



New inequality in equality: An empirical study on the effects of device and physical environment appropriateness divide on E-learning outcomes

Cuicui Cao^a, Yuni Li^a, Ling Zhao^{b,*}, Yuan Li^c

^a School of Information Management, Institute of Big Data and Digital Economy, Hubei University of Economics, #8 Yangqiaohu Road, Wuhan, China

^b School of Management, Huazhong University of Science and Technology, #1037 Luoyu Road, Wuhan, China

^c Optics Valley Institute of Education Development, #777 Gaoxin Road, Wuhan, China

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ABSTRACT

The high penetration rate of smartphones in recent years has alleviated the concern regarding Internet access in China and facilitates e-learning, especially in rural areas. In such e-learning practice, device appropriateness becomes a new source of the digital access divide. Also, effective access to e-learning depends on the physical environment, which may further weaken or strengthen the influence of device appropriateness divide. However, previous studies have mainly focused on the access dichotomy or quality divide and investigated its downstream influences without considering the physical environment. Thus, this study aims to investigate: (1) does the device and physical environment appropriateness divide exist between rural and urban students? (2) how do these two types of appropriateness divide interact to influence students' e-learning outcomes? To empirically examine these research questions, we applied the chi-square test, the independent sample *t*-test, structural equation modeling, and Process Macro. Our results reveal some significant and interesting findings. First, we confirmed the existence of device appropriateness divide, whereas partially confirmed the existence of physical environment appropriateness divide between rural and urban students. Second, we validated the significant interactive effect of these two types of appropriateness divide on e-learning outcomes. Our study offers several valuable theoretical and practical implications.

1. Introduction

E-learning, which is a form of learning based on information and communication technologies (ICTs), refers to “learning experiences in synchronous or asynchronous environments using different devices (e. g., smartphones, laptops, etc.) with Internet access” (Dhawan, 2020). It is easily accessible and promotes greater access to quality education, providing all students with equal learning opportunities (Guo and Wan, 2022; Welser et al., 2019). Nowadays, e-learning has become an important supplement to offline education for K–12 students in China. The construction of more educational platforms such as Smart Education of China led by the government (Ministry of Education of the People's Republic of China, 2022), also shows that e-learning will continue to coexist with offline education. To ensure that students from advantaged and disadvantaged areas can benefit equally from e-learning, filling the first-level digital divide (i.e., digital access divide), which refers to inequality in ICT access, is essential (Azubuike et al., 2020). In China, due to the high penetration rate of smartphones in recent years, Internet

access is near-universal and facilitates e-learning, especially in rural areas (CNNIC, 2023). For instance, by June 2023, the proportion of people who use smartphones to access the Internet reached 99.8 %. This raises the question of whether ICT access is still a source of digital access divide in the e-learning practice.

The answer would be optimistic if we follow the major view of prior studies, in which the digital access divide is viewed as differences in access dichotomy (i.e., presence or absence) or access quality (e.g., Azubuike et al., 2020; Guo and Wan, 2022; van de Werfhorst et al., 2022; Wei et al., 2011). Due to the ubiquity and completeness of the ICT infrastructure, the nature and scope of the digital access divide have shifted to a more nuanced perspective (Van Deursen and Van Dijk, 2019). This shift can be evidenced by the fact that some scholars have raised concerns regarding whether the device to access e-learning is appropriate (Hoskins and Wainwright, 2023; Law et al., 2022; Lythreath et al., 2021). Under these circumstances, if we continue viewing the digital access divide from the perspectives of dichotomy or quality, we will be unable to identify the disadvantaged groups. Thus, the present

* Corresponding author.

E-mail addresses: caocuicui@hbue.edu.cn (C. Cao), evelynliyuni@hust.edu.cn (Y. Li), lingzhao@mail.hust.edu.cn (L. Zhao).

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study proposes the concept of *device appropriateness divide*, defined as the inequality in the extent to which the available devices are appropriate for the specific task execution. This concept captures a new form of digital access divide resulting from the use of various types of devices. However, it does not directly indicate that regular devices (e.g., computers) are always superior to smartphones, but rather that when the device used is not suitable for the task, the device appropriateness divide exists.

Why does device appropriateness emerge as a new source of digital access divide in such e-learning practice? First, smartphones are more suitable for fragmented and flexible learning than computers due to their smaller screen sizes, greater scrolling requirements, and awkward text entry (Gan, 2019; Tossell et al., 2015). Second, smartphones tend to have various applications for other purposes, which can create distractions (Hoskins and Wainwright, 2023; Maniar et al., 2008; Molnar, 2017; Pal and Patra, 2021). However, the e-learning tasks of K–12 students require continuous and deep concentration on systematic rather than fragmented content (Dong et al., 2020; Yan et al., 2021). Thus, smartphones may be less inappropriate for their e-learning. This new form of divide may intensify the existing second and third-level digital divide, which concerns inequality in digital capability and outcome (Betthäuser et al., 2023), especially when surveys indicate that 73 % of students use smartphones and only 20 % use computers/tablets to access e-learning (Xinhuanet, 2020). Furthermore, this device appropriateness divide becomes more noticeable between rural and urban students (DRCSC, 2020). Although a few studies have revealed this divide (e.g., Frei-Landau and Avidov-Ungar, 2022; Law et al., 2022; Yan et al., 2021), they have not specified the type of digital divide to which it belonged, and most were qualitative and exploratory. Thus, empirical research is needed to examine who is on the (dis)advantaged side of the device appropriateness divide and its consequences.

While previous studies have explored the consequences of the digital access divide, they have overlooked the fact that its influence may be contingent on the physical environment (Drabowicz, 2017; Guo and Wan, 2022; Liao et al., 2016; Pal and Patra, 2021; Wei et al., 2011; Zhao et al., 2010). Such an understanding has its roots in the early binary conceptualization of physical and virtual spaces (Castells, 1996). However, students do not take e-learning in a vacuum; they are embedded in their physical environment (Singh et al., 2021). In the current context, when K–12 students use their own devices (e.g., computers or smartphones) to access e-learning in an inappropriate physical environment (e.g., noise, lack of support), they risk being consigned to spectating and not participating and may engage in activities unrelated to learning (e.g., games) due to their poor self-discipline (Singh et al., 2021). In this case, the e-learning outcomes of different devices may depend on the physical environment. Thus, we propose the concept of *physical environment appropriateness divide*, which refers to the inequality in the extent to which the physical environment resources are appropriate for the specific task execution. Some scholars have also raised concerns regarding the physical environment appropriateness divide, whose interlink with the device appropriateness divide may worsen the existing learning outcome inequality (e.g., Law et al., 2022; Singh et al., 2021). Consequently, the question arises concerning how the interaction of these two types of appropriateness divide influences e-learning outcomes.

To fill the above-mentioned theoretical gaps, our study intends to explore the following research questions: (1) *Does the device appropriateness divide and physical environment appropriateness divide exist among students from rural and urban areas?* (2) *How do these two types of appropriateness divide interact to influence e-learning outcomes?*

In addressing these research questions, the remainder of this paper is organized as follows. In Section 2, we cover prior research on the digital access divide, expand on the device appropriateness divide, address the physical environment appropriateness divide with relevant citations, and connect both divides to e-learning self-efficacy and behavioral engagement. In Section 3, we propose the research model and elaborate

on each hypothesis. In Section 4, we describe the variables, datasets utilized in the current study, and the data analysis results. In Section 5, we discuss the research findings, theoretical and practical implications, and limitations and future research directions. Section 6 presents the conclusions of this paper.

2. Literature review

2.1. Previous studies on the digital access divide

2.1.1. Forms of digital access divide

The digital access divide refers to unequal access to ICTs (Bruno et al., 2023; DiMaggio and Hargittai, 2001; Van Dijk, 2005; Wei et al., 2011). Prior studies have tended to investigate the digital access divide from two perspectives: the access dichotomy and the access quality. The access dichotomy divide concerns differences regarding the presence or absence of ICT access (Guo and Wan, 2022; Van Deursen and Van Dijk, 2019). The access quality divide pertains to disparities in the quality of ICT access (e.g., network speed; Guo and Wan, 2022), which is closely related with the characteristics of the ICT resources themselves.

However, the rapid expansion of mobile Internet and rapidly evolving technology have highlighted a third type of digital access divide in recent years: the type of devices to maintain Internet connectivity. For instance, van Deursen and van Dijk (2019) argued that the digital access divide should encompass differences in material access, with a particular emphasis on device type (e.g., desktops, smartphones). Many scholars have underscored the advantages of PCs over mobile phones for engaging in more complex and resource-intensive online activities due to the functional limitations of mobile phones (Brown et al., 2011; Correa et al., 2020; Mossberger et al., 2012; Pearce and Rice, 2013). For example, Pearce and Rice (2013) demonstrated that PC users were more likely to engage in capital-enhancing online activities than mobile phone users. Nevertheless, with the advancement of smartphone functionality, researchers have acknowledged that the effectiveness of a device is largely contingent on the specific tasks it is used for (Rice et al., 2023; Tsetsi and Rains, 2017; Wang and Liu, 2018). For instance, Rice et al. (2023) examined the digital divide in Armenia from 2011 to 2019 and found that both PCs and mobile phones serve as valuable tools, though their utility varies based on timing, context, and the nature of activities.

To emphasize the appropriateness between the device and the task, we argue that the type of device serves as a tangible manifestation of an abstract form of the digital access divide, which we term the “device appropriateness divide”. This concept builds on the user–system–task framework for information system (IS) effective use research (Burton-jones et al., 2013). We define this divide as the inequality in the extent to which the available devices are appropriate for the specific task execution, recognizing that effective use of technology depends not only on the technology itself, but also on its alignment with the tasks to which it is applied (Burton-jones et al., 2013). To distinguish this divide from other forms, we summarize the main focus and manifestations of these three forms of digital access divide in Table 1.

Unlike the access dichotomy or quality divide, which focus on the presence or quality of ICT resources, the device appropriateness divide

Table 1
Forms of digital access divide.

Digital access divide	Focus	Example manifestation
Access dichotomy divide	Presence or absence of ICT resources	Computer ownership, broadband access, smartphone ownership
Access quality divide	Quality of ICT resources	Network speed, network stability
Device appropriateness divide	Appropriateness between the device and the task	Device type

emphasizes the appropriateness between the devices and tasks. This concept is instrumental in evaluating the applicability of different device types across various settings, thereby preventing the over-generalization of a device's impact. For instance, compared with regular devices such as computers, smartphones may convey a perception of better personal economic status but are less suitable for engaging in activities that create economic value (Bartikowski et al., 2018). Therefore, this concept provides a nuanced lens for understanding the contextual effectiveness of different devices in digital engagement.

2.1.2. Prior education-related studies on digital access divide

We summarize prior education-related studies on the digital access divide in Table 2. These studies have mostly focused on access dichotomy and quality divide. Some researchers have investigated the contributing factors to the access dichotomy and quality divide among students from different socioeconomic status (SES) (Azubuike et al., 2020; Cullinan et al., 2021; González-Betancor et al., 2021; Guo and Wan, 2022), as well as the corresponding consequences, such as digital self-efficacy and learning outcomes (Drabowicz, 2017; Guo and Wan, 2022; Lebeničnik and Istenič Starčič, 2020; Liao et al., 2016; Wei et al., 2011; Zhao et al., 2010). They concluded that factors related to access dichotomy and quality divide (e.g., computer ownership, access location, and network quality) positively affected students' digital self-efficacy and learning outcomes (Guo and Wan, 2022; Liao et al., 2016; Wei et al., 2011; Zhao et al., 2010).

In most prior studies, the manifestation of the digital access divide is quite evident, especially when the device used to access the Internet is limited to a single type (e.g., computers) and not available to the entire population. Due to the large variety of devices available to the public, a few researchers in education context also start to focus on the device type, and they have mainly revealed the existence of using different types of devices qualitatively (Table 1). Although some studies have predicted that using mobile devices would compromise e-learning opportunities and experiences (Frei-Landau and Avidov-Ungar, 2022; Law

et al., 2022; Singh et al., 2021; Yan et al., 2021), empirical evidence supporting this claim is lacking. An exception is the study by Pal and Patra (2021), who proposed that students' perception of the usefulness and usage of online video-based learning differed between smartphones and laptops; however, their hypothesis was not supported.

Researchers also pay attention to the social and environmental factors that influence the extent to which a student is digitally excluded. For instance, some researchers emphasized the role of school context (e.g., technology support and teachers' use of technology) in understanding the digital divide (Hohlfeld et al., 2017; van de Werfhorst et al., 2022; Wei et al., 2011). Wei et al. (2011) empirically validated the role of the school IT divide (e.g., training support) on learning outcomes. In the e-learning context, a few qualitative or conceptual studies have raised concerns regarding the appropriateness of students' physical environment, which may exacerbate the existing digital divide (e.g., Hoskins and Wainwright, 2023; Law et al., 2022; Singh et al., 2021). For instance, Singh et al. (2021) emphasized the combination of physical learning environment and material access in shaping e-learning outcomes.

In summary, we identified two main gaps in prior literature. First, previous studies have primarily focused on the access dichotomy and quality divide that exist between students of different socioeconomic backgrounds. While a few studies have examined device type, they are mostly qualitative and exploratory, and further empirical investigation is needed to investigate its existence and how it influences e-learning outcomes. In addressing this question, the current study does not directly predict that computers are always better than smartphones for e-learning, as the existing research suggests. We posit that how device type influences e-learning outcomes depends on whether the device used is appropriate for the specific task execution. Consequently, we regard device type as a manifestation of an overlooked and abstract form of digital access divide in education context, which we have termed as the "device appropriateness divide".

Second, existing studies have mainly investigated the direct

Table 2
Prior studies on the digital access divide.

Authors	Device type	Dichotomy/quality divide	Method	Main findings
Zhao et al., 2010	χ	√	Survey	The digital access divide positively influenced students' Internet self-efficacy and exploratory behavior.
Wei et al., 2011	χ	√	Survey	Computer ownership and school IT divide positively affected students' computer self-efficacy and learning outcomes.
Li and Ranieri, 2013	χ	√	Survey	The dimensions of Internet inequality indicators significantly affected students' Internet self-efficacy.
Liao et al., 2016	χ	√	Survey	Factors related to the digital access divide influenced digital self-efficacy.
Hohlfeld et al., 2017	χ	√	Survey	Florida has improved regarding the digital divide in relation to SES and school type.
Drabowicz, 2017	χ	√	Survey	Access to ICT at home influenced digital usage.
Azubuike et al., 2020	χ	√	Survey	SES influenced students' access to remote learning opportunities.
Lebeničnik and Istenič Starčič, 2020	χ	√	Survey	Access to the Internet and computers influenced students' access to digital content.
González-Betancor et al., 2021	χ	√	Survey	Access to ICT at home was affected by the family's SES.
Cullinan et al., 2021	χ	√	Secondary data	Students' SES influenced students' access to high-quality broadband services.
van de Werfhorst et al., 2022	χ	√	Survey	Schools' ICT infrastructure hardly varied along sociodemographic lines.
Guo and Wan, 2022	χ	√	Survey	The effect of equipment quantity on students' learning outcomes was insignificant and the effect of network quality was significant.
Pal and Patra, 2021	√	χ	Survey (Explanatory)	Device type did not moderate the relationship between usefulness and actual use of video-based learning.
Yan et al., 2021	√	√	Survey (Exploratory)	Access to stable Internet and appropriate devices would prevent students from adapting to online classes.
Singh et al., 2021	√	χ	Conceptual	E-learning outcome inequality will deepen due to the combination of material and learning space inequality.
Law et al., 2022	√	√	Qualitative interview	Limited access to devices compromised learning opportunity and experience.
Frei-Landau and Avidov-Ungar, 2022	√	√	Qualitative interview	The absence of appropriate devices and sufficient network infrastructure created conditions of education inequity.
Hoskins and Wainwright, 2023	√	√	Qualitative interview	The absence of appropriate devices and learning space posed challenges to disadvantaged families in e-learning.

influence of the digital access divide and its related physical environment on learning outcomes. Although some have conceptually mentioned that the influence of digital artifacts on e-learning outcomes may be contingent on the physical environment, empirical studies are lacking. As the Internet becomes a domesticated technology, the boundaries between the physical and digital spaces blur (Scheerder et al., 2019; Singh et al., 2021). This indicates that students do not take e-learning in a vacuum but are embedded in their immediate physical surroundings, which may further weaken or strengthen the influence of device type. Thus, the success of digital access will depend on appropriate physical environment. Correspondingly, empirical research is needed to examine the interaction effect of device and physical environment appropriateness divide (described in Section 2.3) on students' e-learning outcomes.

2.2. A new form of digital access divide: device appropriateness divide

As previously mentioned, the current study focuses on the device appropriateness divide at the rural–urban level and its downstream influences. Specifically, as the functionalities provided by different devices exhibit heterogeneity, we propose device type as an indicator of this divide, which has been widely used in prior studies (e.g., Bartkowski et al., 2018; Correa et al., 2020; Dodel, 2024). For instance, device types in terms of computers and mobile phones are used to identify users who are more likely to benefit from e-government interaction because computers are better suited for most of the tasks citizens are required to conduct online (Dodel, 2024). This type of divide considers the characteristics of both the task and the device, as well as their appropriateness, rather than emphasizing the superiority of certain device across all task types.

Similarly, regarding the device appropriateness divide in the context of e-learning for K-12 students, we consider the various types of devices utilized by students and specifically compare smartphones to computers/tablets. We believe that smartphones are less appropriate than computers/tablets for e-learning tasks for two reasons. First, the characteristics of the device may limit the execution of learning tasks. For example, the screens of smartphones are usually much smaller than those of computers/tablets. To accommodate smaller screens, online learning software on smartphones often limits the display of features on the same interface, or removes some features, which means that users need to scroll the screen continuously or switch the interface to use certain functions, thus raising the cognitive burden accordingly and interrupting learning tasks (Kortum and Sorber, 2015; Maniar et al., 2008; Molnar, 2017). Second, due to the aforementioned characteristics, smartphones are considered more suitable for fragmented and flexible learning (Gan, 2019; Tossell et al., 2015). K-12 students' e-learning content, which is predominantly systematic rather than fragmented, necessitates continuous and deep concentration (Dong et al., 2020; Yan et al., 2021). The inappropriateness of smartphones in the formal education context has been widely acknowledged by scholars (Frei-Landau and Avidov-Ungar, 2022; Pal and Patra, 2021).

2.3. Physical environment appropriateness divide in current study

Besides device appropriateness divide, the physical environment appropriateness divide, defined as the inequality in the extent to which the physical environment to access the device is appropriate for the execution of specific tasks, also plays an important role in students' access to e-learning and their e-learning outcomes. This concept does not necessarily pertain to the home or learning context, as it can be applied to contexts related to other research questions, such as school or work environments.

In the e-learning context, physical environment appropriateness divide mainly concerns whether the supportive resources students can get from the environment are appropriate for their e-learning. The current study considers physical space for e-learning and family

members' social support as indicators of this divide. Physical space for e-learning concerns the availability of a dedicated and distraction-free space for students (Singh et al., 2021), while family members' social support encompasses assistance provided by family members (e.g., parents) in addressing technical or learning-related issues (Zhao et al., 2022). We consider these two types of resources for several reasons. On one hand, e-learning distinguishes itself from other activities, such as online shopping and gaming, due to its immersive nature and requirements for prolonged engagement. For instance, students who learn in a space with distractions may be less able to participate in e-learning lessons because they may be affected by noise or unable to participate verbally in live classes (Singh et al., 2021). On the other hand, e-learning is relatively new for Chinese K-12 students, and they may have limited abilities to use technological tools or software for learning purposes (Blanco et al., 2020; Yan et al., 2021). Additionally, K-12 students generally have poor self-discipline (Dong et al., 2020). Thus, they depend highly on appropriate physical environment to benefit from e-learning.

2.4. Downstream influence of device and physical environment appropriateness divide

As previously mentioned, the current study investigates the interactive effect of device and physical environment appropriateness divide on e-learning outcomes. Building upon previous research, we consider both the second-level and third-level digital divide as consequences. The second-level digital divide (i.e., digital capability divide) encompasses the ability to use the ICT (Wei et al., 2011), while the third-level digital divide (i.e., digital outcome divide) focuses on the outcomes of different capacities and usage of ICTs (Wei et al., 2011). In the current study, we specifically examine e-learning self-efficacy and behavioral engagement.

The term “self-efficacy” refers to an individual's perceptions or evaluations of their ability to successfully execute actions necessary for managing future prospective (Bandura, 1982). Various personal and environmental factors contribute to the development of self-efficacy, including mastery experiences and physiological and emotional reactions, which subsequently influence behavioral outcomes (Bandura, 1997). In the digital divide research, ICT-related self-efficacy is a core concept that has received much attention from scholars. Prior studies have investigated how ICT access (e.g., computer ownership) affects ICT related self-efficacy, which in turn affects specific ICT use outcomes (Hoffmann et al., 2015; Wei et al., 2011). The current study regards e-learning self-efficacy as the domain- and context-specific representation of self-efficacy, defined as an individual's perceptions or evaluations of their ability to successfully complete the specific tasks required in e-learning classes (Zimmerman and Kulikowich, 2016). It has been found that e-learning self-efficacy serves as a predictor for academic performance (Tang and Tseng, 2013; Wang et al., 2013), perceived learning outcome (Alqurashi, 2019; Chu and Chu, 2010), satisfaction (Alqurashi, 2019; Chu and Chu, 2010), and behavioral engagement (Zhao et al., 2022). We also examined behavioral engagement as an indicator of behavioral outcomes in e-learning, focusing on the digital outcome divide, based on previous research (Chiu, 2021; Zhao et al., 2022). It refers to “the behavioral effort exerted by learners to actively engage in e-learning activities, master knowledge, and achieve high-quality performance” (Sun et al., 2019). It is strongly associated with commitment to learning and persistence in learning (Fredricks et al., 2004; Marks, 2000), and is also closely related to academic performance and satisfaction with learning (Christenson et al., 2012).

We posit that both the device appropriateness divide and the physical environment appropriateness divide could lead to disparities in e-learning self-efficacy and further behavioral engagement of K-12 students. This is because they reflect differences in students' ICT use and supportive resources, and more appropriate and favorable resources can lead to better learning outcomes. Furthermore, the domestication

perspective of ICT provides an angle from which to consider the interaction effect of these two types of appropriateness divide on e-learning outcomes (Scheerder et al., 2019). Domestication focuses on the development of what technology means to users and how deeply it is immersed in daily life (Scheerder et al., 2019). Students' immediate physical surroundings greatly influence their e-learning experiences. For instance, smartphones are particularly portable compared to computers/tablets (Tsetsi and Rains, 2017). When students are situated in a physical space with distractions, students who use smartphones to access e-learning can move freely to another distraction-free place, which is inconvenient for students who use computers. Thus, the role of the device type on e-learning outcomes may depend on the physical environment.

3. Research model and hypotheses

Based on the previous discussions, we display our research model in Fig. 1. First, we propose the rural–urban comparison hypothesis of the device appropriateness divide and physical environment appropriateness divide (H1, H2a/b). Second, we investigate their chain effects and hypothesize that device type (i.e., indicators of device appropriateness divide), physical space for e-learning and social support (i.e., indicators of physical environment appropriateness divide) influence e-learning self-efficacy (H3, H4a/b), which in turn affects behavioral engagement (H6). Third, to examine the interaction effect of these two types of appropriateness divide, we hypothesize that physical space for e-learning and social support moderate the relationship between device type and e-learning self-efficacy (H5a/b). Finally, we include gender, grade, and academic performance before full-time e-learning during COVID-19 (APB) as control variables.

3.1. Device appropriateness divide between rural and urban students

The devices used for e-learning are closely related to students' SES. Specifically, students from socioeconomically advantaged backgrounds may have various devices, while students from socioeconomically disadvantaged backgrounds may only have smartphones that are relatively cheaper compared with computers or tablets. In China, students in rural areas are generally more socioeconomically disadvantaged. Statistics show that the smartphone penetration rate between rural and urban students is quite approaching (CNNIC, 2022). Specifically, 90.2 % of urban students and 92.5 % of rural students use smartphones to access the Internet. However, the penetration rate of personal computers or tablets among urban students is much higher than among rural students. For example, 41.4 % of urban students and 29.2 % of rural students use notebook computers to access the Internet. This significant difference in device type became more apparent as students participated in e-learning at home during COVID-19 (DRCSC, 2020). Specifically, 85 % of rural students used smartphones and 7.3 % used computers or tablets to access e-learning, while 75 % of urban students were able to use computers

or tablets. These statistics show that urban students tend to have more appropriate devices for e-learning than rural students. Thus, we hypothesize as follows:

H1. The device appropriateness divide exists between rural and urban students. That is, in comparison to their urban counterparts, rural students are less likely to participate in e-learning with more appropriate devices (e.g., computers or tablets).

3.2. Physical environment appropriateness divide between rural and urban students

When it comes to the physical space for e-learning, we need to be quite cautious about its rural–urban comparison. Physical space for e-learning depends on the usable space available at home. In China, students in rural areas have more usable space, because the average living space per capita in rural areas is larger than that in urban areas (National Bureau of Statistics, 2023). Meanwhile, students in urban areas have more family cultural capital (e.g., cultural resources and practices) (Ren et al., 2022), as urban parents are usually better educated (Liao et al., 2016), which can help create a conducive and appropriate (e.g., distraction-free) space for e-learning (Mohan et al., 2021). Extant studies also suggest that advantaged (e.g., urban) students are more likely to take e-learning in a physical space free of distraction (Mohan et al., 2021; Tate and Warschauer, 2022). In all, despite the larger usable space of rural students, urban students may be more likely to have appropriate space for e-learning due to cultural capital. Thus, we hypothesize as follows:

H2a. In comparison to their urban counterparts, rural students are less likely to participate in e-learning in a distraction-free space at home.

Regarding social support, we posit that there are differences between rural and urban students for the following reasons. First, urban parents have more e-learning experience and are more comfortable with e-learning. Accordingly, they can provide more technical assistance and personalized support (Zhao et al., 2022). Second, rural parents face greater economic uncertainty and may struggle more with household expenses than urban parents (Zhao et al., 2022). Accordingly, they may not have enough time and energy to support their children's e-learning. Thus, we hypothesize as follows:

H2b. In comparison to their urban counterparts, rural students received less social support from their family members.

3.3. Device appropriateness divide and E-learning self-efficacy

As mentioned earlier, how different types of device influence e-learning outcomes depends on the device appropriateness for the tasks. In current study, we believe that computers/tablets possess higher level of appropriateness than smartphones and can provide a better learning experience. Accordingly, we hypothesize that students who use devices

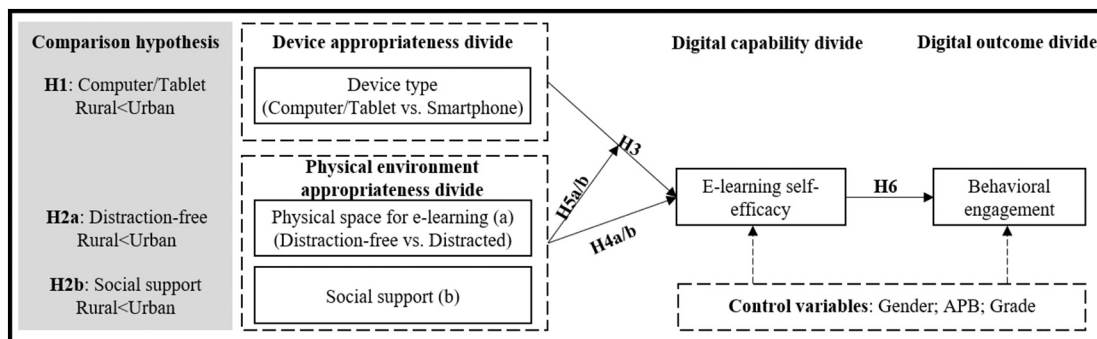


Fig. 1. Research model.

with higher appropriateness to access e-learning have higher e-learning self-efficacy for several reasons. First, smartphones are more suitable for fragmented and flexible learning due to their smaller screen sizes and greater scrolling requirements (Gan, 2019; Tossell et al., 2015). However, K–12 students' e-learning content is typically systematic rather than fragmented. Such content requires students to concentrate on their studies for longer periods (Dong et al., 2020; Yan et al., 2021). Devices with larger screens, such as computers or tablets, enable students to navigate and engage in e-learning more confidently for longer periods of time, thereby increasing their e-learning self-efficacy. Second, the multi-media nature of e-learning, such as live classes, recorded classes, or videos recommended by teachers, requires devices optimized for visual and auditory clarity. Larger-screen devices are better equipped to support these multi-media demands and enable smooth navigation and comprehension (Frei-Landau and Avidov-Ungar, 2022; Guo and Wan, 2022; Kortum and Sorber, 2015; Pal and Patra, 2021). This ease of use strengthens students' belief in their ability to use-learning system, further boosting their e-learning self-efficacy. Third, using smartphones for e-learning causes difficulty in focusing on the learning content and interacting with teachers, given that students are more easily distracted by the various applications (Maniar et al., 2008; Molnar, 2017; Pal and Patra, 2021). Meanwhile, many K–12 students do not possess an exclusive device for themselves and have to use their parents' smartphones for e-learning, which can lead to additional distractions (Weixin, 2020). These distractions negatively affect students' concentration and task completion. In contrast, using more appropriate devices such as computers or tablets increases students' confidence in navigating e-learning systems and completing e-learning tasks efficiently, thereby improving their e-learning self-efficacy. Thus, we hypothesize that:

H3. Students who take e-learning courses using devices with higher level of appropriateness (e.g., computers/tablets) will have a higher level of e-learning self-efficacy than less appropriate devices (e.g., smartphones).

3.4. Physical environment appropriateness divide and E-learning self-efficacy

As mentioned earlier, physical environment appropriateness divide in terms of physical space for e-learning and social support from family members also plays a role in students' e-learning outcomes. We posit that students who take e-learning in a more appropriate physical environment with a distraction-free space have higher level of e-learning self-efficacy for several reasons. First, unlike other online activities such as online shopping, e-learning requires sustained concentration and prolonged engagement (Singh et al., 2021). In this case, a high-quality (e.g., private and quiet) learning space is essential for effective learning (Tate and Warschauer, 2022), as interruptions during a synchronous video class can lead to missed content. On the contrary, if students are in a physical space with distractions, such as a crowded and noisy room, they struggle to focus on the content presented in online classes (Tate and Warschauer, 2022). Thus, the sustained focus on e-learning content brought about by a high-quality learning space boosts students' e-learning self-efficacy. Second, as many students are unfamiliar with e-learning systems (Key, 2020), a distraction-free learning space allows them to carefully review the training materials and gain the confidence needed to use these systems effectively. This sense of mastery over the system is a key component of e-learning self-efficacy, as it directly influences their ability to participate in online classes and interact meaningfully with content, teachers, and peers (Shen et al., 2013). Thus, we hypothesize as follows:

H4a. Students who take e-learning in a more appropriate physical environment with a distraction-free space will have a higher level of e-learning self-efficacy.

Besides physical space for e-learning, we also hypothesize the

positive effect of social support from family members on e-learning self-efficacy for several reasons. First, emotional support from family members can help alleviate students' anxiety and depression caused by COVID-19 as well as the stress associated with online learning (Duan et al., 2020; Szopiński and Bachnik, 2022). Second, tangible support from family members, such as technical and learning support, can help students overcome technical challenges and better adapt to online learning (Gao et al., 2021). Such support increases students' confidence in using e-learning system while reducing boredom and frustration with online learning. Finally, social support, such as emotional encouragement and active involvement in children's learning activities, can foster a sense of competence and enhance students' academic perception of control (Chu and Chu, 2010; Fan and Williams, 2010; Fulton and Turner, 2008; Gao et al., 2021). Thus, we hypothesize as follows:

H4b. Students who take e-learning in a more appropriate physical environment with more family members' social support will have a higher level of e-learning self-efficacy.

3.5. Moderation effect of physical environment appropriateness divide

In addition to the direct effect, we also hypothesize the moderation effect of the physical environment appropriateness divide. That is, it is insufficient to only consider the digital virtual space in shaping e-learning outcomes, whose influence may depend on the actual physical surroundings, since students do not take e-learning in a vacuum and are domesticated in their physical surroundings (Singh et al., 2021). Specifically, we posit that physical space for e-learning and social support from family members moderate the relationship between device type and e-learning self-efficacy for several reasons.

First, the influence of device type on e-learning self-efficacy may depend on the physical space for e-learning. In particular, if students are in a distraction-free space, they are better able to focus on e-learning rather than other activities such as playing games, and leverage the functionalities of computers or tablets to effectively engage with e-learning content. This heightened engagement reinforces their confidence in using these devices for e-learning tasks. On the contrary, if students are in a space with distractions, they can easily be attracted by these distractions (e.g., noise) and have difficulty focusing on e-learning. In such situations, students run the risk of just spectating and not participating, with the device type becoming less important (Singh et al., 2021). Therefore, distractions in such environments weaken students' belief in their ability to use appropriate devices to engage in e-learning.

Second, the influence of device type may also depend on the social support they receive from family members. Since e-learning is relatively new to Chinese K–12 students, many lack the skills to effectively use technological tools or software for learning purposes (Blanco et al., 2020; Yan et al., 2021). When students receive sufficient social support from their family members, including technical assistance and emotional encouragement, they can better adapt to e-learning and be more focused (Ng, 2021). In addition, social support from family members can serve a supervisory role, preventing students from engaging in non-educational activities such as playing games. In such cases, computers/tablets play an important role in fostering e-learning self-efficacy. On the contrary, insufficient social support can lead to technical barriers and challenges in adapting to online learning (Ng, 2021), thereby eroding students' confidence in their capability to use e-learning systems effectively. Without family supervision, students may also struggle with self-discipline and be more susceptible to distractions and activities unrelated to learning, which hampers their belief in their capability to succeed in e-learning. As a result, the benefits of using computers/tablets to enhance e-learning self-efficacy will be constrained. Thus, we propose the following hypothesis:

H5a/b. When in an appropriate physical environment with a distraction-free space (H5a) or higher level of social support (H5b), using more appropriate devices (e.g., computers/tablets) leads to

stronger e-learning self-efficacy than less appropriate devices (e.g., smartphones).

3.6. Effect of E-learning self-efficacy on behavioral engagement

In the current study, we hypothesize the positive effect of e-learning self-efficacy on behavioral engagement for several reasons. First, e-learning self-efficacy significantly influences the level of effort students invest in e-learning (Alqurashi, 2016). During the abrupt transition to fulltime e-learning caused by the COVID-19 pandemic, most students faced a completely new experience that required substantial time and effort to adapt (Alam and Parvin, 2021; Key, 2020). Consequently, higher e-learning self-efficacy can facilitate this adaptation process, leading to greater behavioral engagement. Second, e-learning self-efficacy encourages students to perceive difficulties as opportunities for growth rather than obstacles, which enables them to set more ambitious goals and achieve greater behavioral engagement in e-learning (Zhao et al., 2022). Third, e-learning self-efficacy helps students manage boredom and frustration in online classes, thereby enhancing their overall satisfaction with e-learning (Shen et al., 2013; Tsai et al., 2020). This enhanced satisfaction, in turn, leads students to behave better in e-learning (Sitar-Tăut et al., 2024). Finally, numerous studies have confirmed the positive effect of e-learning self-efficacy on various e-learning outcomes, including perceived learning (Alqurashi, 2019; Lin et al., 2015), academic achievement (Artino, 2008; Joo et al., 2013) and behavioral engagement (Zhao et al., 2022). Thus, we make the following hypothesis:

H6. E-learning self-efficacy has a positive influence on behavioral engagement.

3.7. Control variables

In addition, existing research indicates that some individual factors (e.g., demographic characteristics, academic performance) could affect students' e-learning self-efficacy and behavioral engagement. First, gender would play an important role as male students are generally considered to be more adaptable to computer technology and have higher levels of internet self-efficacy (Zhao et al., 2010). Thus, male students may be more adaptable to e-learning and achieve higher e-learning performance. Second, grade would also influence student's e-learning engagement and performance due to their metacognitive capability. Specifically, K-12 students at different grades exhibit varying levels of metacognitive skills, which in turn lead to differences in their ability to utilize the features of e-learning systems and their behavioral engagement in e-learning classes (Yan et al., 2021). Finally, students' academic performance before full-time e-learning during COVID-19 (APB) may be particularly affected by full-time e-learning during COVID-19 as students' APB determines the extent to which their learning outcomes may improve or worsen during COVID-19 (Guo and Wan, 2022). Thus, we included gender, grade and APB as control variables.

4. Methodology

4.1. Instrument measurement

All constructs in the current study were measured with a 7-point Likert scale by adapting them from prior studies. The measurement items for social support were adapted from Martins and Kellermanns (2004). E-learning self-efficacy was measured with items adapted from Shen et al. (2013). Behavioral engagement was measured with items adapted from Gunuc and Kuzu (2015). Physical space for e-learning was measured with items adapted from Tate and Warschauer (2022) and Singh et al. (2021). Based on prior research (Zhao et al., 2010), we used a five-level gradation of the class ranking to rate students' APB, which

included five ranges, namely top 10 %, 20 %–40 %, 40 %–60 %, 60 %–80 % and last 20 %. Following this approach, we assigned scores of 5, 4, 3, 2, and 1 to represent these levels, respectively.

Given that all the original questionnaire items were in English, we used backward translation to guarantee that the English and Chinese items were similar. Specifically, we invited three bilingual researchers. First, one of them translated all the English items into Chinese. Next, the other two researchers translated the Chinese items into English. Then, we compared these two translated English versions with the original English items and found them highly consistent. Finally, to guarantee content validity, we invited 10 researchers from the information system field to review the wording and format of the questionnaires. Based on their feedback, we made revisions to some items to avoid ambiguity. The basic principle for modifying the items was to ensure that they were easy for middle and primary school students to understand. For instance, one of the items for e-learning self-efficacy was "I am confident that I can adapt my learning styles to meet online course expectations". The learning style in this item may be somewhat abstract for primary school students. Thus, we modified this item to "I am confident that I can completely adapt to online learning." The final questionnaire items are shown in Table A1.

Before the formal survey, we conducted a pretest to guarantee the reliability and validity. We deployed an online version of our questionnaire on Wenjuanxing (<https://www.wjx.cn/>)—one of the largest questionnaire distribution platforms in China. Then, we forwarded the questionnaire URL to the K–12 students we know and encouraged them to post the URL to their classmates. We collected 82 questionnaires in total. The participants received CNY6 as a monetary reward after they completed the questionnaire. Subsequently, we conducted the basic reliability and validity analysis of the collected data. The Cronbach's alpha values for all constructs exceeded 0.7, indicating good construct reliability. Additionally, the average variance explained (AVE) for each construct was larger than 0.5, confirming adequate convergent validity.

4.2. Data collection

After the pretest, we cooperated with the Education Board of East Lake High-Tech Development Zone in Wuhan to conduct our formal data collection in May 2021. We selected this specific region in Wuhan to collect data for a number of reasons. First, the duration of fulltime e-learning for schools in Wuhan lasted more than two months, as the city was under lockdown for over two months during the COVID-19 outbreak. Furthermore, e-learning during the pandemic was mostly imperative rather than an alternative, which made the digital access divide more prominent (Alam and Asimiran, 2021; Tiejun, 2021). Second, the East Lake High-Tech Development Zone, which has been vigorously developed and expanded by the Wuhan municipal government, encompasses both peripheral and central areas. This diversity in location makes it an ideal setting for examining the differences between rural and urban students.

Similar with the pretest, we created an online version of our questionnaire on Wenjuanxing and distributed the questionnaire URL to students through Information Technology (IT) teachers. The IT teachers asked the students to complete our questionnaire during the IT classes. To identify respondents who did not engage in this survey and did not answer the questions carefully, trap questions were included in the questionnaire. For example, one such question was "Please select 'Agree' for this question". If respondents chose other options (e.g., Disagree), they would be unable to proceed to the subsequent questions. Besides, we asked students to fill in their school's name. The answers to this question were manually checked by the researchers and only respondents whose answer matched those of the surveyed schools were considered as valid samples. In addition, we checked the answer duration for each questionnaire and considered those completed in <3 min to be invalid, as this is below the average time required to complete the questionnaire properly. The survey lasted one month and was mainly distributed to junior middle schools and to the upper classes in primary

schools. Given that the IT curriculum begins at different times for specific grades in different schools and that the survey was not compulsory, our sample did not cover students from each grade evenly.

Table 3 displays the sample demographics of the 571 valid questionnaires that were collected. The proportions of male and female students were 55.0 % and 45.0 %, respectively. There were 320 junior middle school students and 251 primary school students; 49.2 % of the students mainly used smartphones for e-learning and 50.8 % used computers/tablets for e-learning. The total number for the e-learning system was 667 as some students used more than one e-learning system. The most widely used e-learning systems were Kongzhongketang (39.8 %) and Tencent Class (29.2 %). Live class was the primary form (82.3 %); 89.3 % of them owned a distraction-free space for e-learning. 31.9 % came from rural areas, while 68.1 % were from urban areas.

4.3. Data analysis

4.3.1. Analysis method

The current study utilized three analysis methods, with structural equation modeling (SEM) serving as the primary approach. The use of SEM was appropriate for several reasons. First, SEM enables the simultaneous estimation of relationships among multiple independent and dependent variables (Dash and Paul, 2021; Gerbing and Anderson, 1988). This advantage for concurrent analysis distinguishes SEM from other estimation methods (e.g., linear regression), which can only estimate a single layer of relationship between independent variables and dependent variables at a time (Gefen et al., 2000). In this study, two-layer relationships are involved: the influence of device and physical environment appropriateness divide on e-learning self-efficacy and the influence of e-learning self-efficacy on behavioral engagement. Second, SEM can simultaneously handle both latent variables (e.g., social support, e-learning self-efficacy, and behavioral engagement) and observed variables (e.g., device type and physical space for e-learning) (Dash and Paul, 2021; Gerbing and Anderson, 1988), which are also collected in our study. Finally, previous empirical studies on the digital divide have also extensively utilized SEM for hypothesis testing (Hsieh et al., 2011; Zhao et al., 2022), which underscores its suitability for analyzing the mechanisms through which the digital access divide affects various individual cognitive and behavioral outcomes. Besides SEM, the chi-square test and the independent-sample *t*-test were used to verify the comparison hypotheses. Specifically, the chi-square test was used to test rural-urban differences in device type and physical space for e-learning

as they were categorical variables; the independent sample *t*-test, designed to compare the means of two groups of people or conditions (Pallant, 2010), was used to test the rural-urban differences in social support that was continuous. These methods have also been widely adopted by prior research for such purposes (Okunola et al., 2017; Park et al., 2024; Szopiński and Bachnik, 2022). Lastly, the PROCESS macro was employed to test the moderation effect of physical environment appropriateness divide and verify the mediation effect of e-learning self-efficacy.

Based on these analysis methods, the data analysis mainly consisted of three parts. First, we used the AMOS 24 software to analyze the reliability and validity of the measurement model. Second, we tested all the hypotheses. Specifically, we applied independent sample *t*-test in SPSS to test rural-urban differences in device type, physical space for e-learning, and social support (i.e., H1, H2a, and H2b); applied the structural model to test the direct influence of device appropriateness and physical environment appropriateness (i.e., H3, H4a, H4b, and H6); and used SPSS PROCESS macro to test the moderating hypothesis (i.e., H5a and H5b). Finally, we conducted the mediation effect analysis for e-learning self-efficacy.

4.3.2. Measurement model test

First, we applied AMOS 24 software to conduct the confirmatory factor analysis. The fit indices are summarized in Table 4, and all these fit indices met the criteria, indicating an acceptable model fit (Bentler and Bonett, 1980).

Then, we examined the reliability and validity of each construct. Table 5 shows that the reliability of all constructs was good, with Cronbach's alpha and composite reliability (CR) larger than 0.7 (Nunnally, 1978). Also, each construct has good convergent validity because all AVEs were larger than 0.5 and factor loadings of each construct item was larger than 0.7 (Fornell and Larcker, 1981). Besides, the discriminant validity between each construct was good, with the square root AVEs larger than the off-diagonal correlation values in their corresponding rows and columns, as shown in Table 6.

Next, we calculated the variance inflation factor (VIF) for all variables to assess multicollinearity. The results are shown in Table B1. All VIF values range from 1.025 to 1.515, below the threshold of 3.3 (Diamantopoulos and Siguaw, 2006). These results indicate that multicollinearity does not pose a threat to the current study.

Finally, as the data were self-reported, we adopted the following two techniques to test the common method bias (CMB). First, Harmon's single-factor analysis was applied (Podsakoff et al., 2003). The first common factor with the largest proportion only accounted for 29.1 % of the variance. Second, following Lindell and Whitney (2001), we adopted the marker variable technique. Specifically, the second smallest correlation coefficient (0.016) was considered as the conservative estimate of CMB, and the correlation coefficient matrix was adjusted accordingly. The results are shown in Table B2. The correlation coefficient's significance remained unchanged, and the differences between the original (the area above the diagonal) and adjusted correlations (the area below the diagonal) were all below 0.07. These results indicated that CMB did not pose a threat to the current study.

4.3.3. Hypothesis testing

4.3.3.1. Comparison hypothesis testing. To confirm whether significant rural-urban differences existed regarding device and physical environment appropriateness divide, we mainly applied the chi-square test and the independent-sample *t*-test. Specifically, the chi-square test was used to test rural-urban differences in device type and physical space for e-learning; the independent-sample *t*-test was used to test rural-urban differences in social support. As shown in Table 7, in comparison to their urban counterparts, rural students were less likely to use computers/tablets for e-learning, thus supporting H1. No significant differences

Table 3
Sample profile.

Variable	Option	N	Percentage
Gender	Female	257	45.0 %
	Male	314	55.0 %
Grade	JMS-Third year	97	17.0 %
	JMS-Second year	101	17.7 %
	JMS-First year	122	21.4 %
	PS-Sixth year	45	7.9 %
	PS-Fifth year	206	36.1 %
Device type	Smartphones	281	49.2 %
	Computers/Tablets	290	50.8 %
Physical space for e-learning	A distraction-free space	510	89.3 %
	A space with distractions	61	10.7 %
Form of e-learning	Live class	470	82.3 %
	Recorded lesson	101	17.7 %
Geographic location	Rural	182	31.9 %
	Urban	389	68.1 %
E-learning system	Dingding	108	18.9 %
	Tencent Class	167	29.2 %
	Tencent meeting	57	10.0 %
	QQ	73	12.8 %
	Kongzhongketang	227	39.8 %
	Others	35	6.1 %

Notes: PS = Primary school; JMS = Junior middle school.

Table 4

Fit indices of the measurement model.

Fit Indices	CMIN/DF	RMSEA	NFI	TLI	CFI	IFI
Recommended Value	<3	<0.08	>0.9	>0.9	>0.9	>0.9
Model Value	1.878	0.039	0.974	0.979	0.988	0.988

Table 5

Reliability and validity.

Construct	Items	Loadings	AVE	CR	Cronbach's alpha
Social support	SS1	0.879	0.794	0.920	0.920
	SS2	0.906			
	SS3	0.888			
E-learning self-efficacy	ESE1	0.851	0.682	0.865	0.858
	ESE2	0.886			
	ESE3	0.732			
Behavioral engagement	BE1	0.889	0.747	0.899	0.896
	BE2	0.834			
	BE3	0.869			

were found regarding physical space for e-learning; thus, H2a was not supported. Rural students had lower levels of social support, thus supporting H2b.

4.3.3.2. Structural model testing. We conducted the structural model test with AMOS 24 software, and all the fit indices are summarized in Table 8. All these fit indices met the criteria, indicating acceptable model fit (Bentler and Bonett, 1980).

We summarized the results of comparison hypothesis test and structural model test in Fig. 2. The explained variances of behavioral engagement and e-learning self-efficacy were 52.5 % and 42.1 % respectively. At the same time, all the hypotheses were supported. Specifically, device type, physical space for e-learning, and social support significantly positively influenced e-learning self-efficacy, thus supporting H3, H4a, and H4b. Besides, e-learning self-efficacy exerted a significantly positive effect on behavioral engagement, thus supporting H6. Regarding the control variables, Grade and APB were found to have significant effects on e-learning self-efficacy. For behavioral engagement, all control variables were insignificant.

4.3.3.3. Moderation effect testing results. To test whether physical environment appropriateness divide moderated the relationship between device type and e-learning self-efficacy, we conducted a moderation test with the PROCESS macro (Model 1) developed by Hayes (2018). To test the significance, we used 5000 bootstrapping samples. Coefficient estimates are statistically significant from 0 when the confidence interval (CI) does not include 0. This macro revealed a significant two-way interaction effect between device type and physical space for e-learning ($b = 0.715$, $boot\ SE = 0.293$, 95 % CI: [0.138, 1.292]). As is displayed in Fig. 3, the simple slope tests displayed a significant and positive slope at a space without distractions ($b = 0.499$, $boot\ SE = 0.095$, 95 % CI: [0.313, 0.685]). When situated in a distracted space, the influence of device type on e-learning self-efficacy was insignificant ($b = -0.216$, $boot\ SE = 0.278$, 95 % CI: [-0.762, 0.331]). These results indicated that computers/tablets (vs. smartphones) would relate more

Table 6

Discriminant validity.

Construct	Mean	SD	SS	ESE	BE
Social support (SS)	5.082	1.549	0.891	0.490**	0.539**
E-learning self-efficacy (ESE)	5.710	1.227		0.827	0.626**
Behavioral engagement (BE)	5.377	1.295			0.864

Note: The bolded diagonal elements are the square roots of AVE values.

** $p < 0.01$.

Table 7

Test results for group differences.

Variable	Means		χ^2/T value	Sig.	Hypothesis support
	Rural	Urban			
Device type	0.313	0.599	40.516	0.000***	H1 supported
Physical space for e-learning	0.857	0.910	3.634	0.057	H2a not supported
Social support	4.802	5.213	2.975	0.003**	H2b supported

Notes: Sig. = Significance.

*** $p < 0.001$.

** $p < 0.01$.

positively to e-learning self-efficacy for a distraction-free versus a distracted space. Thus, H5a was supported. Besides, this macro revealed a significant two-way interaction effect between device type and social support ($b = 0.161$, $boot\ SE = 0.056$, 95 % CI: [0.052, 0.271]). As is displayed in Fig. 3, the simple slope tests demonstrated that among students with higher levels of social support, the positive association between device type and e-learning self-efficacy became stronger ($b = 0.450$, $boot\ SE = 0.109$, 95 % CI: [0.236, 0.664]) than those with lower levels of social support ($b = 0.019$, $boot\ SE = 0.163$, 95 % CI: [-0.301, 0.339]). These results implied that those with lower levels of social support might have lower levels of e-learning self-efficacy even with more appropriate devices (i.e., computers/tablets), thus supporting H5b.

4.3.4. Indirect effect analysis

To test whether e-learning self-efficacy functioned as a mediator between device type, physical environment and behavioral engagement, we conducted a mediation test with the PROCESS macro (Model 4) developed by Hayes (2018) based on 5000 bootstrapping samples. The mediation test results are displayed in Table 9. The indirect effects of device type and physical space for e-learning on behavioral engagement through e-learning self-efficacy were significant. In contrast, the direct effects of device type and physical space for e-learning on behavioral engagement were insignificant. Besides, both the indirect and direct effects of social support on behavioral engagement were significant. Thus, device type and physical space for e-learning enhanced behavioral engagement when fully mediated by e-learning self-efficacy. Social support enhanced behavioral engagement while partially mediated by e-learning self-efficacy.

5. Discussion

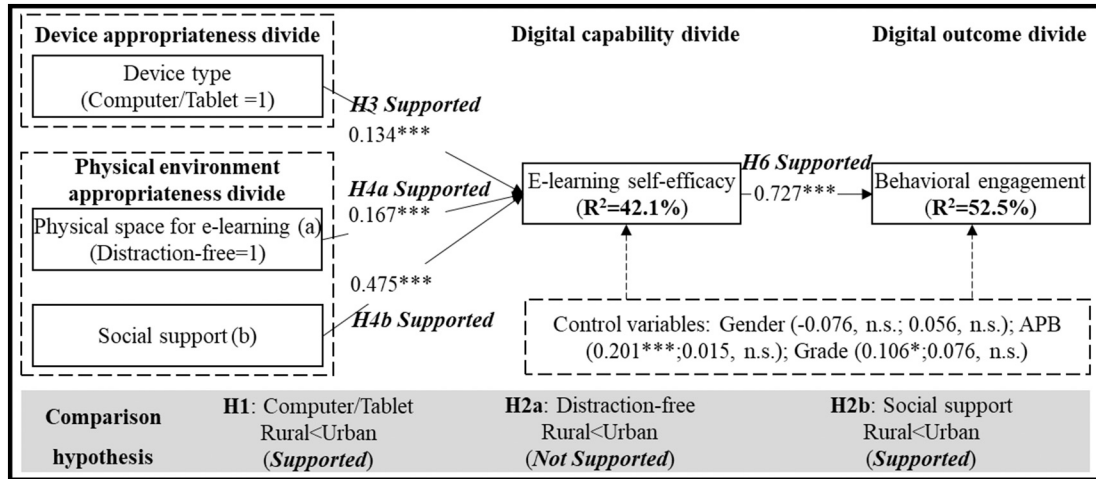
5.1. Summary of findings

The results reveal several significant and interesting findings. First, our study provides empirical evidence of the device appropriateness divide between rural and urban students, confirming that these groups do not have equal access to appropriate ICT resources. This finding aligns with prior studies, which demonstrate that individuals from disadvantaged socioeconomic backgrounds are more likely to be part of vulnerable groups in the digital divide (Azubuike et al., 2020; González-Betancor et al., 2021; Guo and Wan, 2022). However, unlike prior studies that emphasize the access dichotomy or quality divide, our study highlights a novel form of digital access divide—the device appropriateness divide. Moreover, while prior studies have qualitatively discussed the inequality in device types (Frei-Landau and Avidov-Ungar,

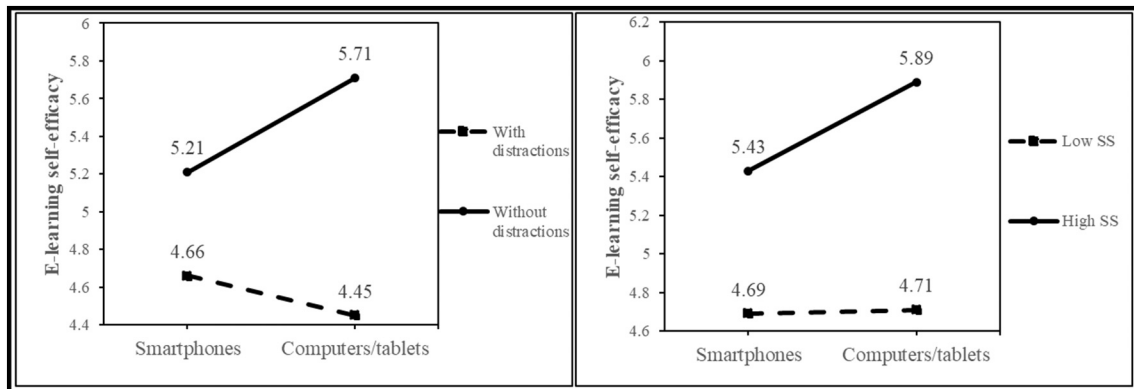
Table 8

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	2.584	0.053	0.963	0.963	0.977	0.977

**Fig. 2.** Path analysis results.

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s. = insignificant; The values after the colon for control variables represent the standardized path coefficients and their significance; APB = Academic performance before full-time e-learning during COVID-19.

**Fig. 3.** Two way interaction between DT and physical environment (PS, SS) on e-learning self-efficacy.

Notes: DT = device type; PS = physical space for e-learning; SS = social support.

2022; Law et al., 2022; Singh et al., 2021; Yan et al., 2021), this study empirically confirmed the existence of this specific divide.

Second, our study uncovered distinct findings regarding the physical environment appropriateness divide, particularly in terms of social support and physical space for e-learning. Specifically, rural students reported lower levels of social support for e-learning compared to their

urban peers. This finding aligns with prior studies highlighting inequalities in social support between rural and urban students (Zhao et al., 2022). However, we observed no significant differences between rural and urban students concerning the physical space for e-learning. This finding challenges the prevailing assumption that rural students are consistently disadvantaged relative to their urban counterparts in terms

Table 9

Mediation testing results.

Paths	Direct effect			Indirect effect			Result
	Coef.	Sig.	95 % CI	Coef.	Sig.	95 % CI	
DT → ESE → BE	0.016	0.843	[-0.158, 0.190]	0.171	0.000***	[0.067, 0.289]	Full
PS → ESE → BE	0.025	0.859	[-0.256, 0.307]	0.356	0.000***	[0.202, 0.579]	Full
SS → ESE → BE	0.254	0.000***	[0.196, 0.311]	0.179	0.000***	[0.133, 0.237]	Partial

Notes: CI = Confidence interval; ESE = E-learning self-efficacy; BE = Behavioral engagement; DT = Device type; PS = Physical space for e-learning; SS = Social support; Sig. = Significance.

*** $p < 0.001$.

of cultural resources (Ren et al., 2022; Zhao et al., 2022). Our findings suggest that the real advantaged and disadvantaged groups regarding the physical environment appropriateness divide in e-learning may not be adequately captured by traditional indicators such as geographic region. Instead, these supportive resources for ICT may manifest in more nuanced ways, which has been ignored in prior studies (Lythreitis et al., 2021; Singh et al., 2021).

Third, we found that device and physical environment appropriateness divide could lead to higher levels of digital divide (e.g., digital capability divide). Specifically, compared with those students who mainly use smartphones for e-learning, students who use computers/tablets tend to have a stronger sense of e-learning self-efficacy and then behavioral engagement. This finding is consistent with prior studies (Tossell et al., 2015; Van Deursen and Van Dijk, 2019), which indicate that the smartphones cannot completely replace computers/tablets in learning activities due to their technological characteristics though they can provide an equal chance to access the Internet and undifferentiated access quality. As to the physical environment appropriateness divide, physical space for e-learning and social support positively influence behavioral engagement through e-learning self-efficacy. Our results indicate that students with a more favorable physical environment (i.e., a distraction-free physical space or more social support) tend to have stronger e-learning self-efficacy regardless of the device type. This finding aligns with prior research, which indicates that an appropriate physical environment is vital for the success of e-learning (Ng, 2021; Singh et al., 2021; Tate and Warschauer, 2022).

Fourth and most important, our study finds that device and physical environment appropriateness divide have an interactive effect on e-learning self-efficacy. When students take e-learning in a distraction-free space or have higher social support, using computers/tablets would lead to higher e-learning self-efficacy than using smartphones. However, this disparity became insignificant and even slightly negative when students were in an unfavorable environment. Unlike prior studies that mainly examine the direct effect of the digital access divide and its related physical environment on learning outcomes (Drabowicz, 2017; Guo and Wan, 2022; Liao et al., 2016; Pal and Patra, 2021; Wei et al., 2011; Zhao et al., 2010), it implies that a physical environment with more supportive resources would benefit students using computers/tablets more than those using smartphones. But a physical environment lacking such supportive resources would diminish the advantages brought by technology-task fit. All these findings also provide empirical support for the study of Singh et al. (2021), which called for more research to investigate the influence of the physical environment and material access on e-learning outcomes.

Finally, in the indirect effect analysis, we found that e-learning self-efficacy fully mediated the relationship between device type, physical space for e-learning, and behavioral engagement. This finding suggests that it is through developing e-learning self-efficacy that those ICTs and their supportive resources can influence behavioral outcomes, which may partly explain why some prior studies did not find a significant direct influence of device-related factors (e.g., device quantity) on learning performance (Guo and Wan, 2022). Besides, we found that e-learning self-efficacy partially mediated the relationship between social support and behavioral engagement. This finding confirms the direct (Zhao et al., 2022) and indirect influence (Gao et al., 2021) of social support on behavioral engagement.

5.2. Theoretical implications

The current research has the following theoretical implications. First, this study introduces the concept of the device appropriateness divide and extends the nature and scope of the digital access divide in prior studies. Previous studies have predominantly focused on access dichotomy or quality divide (e.g., Azubuike et al., 2020; Guo and Wan, 2022; van de Werfhorst et al., 2022; Wei et al., 2011). This concept shifts the focus from the presence or quality of ICT access to the

appropriateness of ICT access (e.g., the suitability of the device for the execution of specific tasks). It is consistent with the analysis framework of user–system–task for IS effective use research (Burton-jones et al., 2013); that is, whether the use of technology produces effective outcomes depends not only on the technology itself but also on the tasks to which it is applied. Our study empirically confirms the existence of a device appropriateness divide between Chinese rural and urban students, and such a divide could lead to disparity in e-learning self-efficacy and behavioral engagement. Our study responds to recent research on the digital divide that calls for a more nuanced understanding of new forms of the digital divide (Lythreitis et al., 2021). The current study can serve as a valuable reference for future research on the digital access divide, and future research is encouraged to examine the device appropriateness divide in diverse contexts, thereby establishing its application boundaries.

Second, the current study contributes to the existing research on digital divide by emphasizing the significance of factors related to the physical environment. Our study addresses Singh et al.'s (2021) call for increased attention towards the physical environment challenges in digital divide research and validates its sequential effects. Specifically, we focused on the physical environment appropriateness divide, which mainly concerns social support and physical space for e-learning. The current study finds that they can significantly influence e-learning self-efficacy and behavioral engagement, thereby playing a crucial role in e-learning of K-12 students. Besides social support, we examined some supportive resources neglected in prior studies, such as distraction-free physical space. It is important to note that if we solely compare the regional background of students, the inequality pertaining to such resources might be disregarded. This provides a new angle for researchers to identify those disadvantaged groups who would benefit less even equal access to ICT resources is provided.

Finally, the current study contributes to the understanding of chain-effects among different levels of the digital divide by investigating the interaction effects of device and physical environment appropriateness divide. In addition to directly influencing the second level digital divide, our study reveals that the physical environment appropriateness divide could also amplify the effects of digital access divide on higher levels of digital divide. While some scholars have separately raised concerns about the appropriateness of device and physical environment (Frei-Landau and Avidov-Ungar, 2022; Law et al., 2022; Singh et al., 2021; Yan et al., 2021), there is a lack of integration of the two. Our study demonstrates that a favorable physical environment can further augment the positive influences of appropriate devices. Conversely, an unfavorable physical environment can weaken the advantages offered by the use of appropriate devices. This finding complements prior studies that have mainly focused on the influence of digital artifacts and ignored the physical environment (Drabowicz, 2017; Guo and Wan, 2022; Liao et al., 2016; Pal and Patra, 2021; Wei et al., 2011; Zhao et al., 2010). Future researchers are encouraged to pay attention to the interaction effect of the device and physical environment appropriateness divide in other contexts and whether they will further aggravate or alleviate it. It can provide valuable insights into adopting appropriate strategies for alleviating the negative effects of different types of the digital access divide.

5.3. Practical implications

The current research also has some practical implications. Based on empirical findings, this study proposes four main practical suggestions: (1) increasing the awareness of the device appropriateness divide in e-learning, (2) creating and maintaining a supportive physical learning environment, (3) cultivating students' understanding of ICT tools and providing appropriate devices if possible, and (4) enhancing students' e-learning self-efficacy. At the same time, we propose specific practical recommendations for different stakeholders, including policymakers and school leaders, parents, teachers, and system developers. Table 10

displays the practical recommendations derived from the current study.

5.4. Limitations and future research

Although our study makes several noteworthy theoretical contributions, some limitations must be taken into account. First, the current study relied solely on self-reported data, which may be susceptible to recall biases. To mitigate this limitation, future research should consider collecting secondary data, such as behavioral metrics of e-learning and examination grades, directly from educational institutions. Second, our study is particularly applicable to countries where Internet access is nearly universal. For countries with limited Internet access, the access dichotomy or quality divide may be more relevant. Future research should investigate the applicability of this research model in countries with diverse levels of Internet penetration. Third, our study primarily focuses on K–12 students who generally exhibit limited self-regulation abilities. The findings may vary for other student populations, such as

university students, who tend to demonstrate more advanced self-regulation skills (Bonneville & Riddell, 2023). Therefore, future research is encouraged to examine the applicability of the research model across diverse student groups, such as university students or adult learners. Comparative studies can help establish the application boundaries of the research model. Fourth, the sample of our study is confined to a specific region (i.e., Wuhan), which might limit the generalizability of the findings. To address this limitation, future research should aim to validate the research model across diverse geographic and cultural contexts. Implementing multi-site sampling strategies would likely yield a more representative dataset, thereby enhancing the external validity of the results. Finally, this study mainly focuses on device appropriateness divide in e-learning context. Future research can extend this concept to other domains (e.g., online shopping) and examine its influence. For instance, researchers can investigate how device types affect consumers' online shopping experiences and ultimately their well-being.

Table 10

Practical recommendations of the current study.

Main recommendations	Recommendations for related stakeholders
Increase awareness of the device appropriateness divide in e-learning	<p>Policymakers and school leaders</p> <ul style="list-style-type: none"> ✓ Recognize the problem of device appropriateness divide at the rural–urban level ✓ Abandon the notion that the digital access divide is simply a dichotomy or quality distinction and instead focus on the device appropriateness dimension ✓ Launch public campaigns to educate relevant stakeholders about the impact of device appropriateness divide on e-learning outcome ✓ Provide customized support targeting disadvantaged students, such as providing computers for them to access the e-learning <p>Teachers</p> <ul style="list-style-type: none"> ✓ Strengthen communication with parents and fully understand the e-learning conditions of students, including devices and the physical environment they are embedded in ✓ Focus on students who are disadvantaged in device appropriateness divide and provide personalized tutor if possible ✓ Design e-learning activities with device appropriateness divide in mind, ensuring that students using smartphones do not face disadvantages
Create and maintain a supportive learning environment	<p>Policymakers and school leaders</p> <ul style="list-style-type: none"> ✓ Reduce the duration of class sessions to overcome obstacles that hinder disadvantaged students from participating ✓ Deliver online classes by asynchronous means <p>Teachers</p> <ul style="list-style-type: none"> ✓ Provide students with access to pre-recorded lectures before class sessions to enhance interactivity and engagement ✓ Provide students with recordings of class sessions to help them review any material that they may have missed during a live session ✓ Create online discussion groups on social media platforms such as WeChat to engage students <p>Parents</p> <ul style="list-style-type: none"> ✓ Provide their children a distraction-free physical space to engage in e-learning ✓ Provide technical assistance and emotional encouragement to help their children overcome obstacles in e-learning. ✓ Play a supervisory role, preventing students from engaging in activities unrelated to learning (e.g., playing games)
Cultivate students' understanding of ICT tools and provide appropriate devices	<p>Teachers</p> <ul style="list-style-type: none"> ✓ Cultivate students' ability to use ICT tools for independent learning and encourage children to use ICT tools for knowledge discovery and knowledge innovation ✓ Help students scientifically and rationally understand ICT tools and help them avoid indulging in online entertainment activities ✓ Collaborate with parents if possible <p>Parents</p> <ul style="list-style-type: none"> ✓ If possible, provide their children with more appropriate devices such as computers or tablets to access e-learning ✓ Ask for help from teachers and schools regarding how to cultivate students' ability to use ICT tools for e-learning <p>E-learning system developers</p> <ul style="list-style-type: none"> ✓ Give priority to usability on smartphones as it is broadly covered and is unfavorable to students' e-learning ✓ If possible, develop different versions that are compatible to different devices, which can offer better learning experiences for students ✓ Provide functions such as intelligent monitoring and feedback to prevent students from distractions
Enhance students' e-learning self-efficacy	<p>Policymakers and school leaders</p> <ul style="list-style-type: none"> ✓ Measure students' e-learning self-efficacy and provide support to those who are at lower levels ✓ Organize regular training for students who are not accustomed to e-learning <p>Teachers</p> <ul style="list-style-type: none"> ✓ Share their experiences of e-learning, which can help cultivate students' e-learning self-efficacy ✓ Interact frequently with their students to know about their difficulties in e-learning and help them overcome them <p>Parents</p> <ul style="list-style-type: none"> ✓ Offer valuable suggestions to teachers and schools based on their observations of their children's e-learning experience ✓ Parents who have experience in e-learning can share their experiences of e-learning, which can increase their children's confidence in e-learning <p>E-learning system developers</p> <ul style="list-style-type: none"> ✓ Develop forums in which students and teachers can share their e-learning experience ✓ Provide functions that can enable students to ask questions and interact with teachers and students easily

6. Conclusion

This study investigated whether the device appropriateness divide exists at the rural–urban level in China and how the physical environment appropriateness divide interacts with the device appropriateness divide to influence e-learning outcomes. Our results show that the device appropriateness divide and physical environment appropriateness divide exist in the dimension of social support between rural and urban students. The physical space for e-learning did not differ significantly between rural and urban students. Besides, it was also found that these two types of digital divide significantly influenced e-learning self-efficacy and then behavioral engagement in e-learning. Further, the physical environment appropriateness divide moderated the relationship between device appropriateness divide and e-learning self-efficacy. Our study provides an insightful understanding of the device appropriateness divide, which can offer relevant stakeholders practical suggestions to enact better e-learning strategies.

CRedit authorship contribution statement

Cuicui Cao: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis,

Conceptualization. **Yuni Li:** Writing – review & editing, Validation, Software, Methodology. **Ling Zhao:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Yuan Li:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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Appendix A. Instrument measurement items

Table A1
Instrument measurement.

Construct	Items	Source
Social support (SS)	My family always gives me encouragement regarding e-learning during COVID-19. My family provides the necessary help and resources to get me used to e-learning during COVID-19. I am always supported and encouraged by my family to learn online during COVID-19.	(Martins and Kellermanns, 2004)
E-learning self-efficacy (ESE)	I am confident in my ability to master new materials in online learning situations. I am confident in my ability to complete related homework after taking online lessons. I am confident that I can completely adapt to online learning.	(Shen et al., 2013)
Behavioral engagement (BE)	I follow the rules in online classes. I am an active student in online learning. I do my homework in time after online classes.	(Gunuc and Kuzu, 2015)
Physical space for e-learning (PS)	I have a quiet room in which I can take e-learning without interruptions. (Yes (A distraction-free space); No (A space with distractions))	(Tate and Warschauer, 2022; Singh et al., 2021)
Academic performance before full-time e-learning during COVID-19 (APB)	Overall, which rank could accurately reflect your academic performance in your class before full-time e-learning during COVID-19? Top 20 % of your class; 20 %–40 % of your class; 40 %–60 % of your class; 60 %–80 % of your class; Last 20 % of your class	(Zhao et al., 2010)

Table B1
Variance inflation factor test.

Variables	VIF	1/VIF
Social support	1.336	0.749
E-learning self-efficacy	1.515	0.660
Device type	1.146	0.873
Physical space for e-learning	1.143	0.875
Grade	1.154	0.867
APB	1.087	0.919
Gender	1.025	0.976

Note: APB = Academic performance before full-time e-learning during COVID-19.

Table B2
Marker variable technique.

	SS	ESE	BE	DT	PS	Grade	APB	Gender
SS		0.490**	0.539**	0.092*	0.203**	0.020	0.161**	−0.094*
ESE	0.482**		0.626**	0.179**	0.288**	−0.076	0.272**	−0.121**
BE	0.532**	0.620**		0.137**	0.190**	0.016	0.225**	−0.035
DT	0.077	0.166**	0.123**		0.068	−0.276**	−0.101*	−0.060
PS	0.190**	0.276**	0.177**	0.053		−0.192**	0.048	−0.029
Grade	0.004	−0.093*	0	−0.297**	−0.211**		0.032	0.061
APB	0.147**	0.260**	0.212**	−0.119**	0.033	0.016		0.012
Gender	−0.112**	−0.139**	−0.052	−0.077	−0.046	0.046	−0.004	

Note: The area above the diagonal represents the original correlations, The area under the diagonal represents the adjusted correlations; BE = Behavioral engagement; ESE = E-learning self-efficacy; PS = Physical space for e-learning; DT = Device type; SS = Social support; APB = Academic performance before full-time e-learning during COVID-19.

** p < 0.01.

* p < 0.05.

Data availability

Data will be made available on request.

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Cuicui Cao is currently an assistant professor from the School of Information Management, Hubei University of Economics in China. She received her Ph.D. from Huazhong University of Science and Technology. Her research interests include user behaviors in the context of artificial intelligence (AI) applications, human-AI interaction and digital divide. She has published in *Computers in Human Behavior* and *Pacific Asia Conference on Information Systems (PACIS)*.

Yuni Li is currently an assistant professor from the School of Information Management, Hubei University of Economics in China. Her research interests include crowdsourcing, digital divide and algorithmic management. She has published in *Information & Management*, *Computers in Human Behavior* and *Pacific Asia Conference on Information Systems (PACIS)*.

Ling Zhao is a Professor from the School of Management, Huazhong University of Science and Technology in China. Her research focuses on user behaviors in the context of e-commerce and social commerce, IT ethical issues such as information security and user privacy, digital divide, and etc. Her research has appeared in journals such as *Decision Support Systems*, *Information & Management*, *International Journal of Information Management*, *Internet Research* and *Computers in Human Behavior*, and etc.

Yuan Li is a researcher from the Optics Valley Institute of Education Development in China. Her research focuses on digital divide and IT usage of K-12 students. Her research has appeared in journals such as *Computers in Human Behavior*.