). Third, perhaps most importantly, we found that these different levels of habitus and forms of capital contribute to the digital outcome

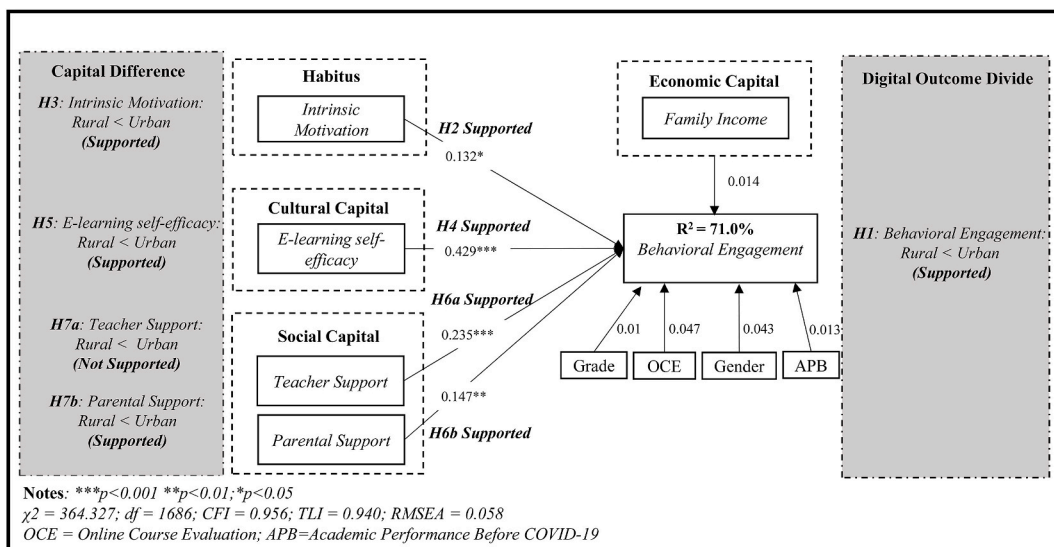


Fig. 3. Summary of results.

Table 10
Blinder-oaxaca decomposition results.

	Coefficient	Bootstrap Std. Err.	P> z	Contribution
Rural	5.604***	0.084	0.000	
Urban	5.997***	0.067	0.000	
Differences	-0.393***	0.111	0.000	100.0%
Characteristics Effect	-0.287**	0.091	0.002	72.9%
Association Effect	-0.106	0.066	0.109	27.1%

Note: ***, **, * indicate the significance at the 0.1%, 1%, and 5% levels, respectively.

Bootstrapped standard errors with 500 replications are reported.

divide between rural and urban students. Specifically, rural students had lower levels of intrinsic motivation, e-learning self-efficacy, and parental support regarding e-learning classes compared with their urban peers (supporting H3, H5, H7b), which lead to the inequality of behavioral engagement in e-learning. This finding is consistent with the finding of [Bacher-Hicks et al. \(2021\)](#), which indicated that inequality in parental support existed between students from different geographic locations (i.e., rural or urban). However, no significant difference was found in terms of the level of teacher support between rural and urban students (H7a not supported). This is a counterintuitive finding since most previous studies suggested that teachers in urban areas are more capable of teaching online and can provide more support for their students (e.g., [Azubuikwe et al., 2020](#); [Guo et al., 2020](#)). One possible explanation could be that teachers in rural schools have tried to provide additional support for rural students in response to government initiatives to eliminate the digital divide ([MOEC, 2020a](#)). Thus, the inequality in teacher support between rural and urban students might have been alleviated through the extra effort.

4.2. Theoretical implications

This study has several theoretical implications. First, this paper contributes to the digital divide literature by providing evidence of the digital outcome divide between Chinese rural and urban students. Previous studies primarily focused on the first and second level of the digital divide (e.g., [Cruz-Jesus et al., 2016](#); [Hohlfeld et al., 2017](#); [Liao et al., 2016](#)), with less emphasis on the digital outcome divide ([Scheerder et al., 2017](#)). The results of this study confirmed the third level of the digital divide between rural and urban students, that is, that rural students have a lower behavioral engagement level in e-learning and are less likely to benefit from learning through the Internet than their urban peers. Besides, this study manifested the digital outcome divide in current context as different engagement levels in e-learning between different social groups (e.g., rural and urban students), which might be helpful for future empirical studies to measure the digital outcome divide.

Second, this study contributes to the digital divide literature by revealing the determinants of the digital outcome divide in current context. As mentioned, there is a dearth of research on the determinants of the digital outcome divide ([Scheerder et al., 2017](#)), and only a small number of studies have investigated demographic or socio-economic determinants, such as gender ([Wei et al., 2011](#)) and region ([Song et al., 2020](#)). The current study complements these studies by using the capital perspective to emphasize individuals' habitus and forms of capital within the social context of ICT use. Specifically, we found that besides habitus (i.e., intrinsic motivation) and cultural capital (i.e., e-learning self-efficacy), the social support (i.e., teacher support and parental support) that students can obtain is also important for their digital outcome. Furthermore, consistent with previous findings that different levels of the digital divide require different responses ([Cruz-Jesus et al., 2016](#); [Epstein et al., 2011](#)), the results of our study demonstrate that, unlike the first or second levels of the digital divide, which may be bridged by subsidizing ICTs or skills and awareness training in relation to ICTs ([Cruz-Jesus et al., 2016](#); [Epstein et al., 2011](#)),

Table 11
Detailed decomposition results of the characteristics effect.

Variable	Coefficient	Bootstrap Std. Err.	P> z	Contribution
IM	-0.048*	0.024	0.046	16.8%
ESE	-0.096*	0.046	0.039	33.4%
PS	-0.056*	0.027	0.037	19.5%
TS	-0.043	0.028	0.131	14.8%
Grade	-0.005	0.009	0.551	1.8%
Gender	-0.007	0.008	0.363	2.5%
APB	-0.002	0.010	0.862	0.6%
Family Income	-0.013	0.025	0.612	3.3%
OCE	-0.017	0.019	0.353	6.1%

Note: IM = intrinsic motivation; ESE = e-learning self-efficacy; PS = parental support; TS = teacher support; OCE = online course evaluation; APB = academic performance before COVID-19.

***, **, * indicate significance at the 0.1%, 1%, and 5% levels, respectively.

Bootstrapped standard errors with 500 replications are reported.

the third level of the digital divide is determined by individuals' social context where other people, such as the teacher and family members, can be especially influential in individual outcomes. Furthermore, it is worth mentioning that the influence of economic capital, represented as family income, on students' e-learning engagement was found to be insignificant, which implies that socio-economic factors such as family income become less important to the digital outcome divide when we factor in habitus, cultural capital, and social capital as determinants.

Third, this study contributes to the related literature on COVID-19 and the post-COVID-19 landscape by focusing on large-scale e-learning practices in China. The COVID-19 pandemic has brought ICTs to the forefront of human life through accelerated digitalization and provides extraordinary opportunities for IS studies in the post-COVID-19 world ([Barnes, 2020](#)). Related research has found a great deal of evidence of the digital divide in e-learning during the COVID-19 pandemic (e.g., [Andrew et al., 2020](#); [Azubuikwe et al., 2020](#)); however, the underlying reasons and how ICTs can more effectively be used to foster equality and improve well-being are still unclear ([Barnes, 2020](#)). Therefore, the findings of this study provide further evidence of the digital outcome divide in the context of COVID-19 through its investigation of Chinese middle school students. Moreover, we contribute to related research by providing empirical evidence that home-based learning environments such as parental and teacher support are also important for students in e-learning, in addition to their intrinsic motivation and self-efficacy ([Singh et al., 2021](#)).

4.3. Practical implications

This study has several practical implications, which are summarized in the following [Table 12](#). According to the empirical findings, this study mainly proposed suggestions for the practitioners from four aspects, including awareness of the digital outcome divide, providing more resources and designing better mechanisms to encourage the engagement of teachers and parents, creating and maintaining a supportive e-learning atmosphere, and enhancing students' intrinsic motivation and self-efficacy toward e-learning. We also proposed specific mechanisms for key stakeholders (e.g., policy makers, educators, parents, and e-learning system developers) from these four aspects.

5. Conclusions

Our study provides evidence of the digital outcome divide and the underlying differences in e-learning between rural and urban students during the COVID-19 pandemic. The results indicate that, compared with urban students, Chinese rural students were at a disadvantage in terms of learning through ICTs at home. In addition, our findings explained the underlying reasons from the perspective of capital theory and found several directions to promote education equality in the future.

Table 12
Practical suggestions of current study.

Main Suggestions	Recommended Specific Mechanisms
Increase the awareness of digital outcome divide resulted from e-learning during COVID 19	<p><u>For policy makers and school leaders</u></p> <ul style="list-style-type: none"> ➤ Acknowledge the problem of digital outcome divide between rural and urban students, and intervention plans should be prepared as the e-learning might be a normal state after-COVID 19 ➤ Discard the idea that the digital divide is simply an access problem (i.e., digital access) and instead focus on the students' inequality in the outcomes of exploiting and benefiting from e-learning ➤ Focus on the individual-level contextual environment of disadvantaged students (e.g., rural students) they embedded in except the socio-economic factors, to mitigate such divide <p><u>For teachers and parents</u></p> <ul style="list-style-type: none"> ➤ To increase the awareness of their importance and responsibility to assist their children learning at home ➤ Accessibility of e-learning resources would not be sufficient to ensure the effectiveness of e-learning, and parents from rural areas should care more about the e-learning effectiveness of their children
Provide more resources and design better mechanisms to encourage the engagement of teachers and parents	<ul style="list-style-type: none"> ➤ It is important to inform teachers and parents their important role during the e-learning process ➤ Provide teachers in rural areas with more resources and training to provide additional support for their students, such as better Internet access and devices, training and support for effective e-learning platform use ➤ Such training could be implemented through the cooperation with teachers from urban areas ➤ Praise or rewards could be provided for those teachers that provide additional support (e.g., in-class mentoring and after-class supervision) for their students (particularly for rural students) ➤ Provide channels for the parents to provide valuable feedback on the e-learning effectiveness of their children to teachers and ask for help from teachers and schools
Create and maintain a supportive e-learning atmosphere to keep students engaged in	<p><u>For teachers</u></p> <ul style="list-style-type: none"> ➤ Interact frequently with their students during and after the e-class, such as asking questions during the e-learning class, or solving problems after the class ➤ Collaborate with the parents if possible <p><u>For parents</u></p> <ul style="list-style-type: none"> ➤ For those parents who are able to tutor their children, helping their children deal with e-learning obstacles is encouraged ➤ For those parents who are incapable of tutoring their children, it is suggested to provide a quiet and private space for their children to conduct e-learning ➤ And if necessary, parents can provide valuable feedback on the e-learning effectiveness of their children to teachers and ask for help from teachers and schools
Enhance students' intrinsic motivation and self-efficacy toward e-learning, especially for rural students	<p><u>Better E-learning system design</u></p> <ul style="list-style-type: none"> ➤ Provide functions to collect and analyze the performance data of students (e.g., learning time) and add gamification features (e.g., performance rank, "check-in for prize") to encourage participation ➤ Provide functions that enable the students to give feedback and ask questions easily from teachers ➤ Develop forums that enable teachers or students to share their suggestions and experiences about e-learning, which might be especially helpful for those disadvantaged students

First, students' intrinsic motivation toward e-learning contributes to their behavioral engagement, which emphasizes building and enhancing a positive orientation toward learning through the Internet. Furthermore, cultural capital in terms of students' e-learning self-efficacy matters. This was instantiated through the urban students' stronger belief in their ability to use computers for online learning compared to their rural counterparts. Finally, social support, including teacher and parental support, were found to positively influence e-learning outcomes. This research significantly improves our theoretical understanding of the digital outcome divide during a period of large-scale online education, which can assist educators and parents in mitigating the divide.

6. Limitations and directions for future studies

Some limitations exist for current study. First, findings of this research might be only applicable for areas where digital construction is well developed, such as Netherlands and China. Notably, for other countries or areas where Internet is less universal, focusing on the first and second-level digital divide might be more practical and urgent. Second, this research is based on the self-reported responses of students. Though we have excluded the influence of common method bias, further studies are recommended to collect the natural data from the school (e.g., examination grades). Third, the main target of this study emphasizes the digital divide during the COVID-19 pandemic, however, the

influence of digital divide might keep after the COVID-19. Thus, it is recommended that future studies could compare the digital divide between COVID-19 and post COVID-19 era. Finally, we applied the twofold Blinder-Oaxaca decomposition, which did not consider the interaction of the characteristics effect and the association effect due to our research target. Future studies are suggested to use the threefold decomposition and investigate the interaction effects.

Credit author statement

Ling Zhao: Conceptualization, Methodology, Writing - review & editing, Supervision; Cuicui Cao: Conceptualization, Software, Formal analysis, Writing - original draft; Yuni Li: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing; Yuan Li: Investigation – data collection, Writing - review & editing.

Acknowledgement

This paper is supported by grants from the National Natural Science Foundation of China (71771097, 71810107003), a grant from the Humanities and Social Sciences Foundation of the Ministry of Education (17YJA630140), a grant from the National Social Science Fund of China (18ZDA109).

Appendix

Table A.1

Marker Variable Technique

	IM	PI	BE	TS	ESE	OCE	GB	Gender	Grade
IM		0.554**	0.582**	0.459**	0.582**	0.609**	-0.182**	-0.071	0.011
PI	0.549**		0.557**	0.462**	0.533**	0.495**	-0.115*	0.007	0.143**
BE	0.578**	0.552**		0.600**	0.691**	0.596**	-0.204**	0.024	0.094*
TS	0.453**	0.456**	0.596**		0.547**	0.610**	-0.163**	0.067	0.083
ESE	0.578**	0.528**	0.688**	0.542**		0.630**	-0.282**	-0.051	0.075
OCE	0.605**	0.49**	0.592**	0.606**	0.626**		-0.280**	-0.067	0.013
GB	-0.195**	-0.127**	-0.217**	-0.175**	-0.296**	-0.294**		-0.014	0.117**
Gender	-0.082	-0.01	0.014	0.057	-0.062	-0.079	-0.025		0.139**
Grade	0	0.134**	0.084	0.073	0.065	0.003	0.108*	0.13**	

Note: OCE = online course evaluation; APB = academic performance before COVID-19.

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