



Learning and Assessment for  
**DIGITAL CITIZENSHIP**

# Hong Kong Students' Digital Citizenship Development 2019-2021

Findings from a longitudinal study

Hong Kong  
May 2022







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## Website

Please visit the following website for more information about the project and current events: <https://ecitizen.hk>.

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# Foreword

Learning and Assessment for Digital Citizenship (eCitizenship for short) is an interdisciplinary research project which examines the impact of digital media on the everyday life of children and youth and on their development as citizens in an increasingly technology-intensive and globally connected world. This project, funded under the Theme-based Research Scheme of the Research Grants Council of the HKSAR Government (#T44-707/16N), was conducted between November 2016 and March 2021. It was led by an interdisciplinary team of researchers from The University of Hong Kong and The Hong Kong University of Science and Technology from the fields of education, human development, humanities, information science and computer engineering.

A core component of the project was a longitudinal study to assess the growth and development of key digital citizenship competences, including digital literacy and collaborative problem-solving among students. The project also sought to understand how students' personal, family and school backgrounds contributed to their digital citizenship development and wellbeing. A longitudinal cohort design with three age cohorts from primary to upper secondary tertiary levels was adopted in this component of the project with the main data collection conducted in two waves: Wave 1 in the 2018-2019 school year and Wave 2 in the 2020-2021 school year. The study has developed a theoretically robust and empirically grounded conceptual framework and instruments for measuring digital citizenship development from childhood to early adulthood. Initial findings from the Wave 1 data have been presented in the report *Hong Kong Students' Digital Citizenship Development: Initial Findings*. This report presents key findings from the Wave 2 data as well as the longitudinal analyses of the data collected from the two waves.

With the robust digital literacy assessment and survey instruments developed in this study, and the rigorous analyses conducted, findings revealed the complex nature of the digital divide among students. The digital divide was not only apparent in access to digital technology as often reported in the literature, but we uncovered a less reported divide in digital competence and family support. Our Wave 1 findings alerted the Hong Kong community to the significant digital divides in students' learning and wellbeing that already existed before the onset of the COVID-19 pandemic, and the serious implications of these divides among students when online teaching and learning became necessary during recurring periods of extended school suspension. Our longitudinal analyses using data collected from both waves show that divides in access to digital technology can be mitigated through the concerted efforts of the community and the HKSAR Government. We found that amidst the contextual changes taking place between the two waves of data collection, the digital literacy of all three age cohorts of students improved significantly. However, this was not accompanied by increases in students' collaborative problem-solving abilities. Furthermore, the digital competence divide increased. The findings also show significant relations between students' digital literacy and their wellbeing, both in terms of their online self-efficacy and socioemotional wellbeing. Significant relations were found between a student's digital literacy and wellbeing outcomes and the socioeconomic composition of the school that the student studied in.

Findings from the wave 1 and present report have significant implications for policy and practice in the areas of curriculum and pedagogy, teachers' professional learning, school leadership and management, parenting practices and family support, youth services, as well as innovation and regulations in the e-learning industry. There are also more elements to the eCitizenship project than the assessment and survey components discussed in this report, such as online collaborative problem-solving games, enhancing students' self-regulation and planning through self-tracking,

and the use of advanced AR/VR technologies for teaching and learning. Interested readers can find additional information about the project and research findings to-date on the eCitizenship project website (<https://ecitizen.hk>).

The accomplishment of the project would not have been possible without the dedication and expert contributions of the entire team of project Co-Principal Investigators, Co-Investigators, as well as the commitment and support of various groups and individuals. In particular, I would like to thank all participating schools, teachers and students who gave up their time to take part in this study. I would also like to acknowledge the invaluable support of the eCitizenship Advisory Committee and the Centre for Information Technology in Education at The University of Hong Kong, especially for the critical role they have played in the instrument design and data collection process. Also, I would like to express my deep gratitude to all the contributions provided by the research staff and postgraduate research students in this project.



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# 1. Understanding students' digital citizenship development over time and across age groups

## 1.1. The context of this study

Citizenship has traditionally been defined by membership in geopolitical entities such as nation states, with rights and responsibilities as the common denominator of citizenship. The rapid development of digital technologies has changed the lives of children and young people and points to the need to broaden the definition of citizenship. The Internet and social media allow us to easily connect to and access vast amounts of information. Changes in our society brought about by the development of digital technology have clear implications for the well-being of children and youth growing up in this digital age. It is therefore not surprising that interest in the notion of “digital citizenship” has increased significantly in recent years. In this context, the Learning and Assessment for Digital Citizenship (eCitizen for short) project aimed to address the grand challenge of understanding and enhancing the development of digital citizenship as a multi-faceted human capacity within the diverse educational, social, cultural, and technological contexts in Hong Kong.

The goal of the project was to develop a theoretically robust and empirically grounded conceptual framework and benchmarks for digital citizenship from childhood to early adulthood that encompass the cognitive, metacognitive, social and affective learning outcomes important for personal and social well-being. It also aimed to establish a technology infrastructure that can be used for the cumulative construction of effective models of formal and informal learning at home and in schools for the facilitation of digital citizenship. The five specific objectives of the project included: (1) to develop a conceptual framework for digital citizenship that encompasses the cognitive outcomes for digital literacy (DL), metacognitive and social outcomes for collaborative problem solving (CPS) and affective outcomes for self-regulation, based on the relevant theoretical, pedagogical and assessment research literature; (2) to develop age-appropriate instruments for assessing digital citizenship (age range: 7 to 22); (3) to identify and further develop a set of indicators for digital technology use, family and school environments for formal and informal learning interactions, and different types of activities likely to influence the digital competence; (4) to develop serious game designs (role plays/simulations) to foster digital citizenship for adolescents and young adults within real-life contexts, which will be launched as game competitions for vast numbers of inter-school learner teams based on the assessment framework and to build better learning theory and game designs for digital citizenship development; and (5) to conduct longitudinal studies of the development of digital citizenship that can be continued beyond the project's lifetime.

This report focuses on the longitudinal cohort study that constituted the core of the eCitizen project. It involved three age cohorts: 8-10, 11-14, and 15-18, with main data collection conducted in 2018-2019 and 2020-2021. This was the first education-focused project awarded under the Theme-based Research Scheme of the Research Grants Council of Hong Kong. The project brings together an interdisciplinary team of local researchers at the University of Hong Kong and the Hong Kong University of Science and Technology as well as international experts, from fields including education, learning sciences and learning technology, computer and information science, engineering, social science, humanities, journalism, pediatrics and adolescent medicine. The theoretical contributions and the tools and instruments developed

through the project are expected to have significant implications and potential contributions for policy and practice, not only for curriculum and pedagogy, but also in parenting practices and family support, youth services, as well as innovation and regulations in the e-learning industry.

It was almost prescient that the first wave of the longitudinal data collection was completed before the summer of 2019. Since then, Hong Kong education has experienced significant disruption, which is still ongoing at the point of writing. Hong Kong education was shifted online briefly in late 2019 due to social unrest, but the major disruption was due to the COVID-19 pandemic. Hong Kong schools have possibly experienced the most extended periods of school suspension globally due to the social distancing measures stipulated by the HKSAR Government. Digital technology became the main conduit for formal schooling (with the slogan “suspend schools without suspending learning”) as well as for leisure activities and socialization for children and youth. Thus, even though the longitudinal study was designed to understand the natural changes in students’ digital competence and well-being amid rapid changes in digital technologies, it became a kind of “natural experiment” that allows us to investigate how digital competence mediated the various aspects of a student’s life and well-being within the complex social milieu in which digital technology played a critical role in facilitating and maintaining the normal functioning of a society.

## **1.2. The conceptualization and measurement of digital citizenship and well-being in this study**

Digital citizenship has been a trendy term since the beginning of the millennium (Chen et al., 2021). As a nascent concept, digital citizenship was largely siloed to refer to an individual’s capacities to adhere to the “norms of appropriate, responsible behavior” (Ribble & Bailey, 2007, p. 10) in the use of digital technology. This conceptualization has dominated the education literature as a core competence needed for citizens to live and learn in the 21st century (Law et al., 2018). On the other hand, Mossberger et al. (2007) argued that as a parallel to the broader concept of citizenship, digital citizenship should include “the ability to participate in the society online” (ibid., p.1) in civil, political and social domains. However, as Isin & Ruppert (2020) pointed out, exercising one’s right through online participation is not a given, unlike in the case of traditional citizenship where the right is often an acquired status such as through birth. Digital social participation is a process of self-actualization. Digital citizenship only comes into being when the individual proactively makes claims on those rights. Integrating the above perspectives, our project conceptualizes digital citizenship as the human capacity to leverage the potential of digital technologies to live and learn and to ensure their own well-being, as well as to exercise their responsibility to engage and participate in the globally networked world (Law et al., 2018).

### **1.2.1. Digital citizenship as core to students’ well-being**

Education has long been considered a human right as it is fundamental to a person’s well-being (OECD, 2017). It is important to recognize that well-being is context dependent. For students to thrive in the digital age, they need digital competence for learning, socialization, entertainment, and everyday transactions through engaging in on- and off-line interactions,

as well as to prepare for their future careers. Research shows that digital literacy is an important protective factor contributing to online resilience and mental health (Bosanac & Luic, 2021). It is only with active and responsible engagement can students actualize their rights, defend human dignity, and promote social justice and equity. Digital citizenship needs to be fostered from early years to realize a child's capacities to cope with adversities, engage in lifelong learning, work collaboratively with others in a productive manner, and be empowered to protect the well-being of the society and the environment (OECD, 2017; Richardson & Milovidov, 2019).

### **1.2.2. Digital competence and its measurement**

While the conceptualization of digital citizenship is multifaceted, digital competence is the core capacity through which the rights and responsibilities of digital citizens can be exercised. Thus, the measurement of digital competence is gaining interest from policy makers and researchers. To date, the measurement of digital competence has been primarily confined to DL, and to some extent, collaborative problem-solving (CPS). There are essentially two approaches to the assessment of DL: via self-reported surveys or performance assessment using a digital device. The former has been very popular due to its ease of administration but is more likely to reflect the respondent's self-efficacy with regard to the specific knowledge and skills surveyed rather than actual competence. DL performance assessment tends to be administered as national assessments (e.g., in Australia, ACARA, 2011; 2018) or in international comparative studies, such as in ICILS (Fraillon et al., 2014; Fraillon et al., 2019) due to the complexities required in terms of instrument design, validation and analysis. It is important to point out that performance assessments of DL for primary school students are extremely rare. A major contribution of the eCitizen project is the development of a validated instrument that can measure and compare DL performance across a wide range of age cohorts, using the DigComp 2.1 framework (Carretero et al., 2017) developed by the European Commission Joint Research Centre as the assessment framework. Further details about the DL assessment framework and the instrument used in this study is reported in [Chapter 2](#).

Another important component of digital competence is CPS. Collaborating to solve authentic problems is important for digital citizens because many workplaces, social and political problems cannot be solved by individuals acting alone. To measure students' CPS skills, the eCitizen project adopted the assessment instrument developed by the Assessment Research Centre (ARC) at the University of Melbourne (Hesse et al., 2015). As this test is considered valid only for the assessment of students aged 11 or above, it was only administered to the two secondary student cohorts in 2019 but included all three of the sampled cohorts in 2021. Details about the CPS assessment framework and instrumentation as well as the findings about students' CPS achievement and development are reported in [Chapter 3](#).

### **1.2.3. Measuring students' digital technology use and their well-being**

The rapid proliferation of digital technology use and its adoption by society have transformed how we interact with and relate to others formally and informally in environments in which digital technology is pervasively integrated. As a result, our individual and social well-being are now closely linked to the state of our information environment and the digital competences



that mediate our interaction with it (Floridi, 2014). In this report, we conceptualize wellbeing as comprising both general and digital wellbeing. For the former, we collected data on measures of general health (incl. physical activity, sleep, and general mental health). For the latter, we adopt the conceptual framework of EU kids Online (Livingstone et al., 2015) to examine the relationship between digital technology use, the risk factor associated with digital activities and the possible harm that such risks may bring. Details about the design of the study component on students' digital technology use and well-being as well as the findings are reported in [Chapter 4](#).

#### **1.2.4. Personal and family background factors influencing students' digital citizenship capacity development and well-being**

The development of students' digital citizenship competence and well-being depends on both individual and family factors. The inequalities in access to economic and intellectual resources as well as socioemotional care and learning support could influence students' digital competence development. van Deursen & Helsper (2015) differentiated three levels of digital divide. The first-level divide refers to the unequal access to digital technologies between the haves and have-nots; the second-level divide is the gap in digital usage and skills; and the third-level divide concerns discrepancies in the returns from individuals' technology usage. In Hong Kong, while 94% of households had access to the Internet in 2019, the proportion of poor families (i.e., those with monthly household income below HK\$10,000) having access was much lower at 71% (Census and Statistics Department, 2020). Findings from the Wave-1 results of this project show that up to 13% of primary students and 10% of secondary students did not have access to a large screen device (which could be a computer, a laptop or a tablet) when surveyed in 2019 (Reichert et al., 2020). Overall, nearly 40% of the surveyed students had to share their large screen devices with other family members. Additionally, existing research reported that students from affluent households were more willing to engage in educational activities to learn digital skills and showed a higher level of digital competence than their less socioeconomically advantaged counterparts (Harris et al., 2017). Thus, the lack of adequate access to digital devices due to contextual factors might hinder the development of children and young people's digital competence, which in turn may have a cascading effect on their digital well-being.

### **1.3. Research questions addressed in this report**

Based on the theoretical underpinnings discussed above, [Figure 1.1](#) provides a diagrammatic overview of the conceptual framework relating digital competence as a digital citizenship capacity to wellbeing and digital technology use. This framework is grounded on the assumption that digital competence is important for ensuring the wellbeing of digital citizens, which has two aspects. The first is its positive contribution to citizens' ability to exercise their rights and responsibilities in the digital age, which has been discussed in the previous sections. The second relates to adverse effects that digital technology use may have on citizens' wellbeing, including mental health problems, Internet addiction, game addiction, etc. and whether digital competence may have any influence on such negative effects. Based on this conceptual framework, this report addresses four key research questions:



1. What level of digital citizenship capacity did students reach and whether these were influenced by the students' family socioeconomic background?
2. Did students' digital citizenship capacity influence the extent to which students had experiences indicative of adverse wellbeing?
3. Whether and how did different uses of digital technology correlate with students' digital citizenship capacity?
4. What were the changes that took place between the two waves of data collection in 2019 and 2021? Which of the changes observed were likely to be related to the tsunamic social and schooling changes that took place due to the COVID-19 pandemic induced extended disruptions that started since February 2020?

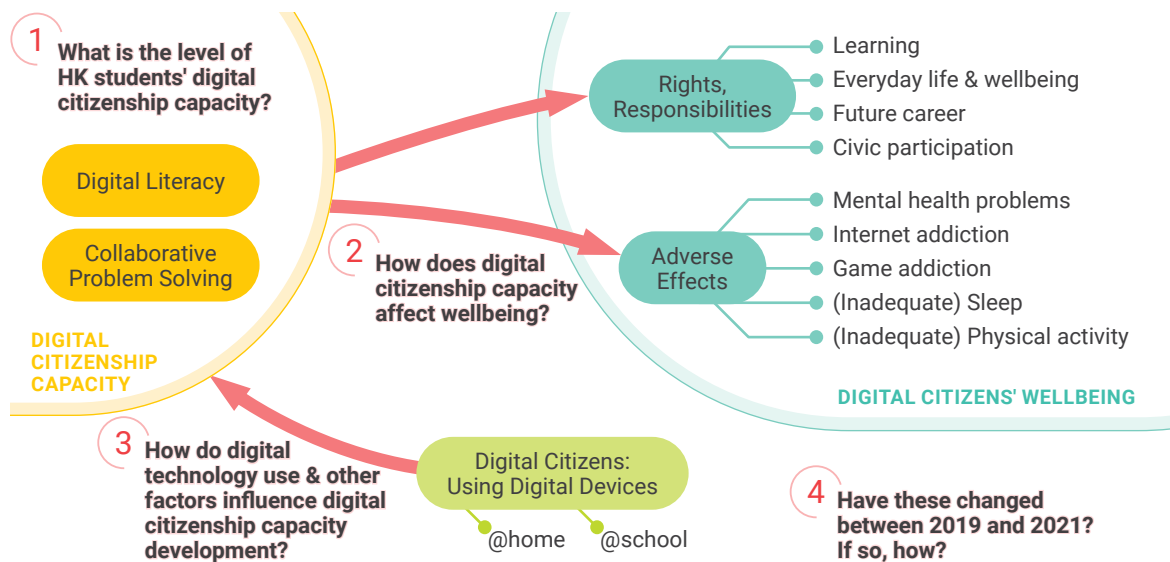


Figure 1.1. The Conceptual Framework and Research Questions Underpinning this Study.

## 1.4. Study design

The project adopted a cross-cohort longitudinal design (see Figure 1.2) to examine performance differences among students in three different age cohorts, including one cohort of primary school students (Cohort 1: P3 in 2018/19 and P5 in 2020/21) and two cohorts of secondary students (Cohort 2: S1 in 2018/19 and S3 in 2020/21; Cohort 3: S3 in 2018/19 and S5 in 2020/21) in Hong Kong. Cohort 2 and cohort 3 students were sampled from the same schools such that we can compare the data from S3 students in 2019 with S3 students in 2021 from the same schools to identify whether there were significant differences between these two groups of students that are possibly due to extraneous factors beyond the family and school levels. Wave-1 data collection (pretest) in the 2018/19 school year was conducted during the period from January to June 2019, and Wave-2 data collection (posttest) in the 2020/21 school year was conducted during April to July 2021. Such a study design is suitable to observe intra-individual development of digital citizenship (longitudinal component) and to understand inter-individual differences in students' digital citizenship across different age cohorts (cross-cohort component).

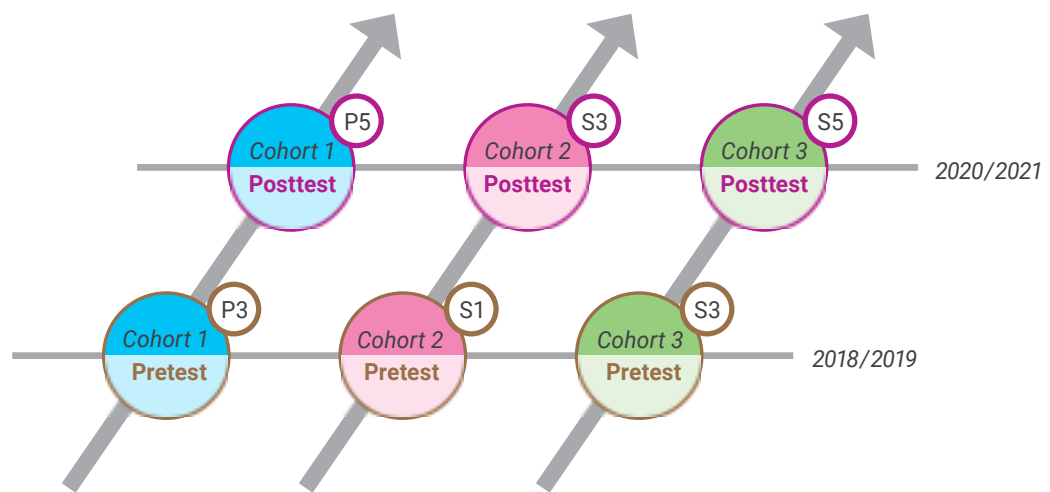


Figure 1.2. A Cross-cohort Longitudinal Design of this Study.

The current report focuses on students' digital competence and other measures using data from the two waves of data collection conducted in the 2018/2019 and 2020/2021 school years. Specifically, assessment data were collected to capture DL and CPS as crucial digital citizenship competences. Supplementary data were collected through online questionnaires to learn about students' digital access and usage, online activity, risky online behaviors/ experiences, and digital safety. Additional data were also gathered from teachers and principals as school factors can influence students' digital citizenship development. However, reporting on school level factors is beyond the scope of this report.

## 1.5. Sampling

The sampling design used stratified random sampling with districts selected based on geography and socioeconomic status. For the current project, four districts were selected to include a diversity of average household income according to the census statistics in Hong Kong: North (New Territories East Region), Tuen Mun (New Territories West Region), Sham Shui Po (Kowloon Region) and Wan Chai (Hong Kong Region). Primary and Secondary schools were then randomly selected within each of the sampled districts. If an originally sampled school declined to participate, a replacement school was randomly selected from the same district as the original sampled school. A total of 18 primary schools and 14 secondary schools took part in the study in Wave-1. In most schools, students from two classes of each cohort were randomly selected to participate in the study, while in some schools, the classes were recommended by the school principal. Over 2,000 students completed the assessment and/or survey, and about 360 teachers and principals of the sampled students responded to short questionnaires. Ethical clearance approval was obtained from the Human Research Ethics Committee of the University of Hong Kong for this study. Written consent was obtained from school principals for their school's participation. For primary students, written assent was obtained from them, and written consent was obtained from their parents. For secondary students, written consent was obtained from them; their parents were informed and could object to their children's participation.

In Wave-2, 12 of the 18 primary schools and 11 of 14 secondary schools in Wave-1 agreed to participate. Since the students who participated in Wave-1 in the two sampled classes from

each school may be placed in different classes when they entered a higher grade level, two to six classes in each school were selected for the study in Wave-2, in order to retain the maximum number of participating students from Wave-1. Around 2,000 students completed the Wave-2 assessment and/or survey, of which 886 students also participated in Wave-1. The 886 students are therefore the **common sample** on which we can conduct longitudinal data analysis. In addition, over 300 responses were received from school leaders (including the principals) and teachers from the participating schools. Table 1 presents the sample information for both waves of data collection.

Table 1  
Number of Participating Schools, Classes, Students, Teachers and Principals

Sample information					Responses							
Cohort	Schools		Classes		DLA		CPS		SVY		Teachers & School leaders	
	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021	2019	2021
C1	18	12	39	48	750	507	-	307	736	449	178	155
C2	14	11	27	39	715	839	705	682	711	828	201	146
C3			29	38	581	625	593	507	581	606		

Note. DLA = assessment of digital literacy, CPS = assessment of collaborative problem solving, SVY = student survey questionnaire.

## 1.6. Structure of the report

This report is presented in seven chapters. Chapter 1 introduces the context, conceptual framework, goals, research questions and research design of this study. Chapters 2 to 6 report on the empirical findings from the assessment and survey data collected from students to address the first three research questions, respectively, as well as analyze the changes that took place between the two waves of data collection with respect to the analytical focus of the chapter. In particular, Chapter 2 addresses part of Research Question 1 by reporting on students' DL development over time and across age groups, as well as the relationship between family factors and students' DL development and growth. Chapter 3 addresses the second part of Research Question 1 by reporting on students' development and growth in the CPS skills component of digital competence. Chapter 4 addresses part of Research Question 2 by reporting on the digital access, usage, and wellness situations of the three cohorts of students and their changes over time. Chapter 5 addresses Research Question 3 by reporting on students' engagement in different activities involving the use of digital technologies and whether such engagement correlated with their level of digital competence. Further, it is not conceptually sound to assume that digital competence per se would directly affect students' experiences associated with adverse well-being. Rather, we conceptualize that digital competence may serve as a mediator between students' digital technology use and their well-being. Thus Chapter 5 also reports on the modeling results from the mediation analysis. Chapter 6 addresses the second part of Research Question 4: whether there is an indication that there are extraneous factors at the social and/or technological level between the two waves of data collection that contributed to the changes observed. To address this question, we modeled the relation between various online activities and digital competence among S3 students in both 2019 (Cohort 3) and in 2021 (Cohort 2). Chapter 7 summarizes the findings, discusses the implications and provides recommendations for research, policy and practice.

## 2. Students' digital competence development

### 2.1. Introduction

#### 2.1.1. Digital literacy assessment framework

The development of a robust assessment instrument that can be used to measure the digital literacy achievement of students from P3 to S5 according to a well-accepted assessment framework is a key challenge for the present study. A detailed description of this component of our research undertaken for Wave-1 of this study was reported in Jin et al., (2020). Briefly, the Digital Literacy Assessment (DLA) instrument used in this study was developed using the European Commission's Digital Competence Framework 2.0 (DigComp 2.1) (Carretero et al., 2017; Vuorikari et al., 2016) as the assessment framework. [Figure 2.1](#) shows the five competence areas in the framework.



Figure 2.1. The Five Competence Areas in the DigComp 2.0 Framework (Carretero et al., 2017).

#### 2.1.2. Digital literacy assessment

Our team developed a computer-administered DLA with all items mapped onto the five competence areas and associated sub-competences in the DigComp 2.0 framework, as indicated in [Table 2.1](#). Items developed according to the assessment framework were assembled into three booklets, one for each age cohort, with some common items across the booklets to equate performance across the booklets. Pilot studies were carried out to ensure the validity and reliability of the DLA. Detailed reporting of the instrument development has also been reported in Jin et al., (2020).

In the *Wave-1* DLA, three booklets with a total of 80 items were administered to three student cohorts (P3, S1, and S3). In the *2021* DLA, the assessment instrument was amended to measure DLA again 2 years after *Wave-1*, and comprised three booklets with a total of 95 items administered to the three student cohorts (P5, S3, and S5) from April to July 2021. The *2021* DLA contained several common items across the three cohorts to allow comparisons

among students. Moreover, some common items were included across 2019 and 2021 DLAs to track the students' performance over time. Table 2.1 shows the distribution of items per sub-competence for all three cohorts across the two waves.

Due to the long periods of school suspension during the 2020-21 school year, arranging for onsite data collection in Wave-2 was a major challenge. In order to maximize the participation sample, the research team piloted and refined in Wave-2 two further modes of data collection in addition to the onsite mode adopted in 2019: online supported and online self-directed. Schools could select one of the three modes of data collection for their students. Careful statistical analyses showed that the three modes of assessment were valid and fair (Pan et al., 2022). Further statistical analyses were conducted to ensure the quality of the assessments (the fairness of the DLA between genders and SES groups). Finally, we estimated the students' 2021 DL competence using a multigroup item response model based on common items across the different cohorts. The scores were transformed based on 30 common items across the two DLA waves, which allowed comparisons between 2021 and 2019 DLA by using the Stocking-Lord method (Stocking & Lord, 1983). The reliability of 2021 DL scores was 0.91, which indicates that the 2021 DLA results were highly robust.

Table 2.1

*Item Distributions of the 2019 and 2021 DLAs Mapped to the DigComp 2.0 Framework*

Competence Areas	Sub-competences	2019	2021
1. Information and data literacy	1.1. Browsing, searching, filtering data, information and digital content working	5	4
	1.2. Evaluating data, information and digital content	4	4
	1.3. Managing data, information and digital content	6	4
2. Communication and collaboration	2.1. Interacting through digital technologies	5	3
	2.2. Sharing through digital technologies	8	6
	2.3. Engaging in citizenship through digital technologies	3	4
	2.4. Collaborating through digital technologies	0	5
	2.5. Netiquette	4	3
	2.6. Managing digital identity	2	4
3. Digital content creation	3.1. Developing digital content	4	1
	3.2. Integrating and re-elaborating digital content	0	4
	3.3. Copyright and licenses	3	3
	3.4. Programming	0	11
4. Digital safety	4.1. Protecting devices	7	6
	4.2. Protecting personal data and privacy	11	6
	4.3. Protecting health and wellbeing	5	2
	4.4. Protecting the environment	1	4
5. Problem solving	5.1. Solving technical problems	11	7
	5.2. Identifying needs and technological responses	0	6
	5.3. Creatively using digital technologies	0	4
	5.4. Identifying digital competence gaps	1	4
Total		80	95

### 2.1.3. Study design

**Sample** The 2019 DLA was administered to over 2,000 students from 18 primary schools and 14 secondary schools. Among the 32 2019 schools, 23 schools (12 primary schools and 11 secondary schools) participated in the 2021 data collection, with over 1,900 students completing the DLA (Table 2.2). As schools might rearrange the assignment of students to different classes during different school years, some of the students in the original cohorts were moved to different classes. However, for simplicity in test administration, some schools chose intact classes in 2021 for data collection. Thus the 2021 sample included new students who had not participated in 2019 as well as lost some from the original Wave-1 sample. Among all 2021 participants, about 45% participated in both 2019 and 2021 studies.

Table 2.2  
Number of Participating Schools, Classes, and Students in 2019 and 2021

Cohort	Schools		Classes		Students		
	2019	2021	2019	2021	2019	2021	Common
C1	18	12	39	48	750	570	234
C2	14	11	27	39	715	839	389
C3			29	38	581	625	264

Note. Common: students who completed both 2019 and 2021 DLAs.

**Purpose** Table 2.2 shows the three samples from both waves. Based on the study design and the challenges of 2021 data collection as explained, there were three student samples: (1) 2019 full samples from those completing 2019 DLA, (2) 2021 full samples from those completing 2021 DLA, and (3) Matched samples from those completing both 2019 and 2021 DLAs (See Figure 2.2 for a schematic of the three samples).

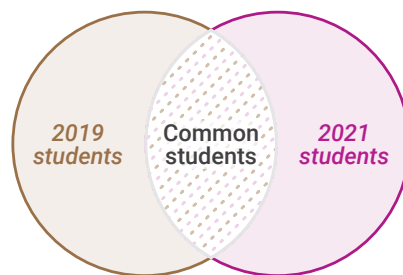


Figure 2.2. Venn Diagram for the Samples Used in this Chapter.

This chapter aims to provide details of: (1) the students' DL development from 2019 to 2021 based on the full sample of all students completing the two waves, and (2) students' DL growth based on matched samples (students completing both waves of DLA over time).



## 2.2. Development of students' digital literacy from 2019 to 2021

### 2.2.1. The widening of digital literacy throughout the three age cohorts

Compared to 2019, the DL performance of students in all cohorts generally increased in 2021. As shown in Figure 2.2, the DL scores in each student cohort improved over the 2 years. The gaps between the lower quartile (25%) and the upper quartile (75%) in all three cohorts widened between 2019 and 2021. Notably, in 2019, primary school (P3) students had significantly lower scores than secondary school students, but there were no significant differences between Secondary 1 (S1) and Secondary 3 (S3) students. However, in 2021, the between-cohort differences were statistically significant; S3 students had significantly higher scores than Primary 5 (P5) students and Secondary 5 (S5) students had significantly higher scores than S3 students. Figure 2.3 describes the distributions of both 2019 and 2021 DL scores across all participants.

Each box presents the DL score distribution in each cohort, with the blue, red, and green boxes representing the DL scores of cohorts 1, 2 and 3 for 2019 (light color) and 2021 (dark color), respectively. The y-axis presents the DL scores, where 0 is the average score of 2019 DL scores across all cohorts. The top and bottom borders represent the 75<sup>th</sup> and 25<sup>th</sup> percentile of the DL scores and the middle line represents the 50<sup>th</sup> percentile, respectively. In addition, the whiskers (two lines outside the box) extend from the minimum to the 25<sup>th</sup> quartile (the start of the box) and from the 75<sup>th</sup> quartile to the maximum, with dots representing outliers, if any. Notably, each boxplot represents all participants in the respective cohort in each wave, including both common students and students who only participated in 2019 or 2021 DLAs.

The boxplots in Figure 2.3 show that P5 students in 2021 demonstrated digital literacy nearly equivalent to S1 students in 2019. Moreover, S3 students in 2021 performed significantly better than S3 students in 2019.

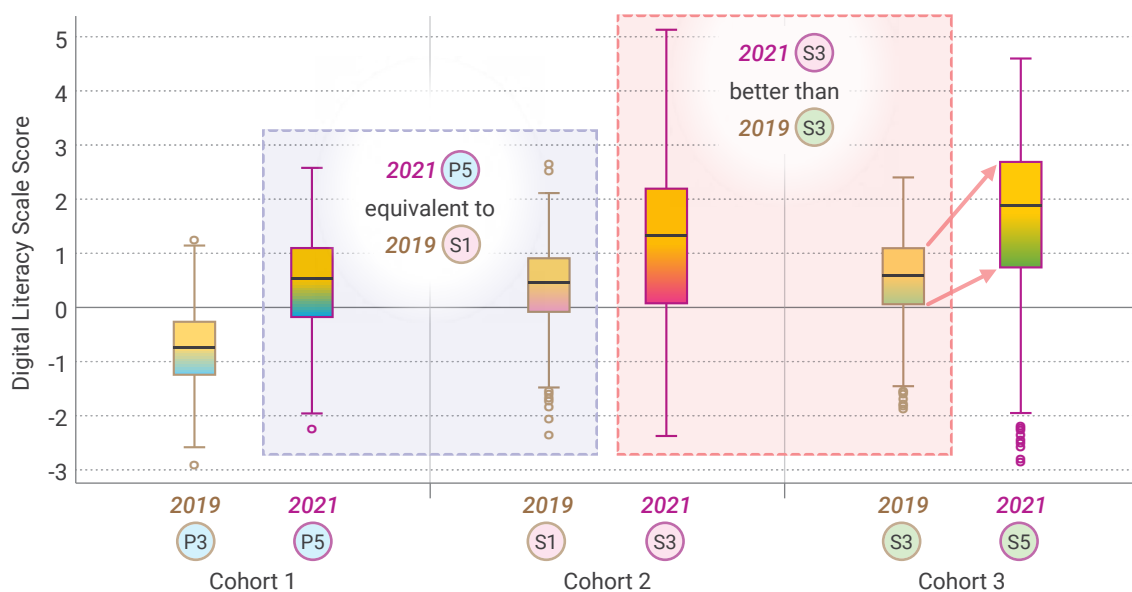


Figure 2.3. Boxplots of Students' Digital Literacy Scale Scores by Cohort in 2019 and 2021.



### 2.2.2. Development of digital literacy by gender

Figure 2.4 displays the DL differences by gender across the two waves. Similar to the 2019 results, girls did not have significantly higher scores than boys in cohorts 1 and 3, but girls had significantly higher 2021 DL scores than their male peers in Cohort 2.

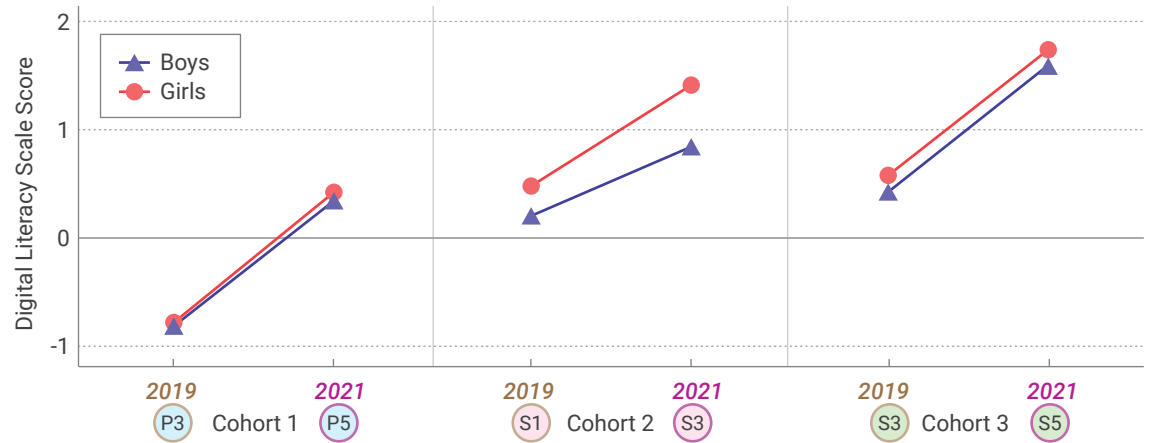


Figure 2.4. Students' Digital Literacy Scale Scores by Gender and Cohort in 2019 and 2021.

### 2.2.3. Digital literacy and development divide within and between schools

In this section, we examine the DL performance of students by school across the two waves for each cohort. Figure 2.5 shows the boxplots of the DL performance of students from each of the participating primary schools in 2019 and 2021, colored in light and dark blue, respectively. Schools X and U showed relatively large improvements between the two waves of data collection. It should be noted that each boxplot represents all participants in one school including both common students and students who only participated in one of the two waves.

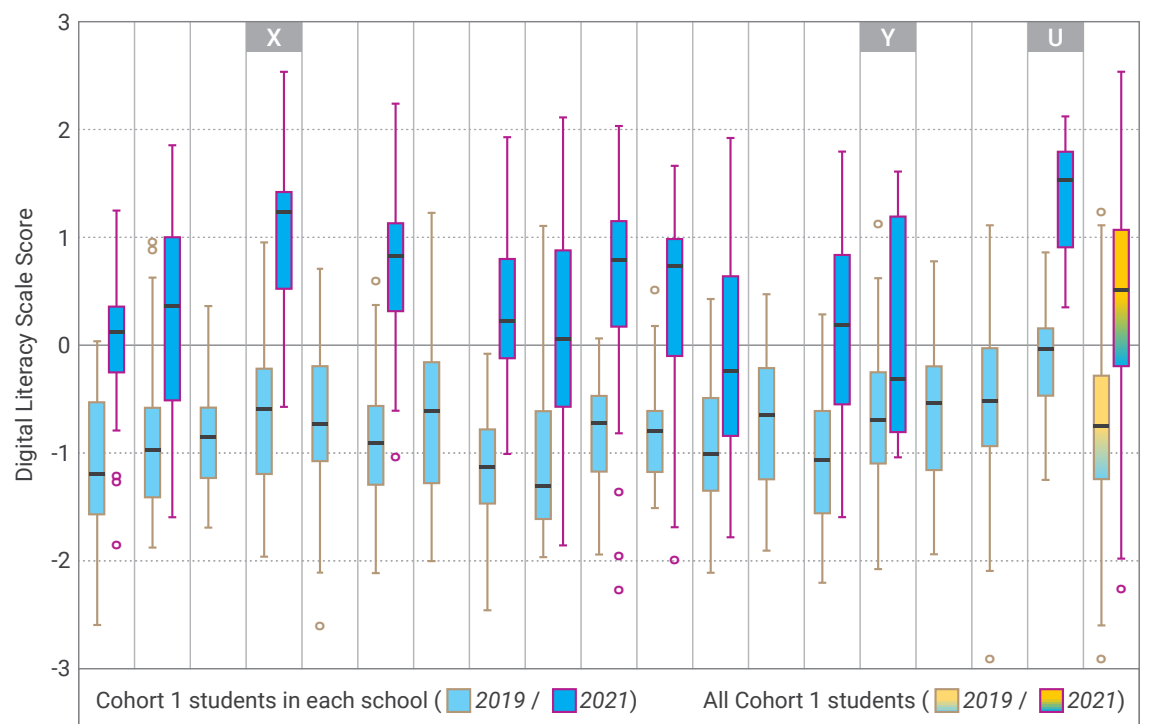


Figure 2.5. Boxplots of Primary School Students' Digital Literacy Performance by School in 2019 and 2021.

The horizontal line within each box indicates the median DL score for the respective sample. Based on the standardized score computed using the total sample from 2019, the median DL score for Cohort 1 was -0.76 in 2019, and 0.52 in 2021. However, we can see from [Figure 2.5](#) that there were large interschool differences in DL achievements in both waves. In 2019, the lowest school median score was -1.30, and the highest school median score was -0.04, indicating an interschool DL divide of 1.26 in the median scores in *Wave-1*. In 2021, the lowest school median score was -.31, and the highest school median score was 1.53, indicating an interschool DL divide of 1.84 in the median scores in *Wave-2*. Hence, we can see that not only was there a large interschool DL divide, but also that the interschool differences increased over time.

Another interschool divide is in the growth in DL demonstrated by students in each of the participating schools. For Cohort 1, the smallest school level growth in median DL score was 0.39, while the largest growth was 1.81.

Other than interschool divides, there were also notable intraschool divides, which are indicated by the box lengths and whisker lengths. In many primary schools, the intraschool differences increased in 2021 compared to 2019. The intraschool differences and the changes in the DL performance divide between the two waves of data collection differed greatly across schools. For example, School Y's box length was 0.86 (standardized score) in 2019, which was about the average box length for the entire sample in 2019, but it grew to be the largest in 2021 at 1.99, showing that the cohort 1 students' DL in this school widened tremendously between the two waves of data collection. What might have led to such large differences in the change in within-school DL performance divide? We do not have direct evidence to answer this question. However, the boxplots show that schools with the largest box lengths tend to be those that had the lowest lower quartile scores. It could be the case that in all schools, there were students who were able to acquire high levels of DL competence without the support of their teachers or schools, as well as students who would not be able to gain much improvement without appropriate guidance and support from their teachers. Schools that showed relatively smaller box lengths (i.e., smaller intraschool differences in DL) were able to provide learning experiences and/or guidance that helped even the lower achievers to make strong progress, such as can be seen in School U.

As shown in [Figure 2.6](#) and [Figure 2.7](#), similar trends are observed in the secondary school cohorts between waves. Notably, most secondary schools had improved their median DL scores. The only exception was the cohort 2 students in School Z, which had lower DL score distribution in 2021 than in 2019. Another general trend was that the interschool and intraschool DL divides became larger in 2021. In some high performing schools, such as School W, they have been able to achieve a large improvement in both Cohort 2 and Cohort 3 students, while maintaining a relatively small DL divide even though the achievement gaps has nonetheless widened.

It is evident from [Figure 2.8](#), which presents the boxplots of all participating schools in the three cohorts, that given the much widened intra- and inter-school DL performance divide, the distribution of students' DL performance in primary school could be higher than those in secondary schools. For example, the DL score distribution of P5 students in the highest performing primary school was higher than the score distribution of the entire S3 sample in 2021. Likewise, the score distribution of the S5 students in the lowest performing secondary school was lower than the score distribution of the entire P5 sample in 2021. Such stark competence divides are of serious concern due to the implications these have on students' learning across the curriculum as learning through digital means has become a major conduit for learning interactions during the pandemic and beyond, as well as on students' wellbeing as will be made evident in later chapters.

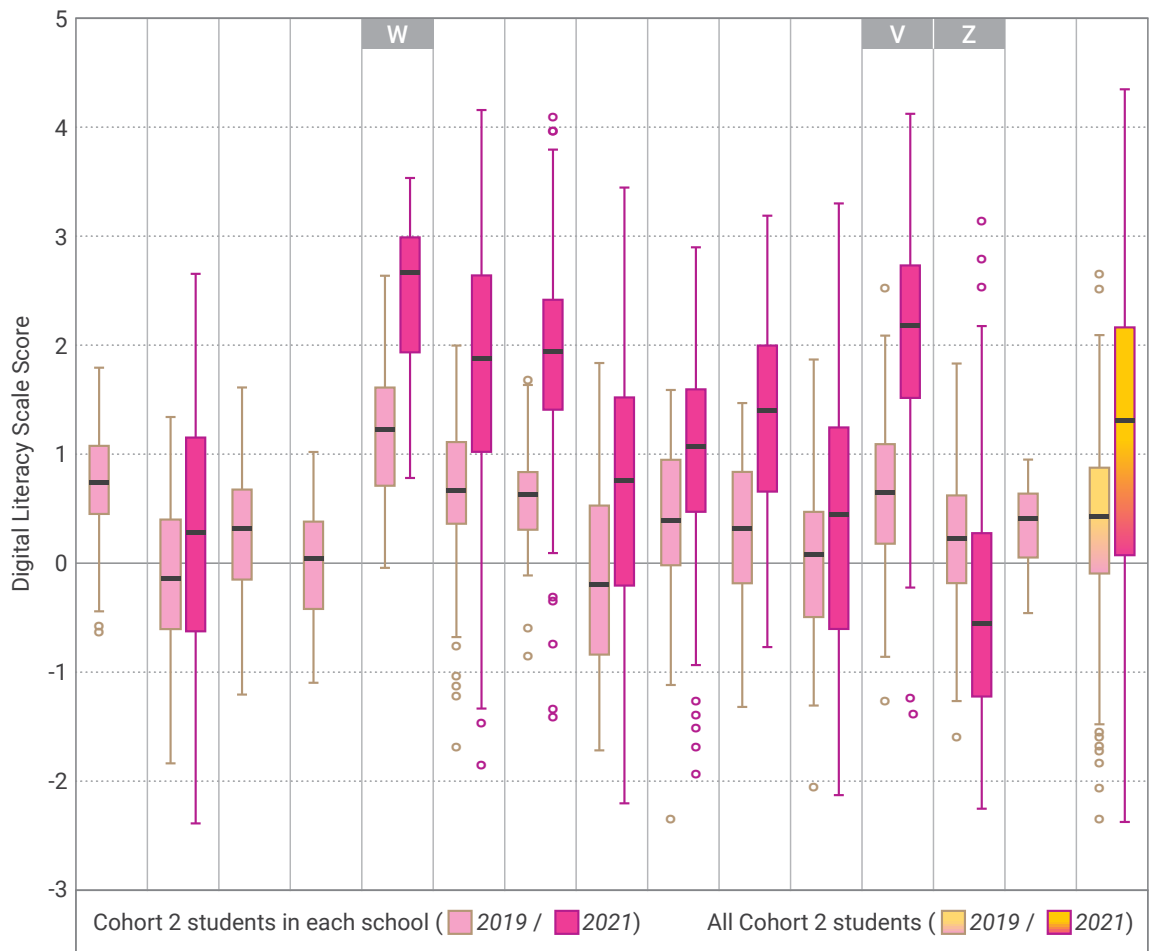


Figure 2.6. Boxplots of Cohort 2 Students' Digital Literacy Performance by School in 2019 and 2021.

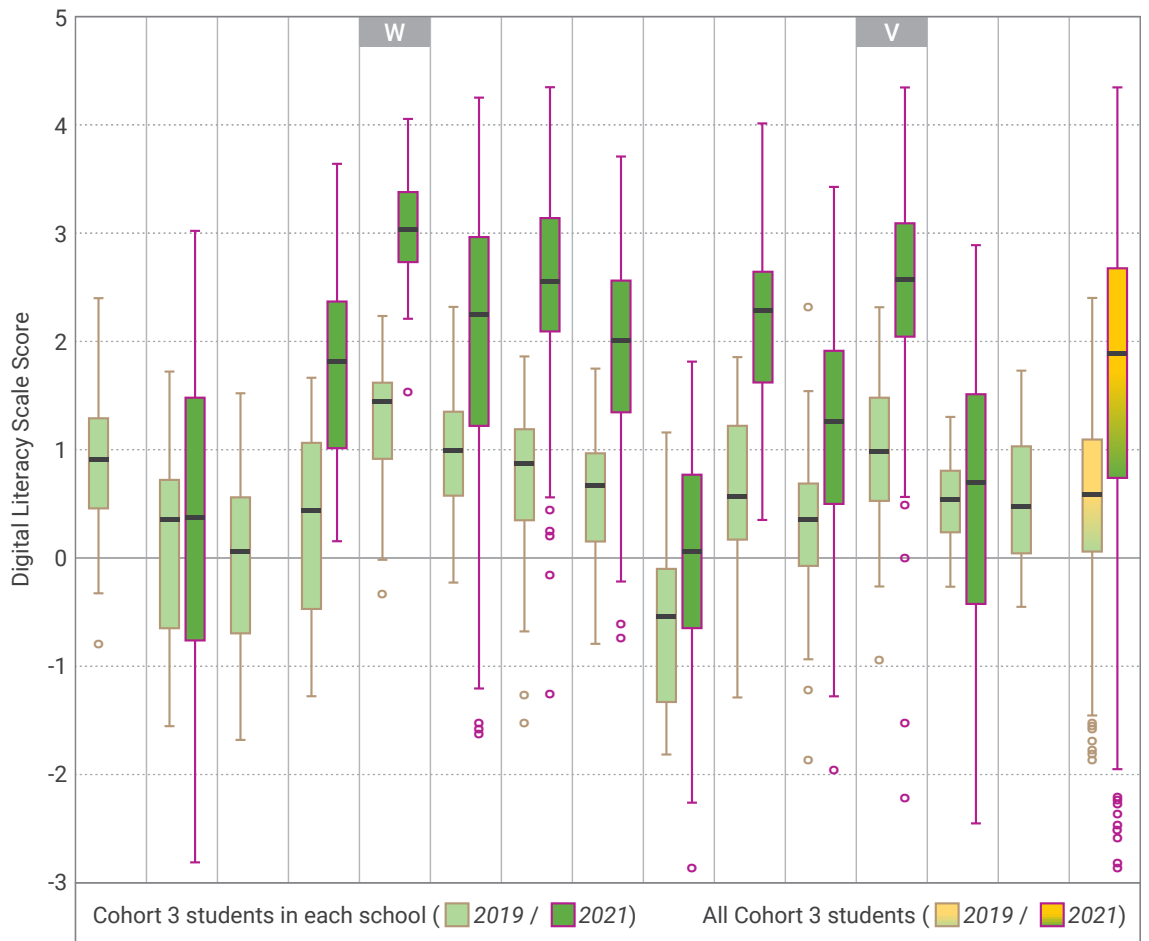


Figure 2.7. Boxplots of Cohort 3 Students' Digital Literacy Performance by School in 2019 and 2021.

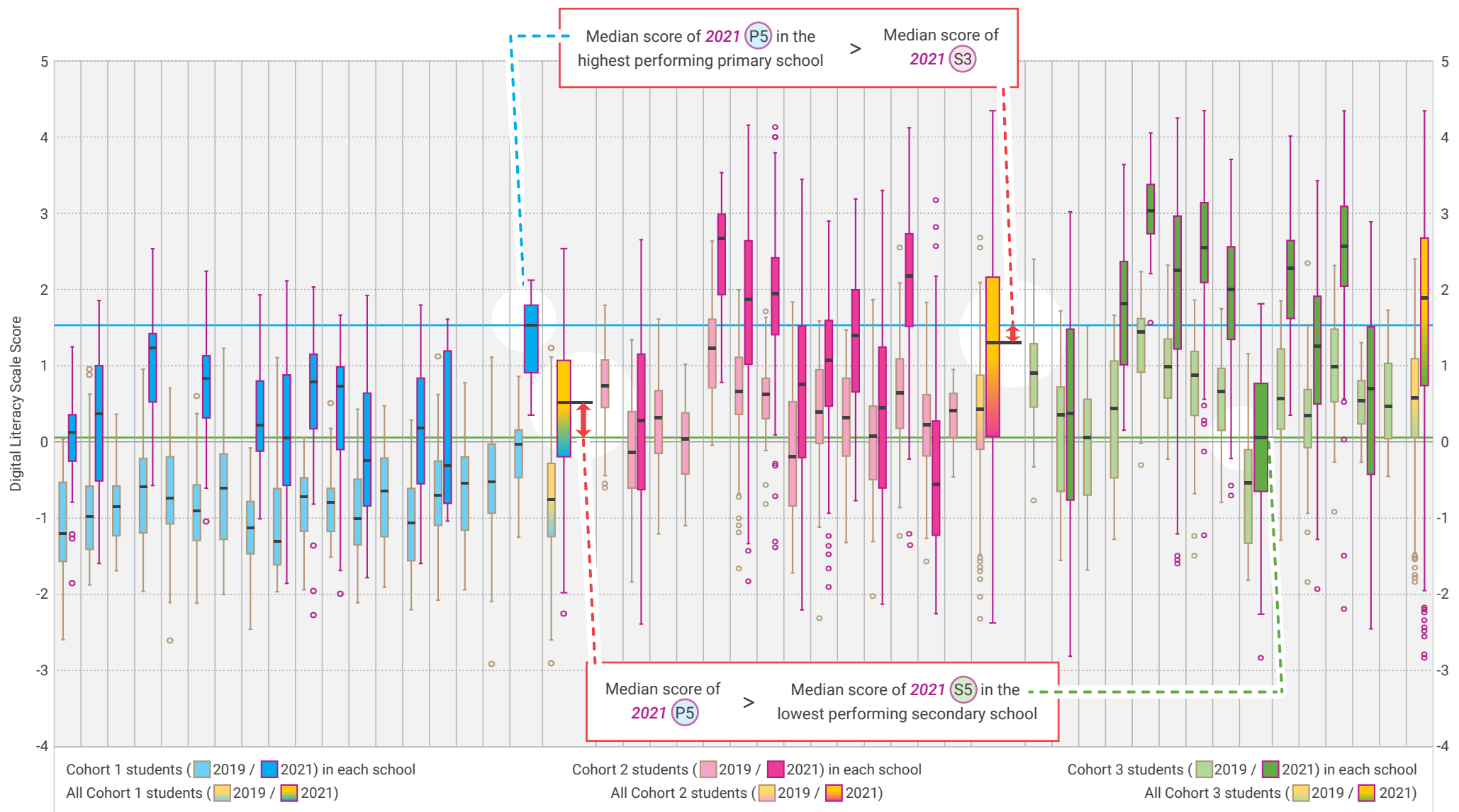


Figure 2.8. Boxplots of all three cohorts' digital literacy performance by school in 2019 and 2021 aligned on the same scale.

## 2.3. Family factors influencing digital literacy development

This section reports on how family factors, including family socioeconomic status (SES) and students' access to large screen devices (LSD) (e.g., desktop computers, laptops, and tablets) at home were related to students' DL development.

### 2.3.1. Students' socioeconomic status

Family SES was measured using a number of SES indicators through the student survey. Factor analysis was conducted on students' responses to the SES related items and identified two family SES factors: (1) academic social capital (ACAD-CAP), computed based on parental education levels and the number of books at home, reflecting the potential academic support likely to be available at home, and (2) home resources (HOME-RES), computed based on whether students have their own room, study desk, and a quiet place to study, and reflecting the availability of economically related physical resources in a student's home that facilitate learning. It should be noted here that in 2019, ACAD-CAP was the only SES indicator included in the student survey. Item response theory (IRT) models were used to calculate the ACAD-CAP and HOME-RES scores. In 2019, ACAD-CAP scores were computed for a total of 1947 students who responded to the related questions in the 2019 student survey. In 2021, ACAD-CAP and HOME-RES scores were computed for 1859 students who responded to the related questions in the 2021 student survey. As shown in Table 2.3, ACAD-CAP and HOME-RES levels in Cohort 1 students were all statistically above the respective average for the entire population sample for the relevant wave of data collection.

Table 2.3  
Mean Scores of ACAD-CAP and HOME-RES for Participants in 2019 and 2021

Cohort	ACAD-CAP Mean (SD)		HOME-RES Mean (SD)	
	2019	2021	2019	2021
C1	0.11 (0.69)	0.15 (0.72)	–	0.11 (0.68)
C2	0.01 (0.70)	-0.01 (0.75)	–	-0.01 (0.76)
C3	-0.15 (0.73)	-0.07 (0.75)	–	-0.04 (0.77)

Note. Both ACAD-CAP and HOME-RES for the whole sample in 2019 and 2021 have a mean of 0.  
– No data was collected.

Past research has shown that SES may have effects at the individual level and/or at the school level. As a first level exploration, we computed the correlations between DLA scores and the two SES indicators in 2021 for each of the three student cohorts at both the individual level and the school mean level, which are shown in Table 2.4. It can be seen that even though all four correlation coefficients were positive and significant for Cohort 1 students, the correlation coefficients for the school level were much higher than for the individual level correlation. It can also be seen that the correlation coefficients were lower for the older cohorts. Given that the effect of SES on students' DL performance operated at both individual and school levels, we further report on our multilevel analyses of these relationships in the next section.

Table 2.4

*Correlations between Individual DL Score and SES (ACAD-CAP and HOME-RES) and between School Mean DL Score and SES across Cohorts in 2021*

Cohort	Correlation between individual DL score and SES indicators		Correlation between school mean DL score and SES indicators	
	ACAD-CAP	HOME-RES	ACAD-CAP	HOME-RES
C1	0.17 **	0.14 **	0.83 **	0.73 *
C2	0.13 **	0.06	0.64 *	0.69 *
C3	0.08	0.02	0.62 *	0.58

Note. \*  $p < 0.05$ , \*\*  $p < 0.01$

### Multilevel impact of SES on students' DL in both waves

We constructed multilevel models to explore the impact of SES on students' DL in both 2019 and 2021 at within-school and between-school levels to answer the following research questions:

1. Did students with higher SES have significantly higher DL scores compared to other students in the same school?
2. Did schools with higher average SES scores have significantly higher average DL scores compared to other schools?

A total of three two-level models were specified, including the 2019 ACAD-CAP model, 2021 ACAD-CAP model, and 2021 HOME-RES model. Students' DL score was the dependent variable in each model, with individual and school means of ACAD-CAP or HOME-RES scores as predictors. The key results from the analysis are presented in [Table 2.5](#).

Table 2.5

*The Regression Coefficients for the Multilevel Structural Equation Models Exploring the Relationship between DL Scores and SES at Student and School Levels*

Cohort	ACAD-CAP				HOME-RES		
	2019		2021		2019	2021	
	Student level	School level	Student level	School level	–	Student level	School level
C1	0.07	0.09	0.07	1.22 **	–	0.08	1.17 *
C2	-0.01	0.08 **	0.01	1.12 *	–	-0.02	2.84 *
C3	-0.07	1.01 **	-0.07	1.75 *	–	-0.03	3.09

Note. \*  $p < 0.05$ , \*\*  $p < 0.01$ .  
– No data was collected.

As shown in [Table 2.5](#), students' SES (ACAD-CAP or HOME-RES) was not significantly associated with their DL scores in both waves after accounting for school-level SES differences, meaning that students with higher SES did not have higher DL scores in both waves in all cohorts compared with other students in the same school. On the other hand, we find that most of the school level regression coefficients were statistically significant, meaning that in those instances, students in a school with the higher mean SES indicator would have a higher probability of achieving higher DL scores. We found that school-level ACAD-CAP

had a significant impact on students' DL scores in both waves for Cohorts 2 and 3, but only in 2021 for Cohort 1. The analysis results also show that HOME-RES had a significant impact on students' DL in 2021 for both Cohorts 1 and 2, but was only marginally significant for Cohort 3. As we did not collect HOME-RES data in 2019, the relevant information is not available.

As predicted by the multilevel analyses results, the two high performing primary schools, Schools X and U (see [Figure 2.5](#)) also had the highest school mean SES scores in both ACAD-CAP and HOME-RES among all primary schools. However, it is important to note that there are also exceptions to the prediction. For example, School V in the secondary school sample (see [Figure 2.6](#) and [Figure 2.7](#)) had relatively higher 2021 DLA scores in both waves, but its mean SES scores were only average level.

### 2.3.2. Students' access to digital devices at home

In both waves, students responded to a range of questions about their access to LSDs (e.g., desktop computers, laptops, tablets) at home and whether the access had to be shared with other family members. In 2019, we found the majority of students in all cohorts had access to at least one of three LSDs, but most had to share these devices with others. In 2021, we found the proportion of students with access to both PCs and tablets and tablets only increased while those having access to PCs only decreased (see [Table 2.6](#)). Moreover, the percentage of students having only shared access or having no access to an LSD decreased over the 2 years (see [Table 2.7](#)).

Table 2.6  
Percentage of Students Having Own Use of Different Large Screen Devices at Home

Cohort	Grade	PC & tablet	PC only	Tablet only
C1	2019 P3	420 (57%)	121 (17%)	96 (13%)
	2021 P5	264 (70%)	22 (6%)	73 (19%)
C2	2019 S1	436 (62%)	147 (20%)	53 (8%)
	2021 S3	540 (69%)	117 (15%)	90 (12%)
C3	2019 S3	318 (55%)	173 (30%)	44 (7%)
	2021 S5	394 (67%)	119 (20%)	53 (10%)

Note. Students who did not respond to the questions or reporting no LSD were excluded from the analysis.  
 PC & Tablet: Students had access to both a desktop/laptop and tablet;  
 PC only: Students only had access to a desktop/laptop at home;  
 Tablet only: Students only had access to a tablet at home.



Table 2.7

Percentage of Students with Different Modes of Access to Large Screen Devices at Home

Cohort	Grade	Shared + own use	Shared use only	Own use only	No LSD
C1	2019 P3	157 (22%)	259 (35%)	221 (30%)	94 (13%)
	2021 P5	89 (24%)	147 (39%)	123 (33%)	16 (4%)
C2	2019 S1	150 (21%)	323 (46%)	163 (23%)	71 (10%)
	2021 S3	242 (31%)	161 (21%)	344 (44%)	35 (4%)
C3	2019 S3	127 (22%)	245 (42%)	163 (28%)	45 (8%)
	2021 S5	179 (31%)	100 (17%)	287 (49%)	19 (3%)

Note. Students who did not respond to the questions were excluded from the analysis.

Shared use only: students shared at least one LSD at home;

Own use only: students had own use of at least one LSD at home;

Shared + own use: students had own use and shared use respectively of at least one LSD at home;

No LSD: students did not have use of an LSD at home.

We next examined the impact of students' access to digital devices at home on students' DL scores in 2019 and 2021 respectively. The results summarized in Table 2.8 show that in 2019, students who had an LSD at home had higher DL scores in Cohort 3 (S3) regardless of the type of LSD or access at home. However, having access to LSD(s) had no significant impact on Cohort 1 (P3) or Cohort 2 (S1) students. In 2021, we found having access to LSD(s) at home had significant positive impacts on students' DL for all cohorts (P5, S3, and S5 students). Altogether, the positive impact of having LSD(s) at home on students' DL increased with age.

Regarding the impact of whether the access to LSDs at home was shared or not on students' DL scores in 2019, we found that shared access benefitted Cohort 1 (P3) students the most, whereas having both shared and own access to LSDs at home benefitted Cohort 3 (S3) students the most. On the other hand, the specific mode of access to LSDs at home did not impact Cohort 2 (S1) students' DL. However, we found that all forms of access to LSDs at home had positive impacts on the DL scores for all student cohorts in 2021.

Table 2.8

Impact of Different Modes of Access to LSD(s) at Home on Students' DL in 2019 and 2021

Cohort/ Grade	Did LSD access in 2019 predict 2019 DL score?
C1 2019 P3	Shared use only > Own use only Shared + own use No LSD
C2 2019 S1	No significant difference across all four access modes
C3 2019 S3	Shared + own use > Own use only No LSD and Shared use only > No LSD
Cohort/ Grade	Did LSD access in 2021 predict 2021 DL score?
C1 2021 P5	Shared use only Own use only Shared + own use > No LSD No other significant difference due to 2021 access
C2 2021 S3	Shared use only Own use only Shared + own use > No LSD No other significant difference due to 2021 access
C3 2021 S5	Shared + own use Own use only > No LSD No other significant difference due to 2021 access

Note. The four access modes of LSD were Shared use only, Own use only, Shared + own use, and No LSD; > refers to significantly higher DL scores at a significance level of  $\alpha = 0.05$ .

## 2.4. Growth of digital literacy over two years (longitudinal analysis)

We matched 887 students in the 2021 sample, with those in the 2019 sample who had DL scores for both waves of data collection (234 Cohort 1, 389 Cohort 2, and 264 Cohort 3 students) to study the growth of their DL over the 2 years. As the students who completed both waves represented only a fraction of all participants, we also compared 2019 DL scores of students who only participated in 2019 with those students who participated in both waves to examine if there are any statistical differences between these two samples.

We found that students in secondary schools who participated in both waves of the study achieved higher scores in 2019 compared to those who only participated in 2019. However, the scores were not significantly different between students in primary schools. These results show that the DL growth of secondary school students from the matched sample might not fully represent the whole 2019 sample.

Figure 2.9 describes the growth trajectories of all common students. The thick black line represents the average growth trajectory in each cohort and each colored line represents the growth trajectory of an individual student.

Regarding the average growth of DL competence, all three cohorts showed improvements in their DL scores over the 2 years—the steeper the black line (average growth trajectory), the larger the growth rate. In general, the DL of Cohort 2 students improved less than Cohorts 1 and 3 students.

Regarding individual growth, we observed that (1) not all students started from the same DL level, as indicated by the wide range of DL scores in 2019, (2) individual differences were even larger after 2 years, as indicated by an even wider range of DL scores in 2021, and (3) some students improved their DL faster than their peers, whereas some students' DL level even regressed.

Altogether, the three cohorts generally showed positive DL growth rates, indicating most students' DL competence improved over time. Nevertheless, it is obvious that students' DL increased at different speeds, with faster growth in some and regression in others.

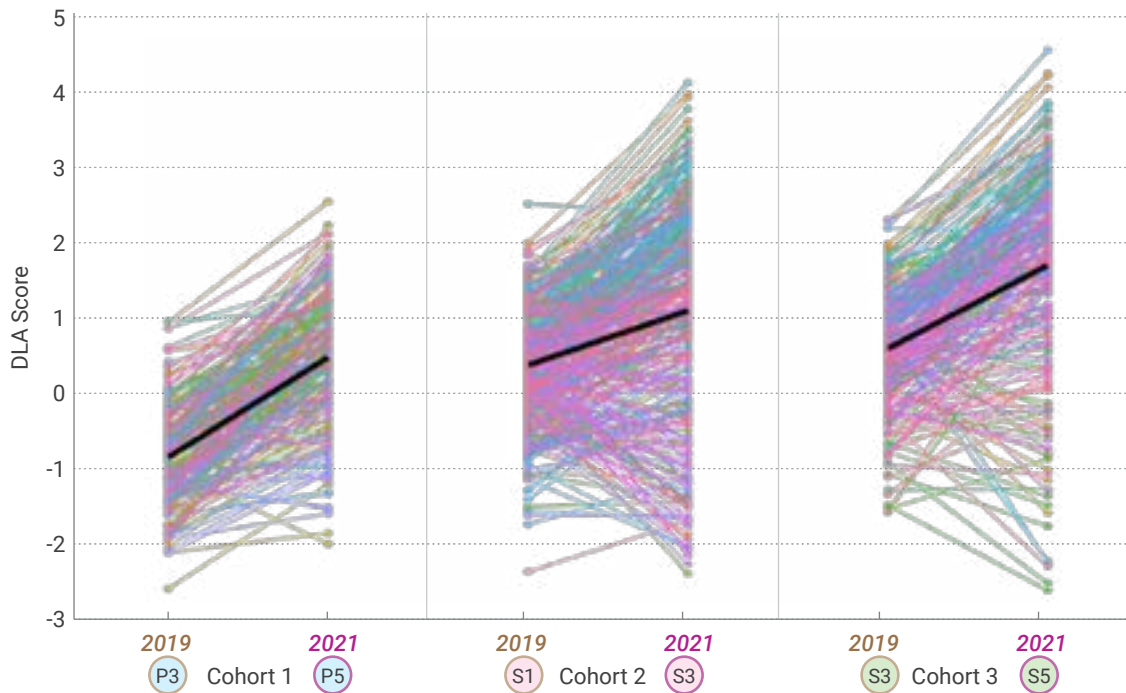


Figure 2.9. Spaghetti Plots of Individual Growth Trajectories of DLA by Cohort.

### 2.4.1. Growth by gender

From the cross-sectional data analysis, we found that girls in Cohort 2 had significantly higher DL scores than boys in both waves, but there were no differences in the other two cohorts. Next, we examined whether girls and boys had the same growth rates over time and found that girls had significantly larger growth rates than boys in Cohort 2 common sample. However, no differences in growth rates were detected in the other two cohorts (See [Figure 2.10](#)).

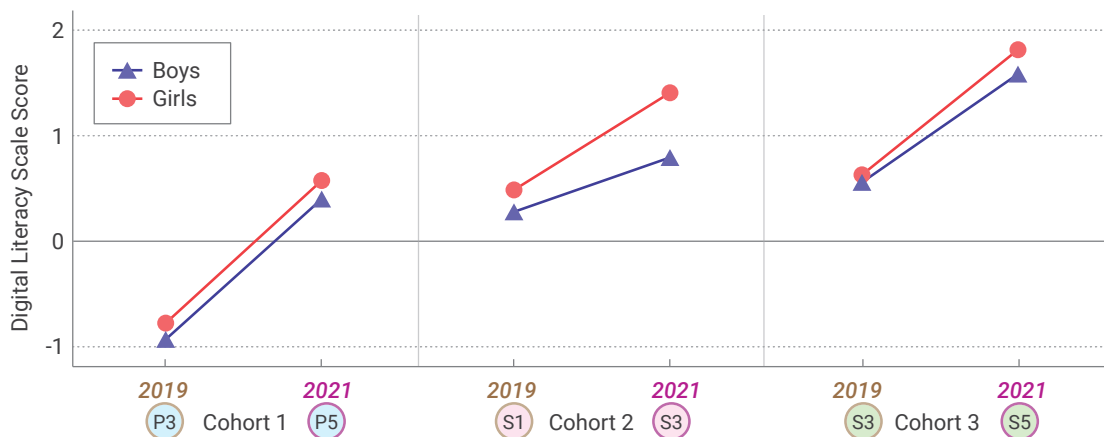


Figure 2.10. Common Students' Digital Literacy Scale Scores by Gender and Cohort in 2019 and 2021.

### 2.4.2. Impact of access to large-screen devices at home on digital literacy growth

We investigated whether and how the device types and modes of LSD access by students at home were related to students' DL growth across the two waves in the common sample. Table 2.9 shows changes in students' access to different types of LSD(s) at home between the two waves. The numbers on the diagonal represent the numbers of students who did not change the type of LSD devices they had access to at home, and the off-diagonal numbers indicate the numbers of students with changes to the types of LSDs they were able to access. It is observed that the number of students who did not have access to LSD(s) at home reduced from 2019 to 2021 for all three cohorts.

Table 2.9  
Students' Ownership of Large Screen Devices at Home between 2019 and 2021

		PC & tablet	PC only	Tablet only	No LSD
Cohort		2021			
C1	PC & tablet	76	4	16	4
	PC only	14	3	10	2
	Tablet only	12	2	7	0
	No LSD	19	2	2	1
C2	PC & tablet	166	18	25	11
	PC only	47	14	2	4
	Tablet only	20	6	7	4
	No LSD	18	12	9	2
C3	PC & tablet	103	22	9	2
	PC only	47	27	5	1
	Tablet only	7	0	10	2
	No LSD	6	4	2	4

Note. Students who did not respond to the questions were excluded from the analysis.

We further classified the students into two groups: LSD group and no LSD group, based on their access to LSDs at home. The changes in students' access to LSDs at home between the two waves then fell into four groups: LSD → LSD, LSD → no LSD, no LSD → LSD, and no LSD → no LSD.

Figure 2.11 shows the DL growth trajectories of students in these four groups across the three cohorts. Among the common students, only a few students did not have access to LSDs across both waves (comprising 1, 2, and 4 students in Cohorts 1, 2, and 3, respectively), and expectedly these students had lower DL scores. However, these observations need to be interpreted with caution due to the small sample sizes (See Table 2.10 for details). Among the other three groups of students, having no access to LSDs at home in 2021 significantly affected DL competence, especially in the older cohorts. A notable finding is that students with no LSD before the pandemic in 2019 but had access at the time of data collection in 2021 were able to catch up with their peers in terms of growth rate for all three cohorts, even though the achievement gap remained for Cohorts 2 and 3.

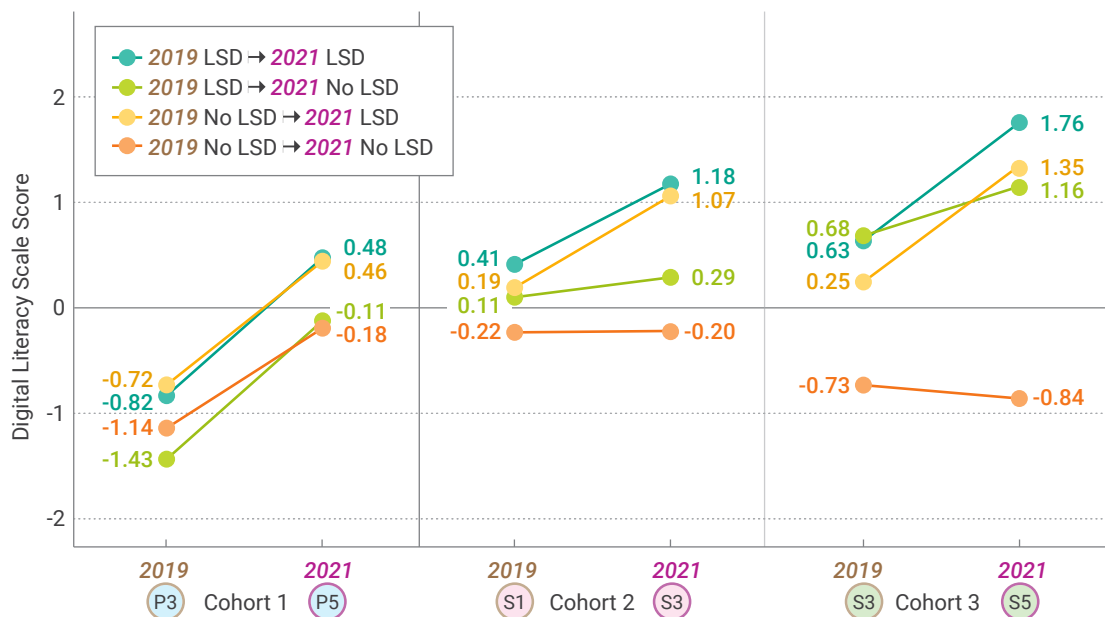


Figure 2.11. Students' Digital Literacy Growth Trajectories for the four groups of students according to changes in their access to LSDs in 2019 and 2021.

Table 2.10

Number of students with Change of Ownership of LSDs at Home between 2019 and 2021

Cohort	LSD → LSD	LSD → No LSD	No LSD → LSD	No LSD → No LSD
C1	144	6	23	1
C2	305	19	39	2
C3	230	5	12	4

To further examine the impact of students' access to LSDs on their DL growth over time, we next investigated how their access to LSDs in 2019 was related to their DL scores in 2021. We found the benefits of shared access in Cohorts 1 and 3 before COVID in 2019 carried over to the improvements in their DL level in 2021, whereas the mode of access in Cohort 2 in 2019 did not appear to influence their DL level in 2021.

Table 2.11

Impact of modes of Access to LSD(s) at Home on Students' DL Growth

Cohort	Did 2019 LSD access mode predict 2021 DL score? (Common students only)
C1	Shared use only > Shared + own use No other significant difference due to 2019 access
C2	No significant difference across all four access modes
C3	Shared + own use > Own use only No LSD No other significant difference due to 2019 access

Note. The four access modes of LSD were *Shared use only*, *Own use only*, *Shared + Own use*, and *No LSD*; > refers to significantly higher DL scores.

## 2.5. Summary

One of the goals of the Learning and Assessment for Digital Citizenship project was to measure the development of students' DL across three cohorts over a period of two years. Therefore, the study conducted two rounds of instrument development by adopting DigComp 2.0 framework and data collection in 2018/19 and 2020/21. A series of psychometric analyses demonstrated that the instrument was able to provide valid and reliable DL scores in both waves. The findings are summarized below:

- ◆ In general, students' DL has improved over two years.
- ◆ Meanwhile, the inter-individual differences, as well as the differences among the four districts, widened as students' literacy grew. Moreover, both inter- and intra- school differences in students' DL were observed.
- ◆ Girls' DL were similar to boys in cohort 1 and cohort 3, but girls performed better than boys in cohort 2.
- ◆ Students' family SES were significantly related to their DL, especially in cohort 1; more importantly, school-level SES played a more important role – a higher school-level SES was associated with a higher level of digital literacy.
- ◆ Students' ownership of a large screen device at home had a positive impact on their DL, and sharing a device was more beneficial to younger students.

# 3. Development of students' collaborative problem-solving capacity

## 3.1. Introduction

The ability to collaborate to solve authentic problems is important for digital citizens, whether in workplaces or for social and political problems encountered in everyday life, as these problems generally cannot be solved by individuals alone. Despite the strong educational interest in CPS, rigorous instruments to assess CPS are rare. One of the most notable such instruments was developed as part of the Assessment and Teaching of 21st Century Skills (ATC21S; Care et al., 2018; Griffin et al., 2012; Griffin & Care, 2015) project by the Assessment Research Centre (ARC) at Melbourne University. A core focus of the ATC21S project was on defining and developing methods to assess skills that will form the basis for 21st-century curricula. We have adopted the CPS assessment instrument from the ATC21S project as part of our digital competence assessment tools in the eCitizen study.

The ARC CPS instrument (Hesse et al., 2015) conceptualized CPS as a complex ability comprising cognitive process skills (including task regulation and knowledge building) and social process skills (including participation, perspective taking, and social regulation). The instrument assigns students to work in pairs to solve interactive tasks online. The test scale is based on the ARC calibrations conducted using international data collected from 16,898 students (aged 11-17) in Australia, Costa Rica, Finland, Netherlands, Singapore, and the United States during the instrument development stage. The data of the whole sample, regardless of age and tasks, were analyzed using item response modeling (Griffin et al., 2015; Harding et al., 2017).

It is important to note that while the students worked in pairs during the assessment process, each student received a separate set of assessment results in the form of proficiency level achieved for each of the two CPS process skills based on their performance and behavior in the process of collaborative task completion. There are six proficiency levels for the cognitive and social process skills, which are summarized in [Table 3.1](#) and [Table 3.2](#), respectively. Each proficiency level describes a distinct level of performance with associated observable behavior. These level descriptors provide a good basis for policy makers and curriculum leaders to develop curriculum guides and pedagogical plans to support students in their development of CPS skills. They also serve as a well-structured framework for teacher professional development programs on fostering and assessing students' CPS skills. An understanding of the students' CPS achievement mapped onto these levels at the school or classroom level would inform schools and teachers on school-based curriculum development as well as on possible intervention targets for specific individuals or groups of students.



Table 3.1  
*Proficiency Levels of Cognitive CPS (Griffin et al., 2015)*

Cognitive Process Skills		
	Level title	Description
Level 1	<b>Exploration</b>	A student working at this level investigates the problem space, but only by following instructions, and concentrating on single pieces of information without trying alternative approaches. The student's trials at solving the problem show little evidence of having an understanding of the consequences of the actions taken, hindering the task progress.
Level 2	<b>Establishing Information</b>	A student working at this level recognizes possible causes and effects of activities, shows a basic knowledge of the task concept, and begins checking on assumptions and rules. The student restricts the problem analysis to possibilities permitted by the resources and knowledge available to them. The student's goal setting is confined to broad objectives.
Level 3	<b>Sharing and Connecting Information</b>	A student working at this level recognizes when additional information is needed and understands that they may not have all of the essential information. They seek to collect and connect pieces of information together as well as provide their own resources to the partner.
Level 4	<b>Strategic Planning and Executing</b>	A student working at this level can recognize connections and patterns among various pieces of information. Through co-planning of task strategies with the partner, the student is able to simplify the problem and narrow down the objective of the collaborative task. The student plans strategic sequences of trials to achieve systematic exploration. Subtasks and simpler tasks can be accomplished by the student.
Level 5	<b>Efficient Working</b>	A student working at this level demonstrates purposeful and thoughtfully planned actions that comprise necessary sequences of subtasks. For both simple and complicated tasks, the student is able to recognize cause and effect, basing their goals on prior knowledge, and adopting appropriate strategies to arrive at a correct solution path. Students can revise and adjust their initial assumptions, test alternative assumptions, and tailor additional or alternative solutions based on the new information.
Level 6	<b>Refined Strategic Application and Problem Solving</b>	A student working at this level can accomplish tasks with less effort and in a short amount of time by conducting sequential explorations and systematic investigations. The student collaborates with the partner to find and utilize only helpful and related information. The student has a good comprehension of the problem and can restructure and/or rearrange it to come up with potential solution paths.

Note. Level 1 indicates the lowest CPS skill level and 6 indicates the highest.

Table 3.2  
Proficiency Levels of Social CPS (Griffin et al., 2015)

Social Process Skills		
	Level title	Description
Level 1	<b>Independent Working</b>	A student working at this level tackles the task independently with little interaction with the partner, and primarily guided by instructions. They can recognize their partner's communication cues, but they have not begun collaboration. Communication mainly occurs at the start of the tasks and only when the instructions to do so are clear.
Level 2	<b>Supported Working</b>	A student working at this level participates actively in the task when scaffolded, but still works mostly independently. Communication with the partner is more frequent but is confined to important events and when information is needed to begin the task.
Level 3	<b>Awareness of Partnership</b>	A student working at this level makes an effort to solve the problem. The partner's role in the collaborative problem-solving process and the importance of engaging with the partner are recognized. There is communication with the partner about the task and his/her own task-related activities, knowing that this contributes to the partner's understanding.
Level 4	<b>Mutual Commitment</b>	A student working at this level shows persistence in completing the task, as evidenced by multiple attempts and/or strategies. Resources and information are exchanged with the partner and communication is adjusted as needed to increase mutual understanding. The student has an awareness of the partner's performance on the task as well as his/her own performance.
Level 5	<b>Appreciated and Valued Partnership</b>	A student working at this level can participate actively in both scaffolded and unscaffolded situations. The student starts and encourages interactions with the partner, as well as responds to and acknowledges the partner's contributions. Differences in understanding may remain unresolved even after the students' attempts to communicate. The student can provide feedback during the partner's task performance.
Level 6	<b>Cooperation and Shared Goals</b>	A student working at this level collaborates in the problem solving process and takes joint responsibility for the task's success. Feedback from the partner is used to improve or make corrections to the solution paths. The student can assess their own and the partner's performance and understanding of the task. The student can appropriately adjust their interactions and handle disagreements with the partner, addressing differences before moving forward with a potential solution path.

Note. Level 1 indicates the lowest CPS skill level and 6 indicates the highest.

As the CPS test is considered valid only for students aged 11 or above, it was administered only to the two secondary school student cohorts in 2019 (i.e., S1 and S3) and to all three cohorts in 2021 (i.e., P5, S3, and S5). The CPS test was administered to 705 Cohort 2 and 593 Cohort 3 students from 14 secondary schools in 2019; 346 Cohort 1 students from four primary schools, and 598 Cohort 2 and 438 Cohort 3 students from seven secondary schools in 2021 (Table 3.3). Students were allowed 60 minutes to complete the test. Similar to the DLA administration (Chapter 2), the 2021 sample included new students who had not participated in 2019 as well as lost some from the original 2019 sample. Among all 2021 participants, about 37% of students completed the CPS tests in both 2019 and 2021. In this chapter, the analyses of students' CPS achievement in 2019 and 2021 are based on the respective full samples, whereas the analyses of students' CPS growth are based on the common sample.

Table 3.3  
Sample Sizes of Students that Took the CPS Test

Cohort	Schools		Students		
	2019	2021	2019	2021	Matched
C1	–	4	–	346	–
C2	14	7	705	596	234
C3			593	438	145

Note. – No data was collected.

## 3.2. Hong Kong students' levels of cognitive and social CPS process skills

Figure 3.1 and Figure 3.2 show the students' cognitive and social CPS skill levels respectively in 2019 and 2021. As shown in the figures, the older cohorts achieved higher levels of competence overall compared to their younger counterparts in the respective waves of the study.

In both 2019 and 2021, most students achieved Level 2 or 3 in the cognitive domain, while very low proportions of students achieved either of the two highest levels of CPS cognitive process skills (Figure 3.1). This was true for all cohorts and for both genders. Based on the level descriptions in Table 3.2, this result indicates that most students had limited abilities in problem analysis and limited awareness of the need for more information in addressing the problem beyond the resources and information they already had. There is thus a serious need to help students develop metacognitive skills for strategic planning, execution and enhanced work efficiency in problem solving.

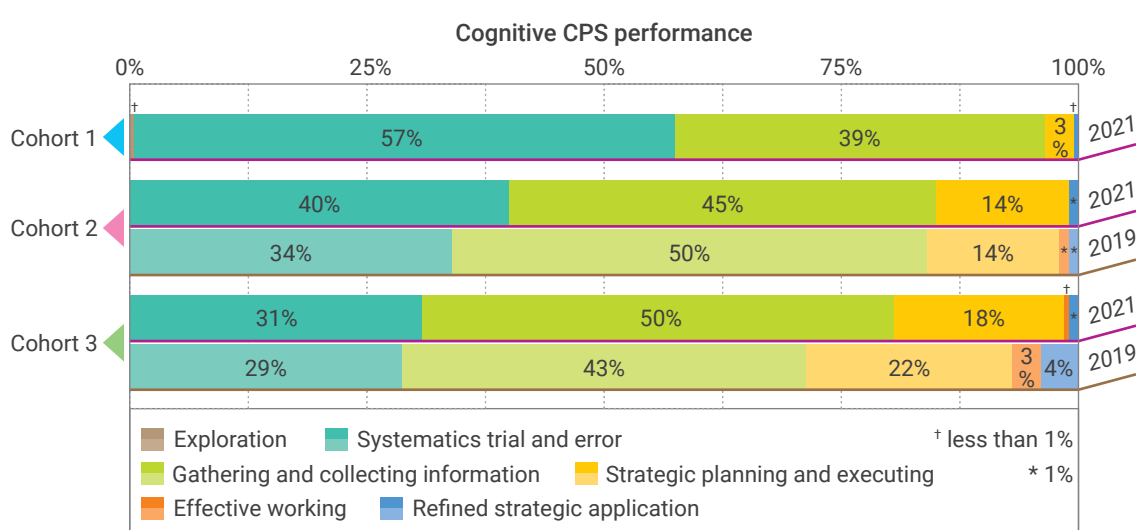


Figure 3.1. Percentage of Students Achieving Different Levels of CPS Cognitive Process Skills.

Comparing the achievement levels shown in Figure 3.1 and Figure 3.2, it can be seen that students in all cohorts in both 2019 and 2021 achieved higher levels in CPS social process skills compared to their CPS cognitive process skills. In all cohorts and in both waves, the

social process skills level attained by the largest proportion of students was Level 5, indicating that a large proportion of Hong Kong students demonstrated that they appreciated and valued partnership, and about 10% of students were able to demonstrate cooperation and shared goals (see Table 3.1 for the level descriptions).

In addition to comparing Hong Kong students' proficiency levels in cognitive and social process skills, Figure 3.1 and Figure 3.2 also allow us to compare students CPS proficiency levels across two time points (i.e., 2019 and 2021). It can be seen that the percentages of Cohort 2 and Cohort 3 students achieving cognitive CPS level 3 or above in 2021 were in fact lower than those in 2019. Similarly, there were more students achieving higher levels of social process skills in 2019 than in 2021 for each of the two older cohorts. These results indicate regression in students' CPS process skills in both the cognitive and social dimensions, with the magnitude of the regression being higher in social process skills. Such regression stands in stark contrast with the significant overall improvements in students' digital literacy between 2019 and 2021 in all three cohorts. This warrants further research, particularly with regard to how schools and other stakeholders could support students in their development of collaborative problem-solving skills under remote learning conditions.

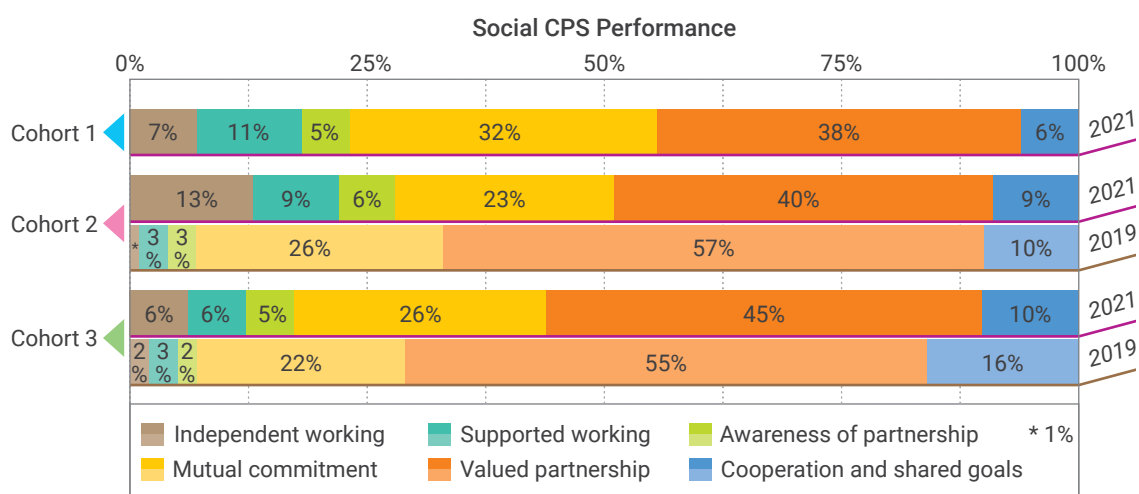


Figure 3.2. Percentage of Students Achieving Different Levels of CPS Social Process Skills.

### 3.3. Students' CPS score changes between 2019 and 2021

In this section, we further investigate Hong Kong students' CPS performance changes between 2019 and 2021, using continuous CPS scores instead of categorical proficiency levels as the former provides a more refined representation of students' achievement that can be used for quantitative analysis. The full sample of cross-sectional data in 2019 and 2021 is used in the analysis.

As shown in Figure 3.3, students' CPS performance scores (in both social and cognitive domains) in 2021 were generally lower in both Cohorts 2 and 3 compared to the scores in 2019, but the differences were not large. For Cohort 2, the gaps between the lower quartile (25%) and the upper quartile (75%) of 2021 CPS scores were wider than the 2019 CPS scores, while these gaps were narrower in Cohort 3.

In 2019, Cohorts 2 and 3 had similar performances in the CPS social domain. Unlike the DL scores, no significant differences were found in the social CPS scores across the three cohorts in 2021, with the very similar medians indicating the primary school students had similar social CPS process skills to that of secondary school students. However, higher grade students (i.e., Cohort 3) had slightly higher CPS cognitive scores compared with lower grade students (i.e., Cohort 2) in 2019. Even though this achievement gap between cohorts 2 and 3 was reduced in 2021, the Secondary school students' performance was generally better than the primary school students' in the CPS cognitive domain.

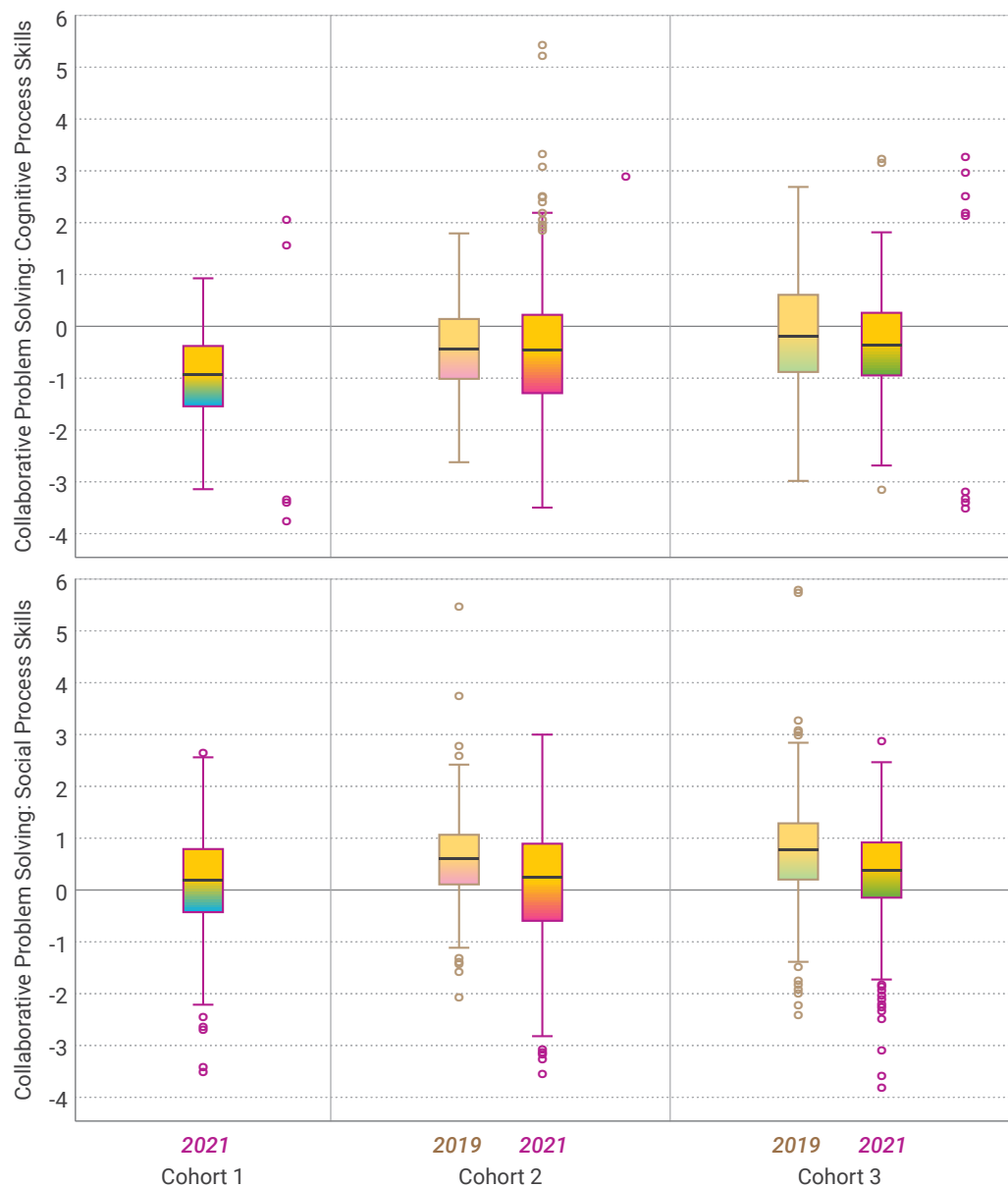


Figure 3.3. Boxplots of Students' CPS Cognitive Scores and Social Scores by Cohort in 2019 and 2021.

### 3.4. CPS performance and development within and across schools

Similar to the performance comparisons on DL, we compared the average student performance in the CPS test across schools. Here, we present the boxplots of the performance scores (rather than the six performance levels), with zero being the mean calibration by ARC (which is not the average score among Hong Kong students) and the vertical axis indicates how many standard deviations (SD) that the scores differed from the ARC mean. This provides a more refined comparison than using performance levels, with higher scores indicating better CPS skills in the respective skill domains.

#### 3.4.1. Primary schools

Figure 3.4 shows the average student' performance in social and cognitive process skills by school in the primary school sample in 2021. The individual schools are shown as blue bars and the gradient bar on the right-hand side is the performance of the entire primary school sample. As shown in Figure 3.4, School X had the highest median social process skills within the entire primary sample, which was very close to the 75% quartile of all primary schools (the purple dashed line). In the boxplots for cognitive process skills, there was no significant difference among the schools, but the 75% quartile of all schools were well below 0, which suggests the overall cognitive CPS process skills of the primary school students were below the mean score (norm) determined by CPS assessment team based on the ATC21S study data.

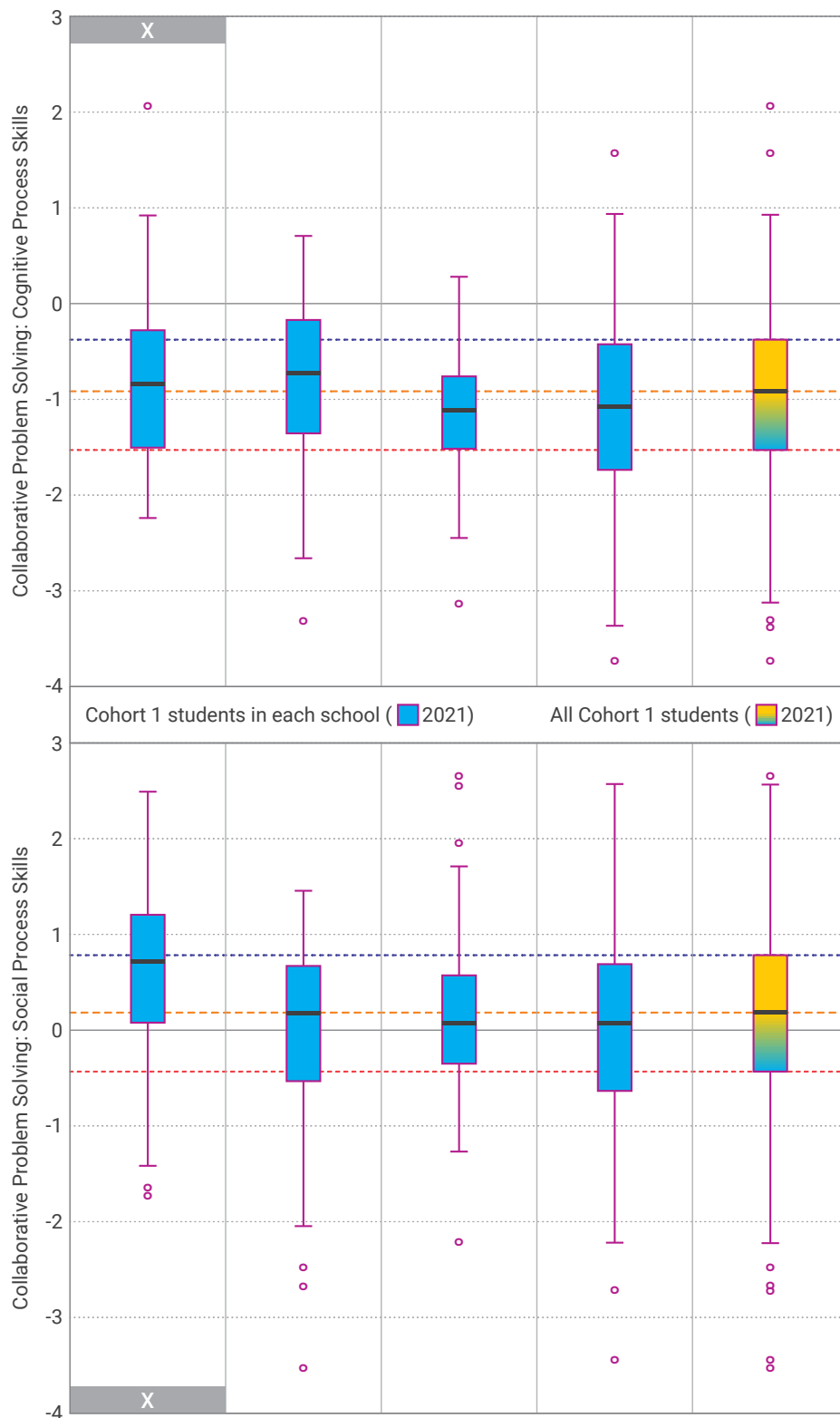


Figure 3.4. Boxplots of Primary school Students' Performance in Cognitive Skills and Social Skills in 2021 by School.



### 3.4.2. Secondary schools

Figure 3.5 and Figure 3.6 show the secondary school student's CPS performance in cognitive and social process skills, respectively, across 2019 and 2021. In these two figures, each pair of red and blue bars represent the performance of students in the same sampled school in 2019 and 2021 respectively. The rightmost pair of bars represent the performance of the entire sample of students in each wave for the two cohorts. The horizontal lines showing a CPS score of 0 indicate the mean score (norm) determined by the ARC assessment team based on the ATC21S study data.

As shown in Figure 3.5, for cognitive process skills, School L had the highest median scores in both Cohorts 2 and 3 in 2021. The median CPS cognitive score of School L was significantly higher than Schools B, H, and J in Cohort 2, whereas it was only significantly higher than the median CPS cognitive score of School B in Cohort 3. In addition, Schools J and H had the lowest median CPS cognitive scores in Cohorts 2 and 3, respectively. Comparing how the same school performed in the two time points, we can see that the medians of the right bars in Cohort 2 were very close, indicating that Cohort 2 students performed similarly in the CPS cognitive domain across 2019 and 2021. For Cohort 3, the overall median CPS cognitive scores in 2021 were lower than the overall median in 2019. Although some schools regressed in cognitive process skills after two years, several schools (i.e., Schools B, I, L, and M) showed improvement.

With regard to social process skills, as shown in Figure 3.6, School L also showed the highest median CPS scores in the social domain. The median CPS social scores of School L were also significantly higher than Schools B, H, and J in Cohort 2. School J had the lowest median CPS social process skills for Cohort 2, and School M had the lowest median CPS social skills for Cohort 3. When we compare CPS performance across time points, the rightmost bars in Figure 3.6 indicate that the overall median CPS social scores of Cohort 2 students in 2021 were lower than in 2019. For Cohort 3, the right bars in Figure 3.6 showed the overall median CPS social scores in 2021 were also lower than the overall medians in 2019. In both Cohorts 2 and 3, except for School L, all schools that participated in both 2019 and 2021 had lower median CPS social scores in 2021 compared to their performance in 2019.

In addition, Figure 3.5 and Figure 3.6 also allow us to compare school performance across cohorts. It is obvious that, generally, Cohort 3 students performed better in cognitive process skills than Cohort 2 students from the same schools. Cohort 3 students also had better performance in social process skills than Cohort 2 students from the same schools, but the differences there were not significant.

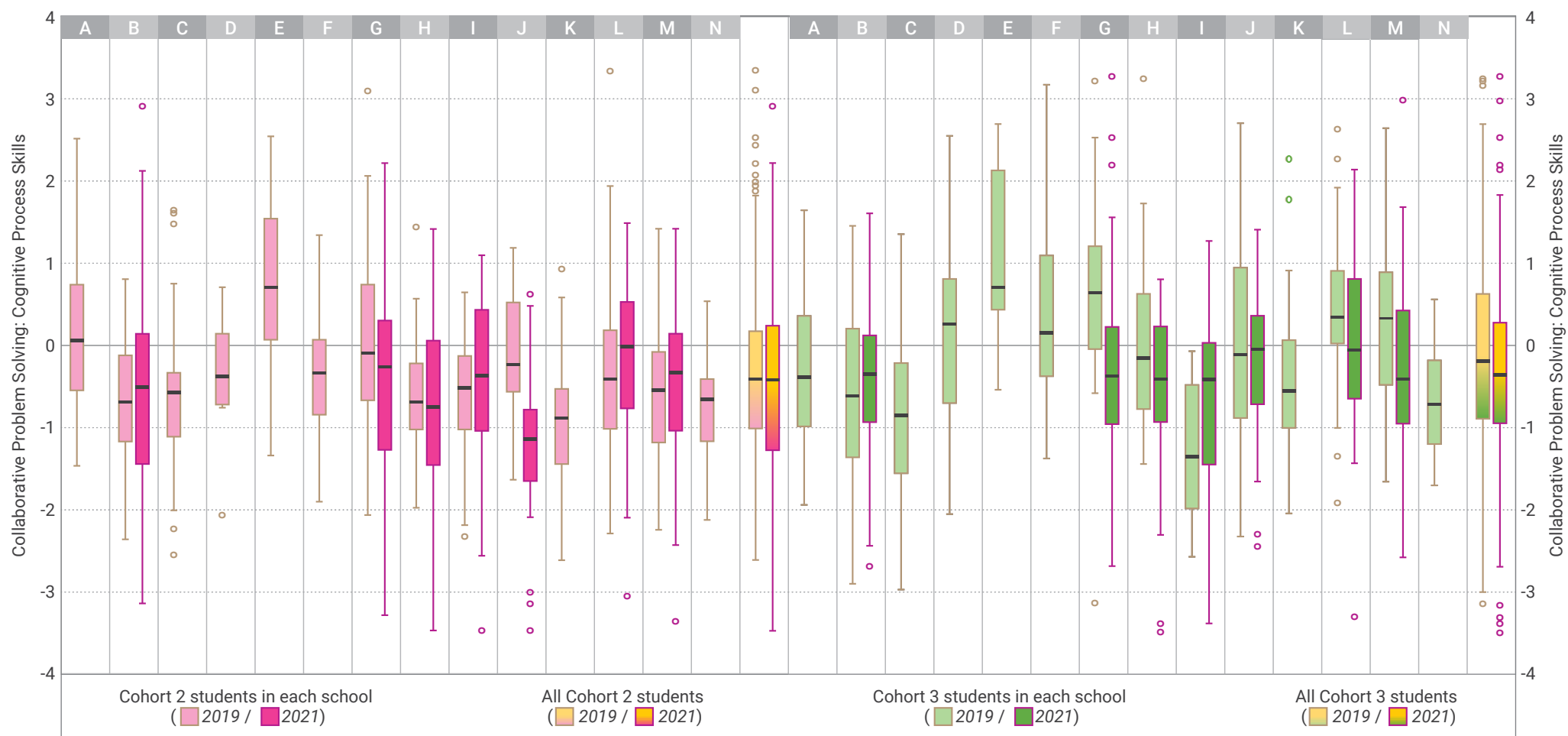


Figure 3.5. Boxplots of Students' Performance in Cognitive Process Skills by School Across 2019 and 2021.

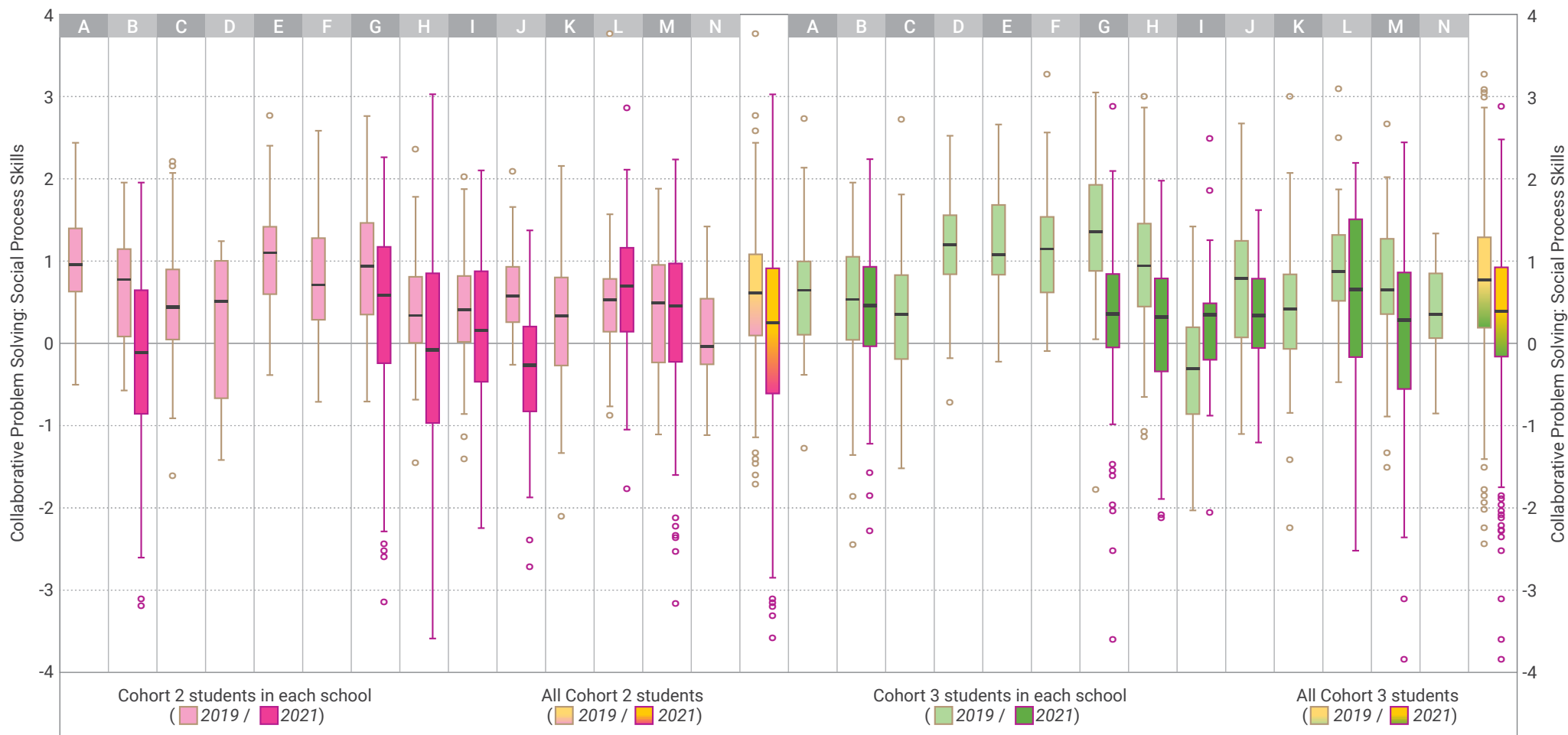


Figure 3.6. Boxplots of Students' Performance in Social Process Skills by School Across 2019 and 2021.

### 3.4.3. Gender differences in CPS performance

To investigate gender differences in students' CPS performance across 2019 and 2021, we conducted a regression analysis using data from the full sample for each cohort in both 2019 and 2021. No significant gender differences were observed for social CPS process skills in both 2019 and 2021. However, girls in Cohort 2 significantly outperformed their male counterparts in the CPS cognitive domain in 2019, whereas in Cohort 3 girls had significantly better CPS cognitive performance than boys in 2021.

## 3.5 Changes in students' CPS performance across time (longitudinal matched data)

As shown in Table 3.3, a total of 379 students (234 in Cohort 2 and 145 in Cohort 3) completed the CPS tests in both 2019 and 2021. Specifically, there were 370 matched students (229 in Cohort 2 and 141 in Cohort 3) who had CPS cognitive scores in both 2019 and 2021, and 370 matched students (227 in Cohort 2 and 143 in Cohort 3) who had CPS social scores in both 2019 and 2021 (Table 3.4). Because the matched students are only part of the full sample, we compared the mean CPS scores between the full sample and the common sample in 2019 and in 2021, respectively, to ensure that the common sample can still represent the full sample. We found no statistical difference between the CPS scores of students in the common sample and the full sample at both time points.

In this section, data from the matched student samples were used to study students' CPS growth over 2 years. Table 3.4 shows the mean and standard deviation of the CPS scores in matched students across 2019 and 2021 by cohort. In the matched Cohort 2 samples, students' cognitive skills did not show significant changes, but social skills regressed from 0.61 to 0.27. For matched Cohort 3 students, both cognitive and social skills regressed on average. Figure 3.7 shows two spaghetti plots of the individual growth trajectories of each CPS skill over 2 years, where the thick black line represents the average growth trajectory and the colored lines represent the individuals' growth trajectories. In terms of the average growth in CPS performance, Cohort 2 showed a flat black line in the cognitive domain, indicating similar performances in cognitive process skills over the two years. However, the black line in the social domain exhibited a downward trend, suggesting that on average Cohort 2 students regressed in social process skills. Cohort 3 showed downward-trending black lines, indicating that these students regressed in both cognitive and social process skills over time. Although students' performances regressed on average, some students showed improvements over time.

Table 3.4  
Matched Students' Average CPS Scores Across 2019 and 2021

Cohort	Cognitive skills			Social skills		
	N	2019 Mean (SD)	2021 Mean (SD)	N	2019 Mean (SD)	2021 Mean (SD)
C2	229	-0.44 (0.85)	-0.40 (1.04)	227	0.61 (0.74)	0.27 (1.10)
C3	141	0.00 (1.15)	-0.31 (0.90)	143	0.83 (0.95)	0.43 (0.84)

Note. N = number of observations; SD = standard deviation

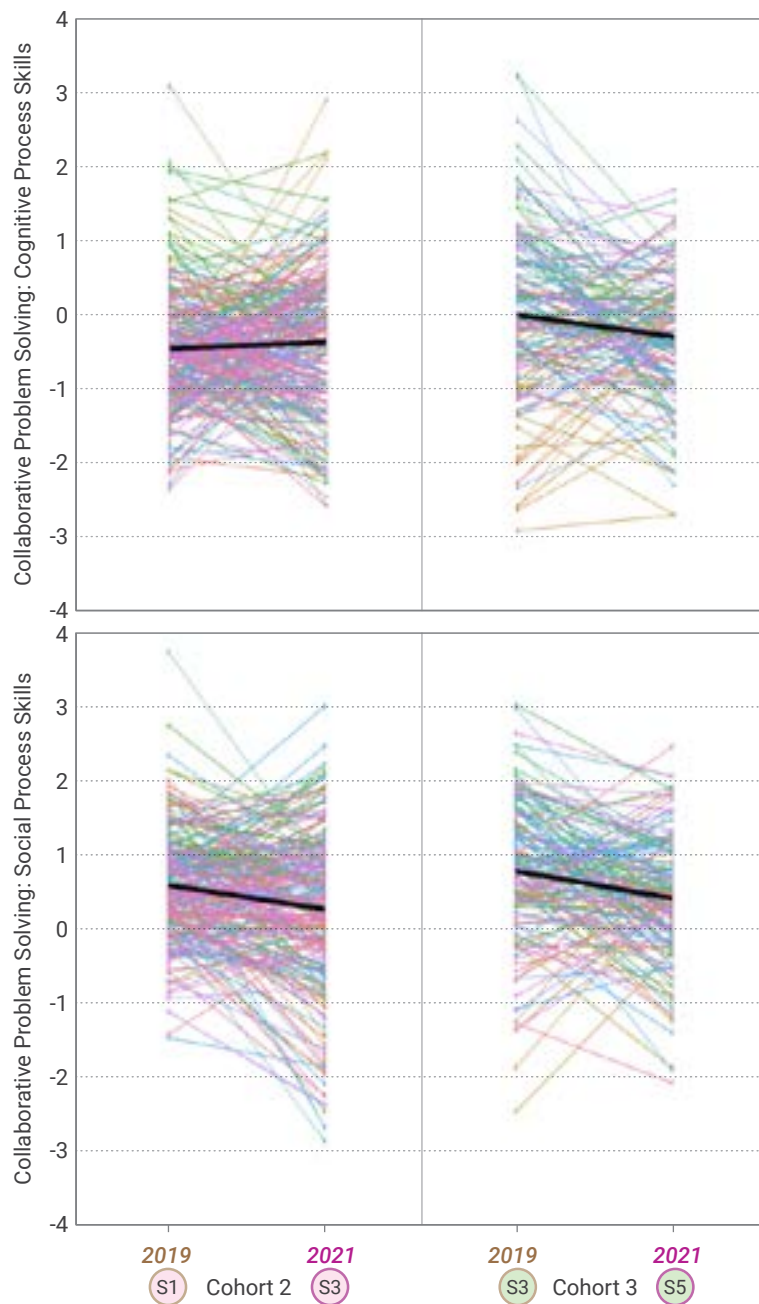


Figure 3.7. Spaghetti Plots of Cohorts 2 and 3 Students' Growth Trajectories in CPS Cognitive and Social Process Skills Performance Across 2019 and 2021.

### 3.6 Family factors influencing CPS performance

We investigated the possible influence of two sets of family factors on students' CPS performance: students' access to LSDs (i.e., desktop computers, laptops, and tablets) at home and family socioeconomic status (SES) using the cross-sectional CPS test data from the full samples in 2019 and 2021. Our analysis shows that access to LSDs at home did not show significant relationships with students' CPS performance.

As mentioned in [Chapter 2](#), two family socioeconomic status (SES) indicators, academic social capital (ACAD-CAP) and home resources (HOME-RES), were measured in 2021, but only ACAD-CAP was measured in 2019. We first computed the correlations between students' CPS scores and the SES indicators for each of the three cohorts in both 2019 and 2021. As shown in [Table 3.5](#), students with higher ACAD-CAP scores tended to perform better in both social and cognitive process skills in 2019 (Cohort 2 and 3). Students' ACAD-CAP scores also had a positive and significant correlation with Cohort 1 students' social process skills in 2021. However, no significant correlation coefficient was found in terms of HOME-RES scores.

Table 3.5  
Pearson Correlation Coefficients Between Students' CPS Scores and SES

Cohort	Grade	CPS cognitive		CPS social	
		ACAD-CAP	HOME-RES	ACAD-CAP	HOME-RES
C1	2019 P3	–	–	–	–
C2	2019 S1	0.13 ***	–	0.14 ***	–
C3	2019 S3	0.15 ***	–	0.14 ***	–
C1	2021 P5	0.13	-0.03	0.23 ***	0.11
C2	2021 S3	0.00	0.03	0.02	0.03
C3	2021 S5	0.09	0.02	0.05	0.03

Note. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .  
– No data was collected.

Similar to the analysis reported in [Chapter 2](#), we furthered our investigations related to SES factors using multilevel modeling analyses, studying students' CPS performance at different within-school and between-school levels for each cohort in both 2019 and 2021. We sought to address the following research questions:

1. Did students with higher SES have significantly higher CPS scores compared with other students in the same school?
2. Did schools with higher average SES values have significantly higher average CPS scores compared with other schools?

The relationships between CPS scores and SES at student and school levels are displayed in [Table 3.6](#). We found that in 2019, the school-level ACAD-CAP scores were significantly related to students' CPS social and cognitive scores in both Cohorts 2 and 3, which indicated that students in schools with higher school-level ACAD-CAP scores had significantly higher CPS scores. Note that Cohort 1 students did not participate in the CPS test in 2019. In 2021, both individual-level and school-level ACAD-CAP scores were significantly related to the CPS social CPS scores for Cohort 1 students, whereas neither individual-level nor school-level ACAD-CAP scores had any significant relationship with students' CPS performance in the other cohorts for either of the process skills domains. Moreover, HOME-RES scores were not related to students' CPS performance in 2021.

Table 3.6

*Multilevel Results Modeling the Relationships Between CPS Scores and SES*

Cohort	Grade	CPS cognitive	CPS social
		ACAD-CAP	
C1	2019 P3	–	–
C2	2019 S1	Schools with higher school-level SES had significantly higher CPS cognitive scores	Schools with higher school-level SES had significantly higher CPS social scores
C3	2019 S3	Schools with higher school-level SES had significantly higher CPS cognitive scores	Schools with higher school-level SES had significantly higher CPS social scores
Cohort	Grade	ACAD-CAP	
		CPS cognitive	CPS social
C1	2021 P5	No significant relation	Both individual-level and school-level SES were significantly and positively related to CPS social scores
C2	2021 S3	No significant relation	No significant relation
C3	2021 S5	No significant relation	No significant relation
Cohort	Grade	HOME-RES	
		CPS cognitive	CPS social
C1	2021 P5	No significant relation	No significant relation
C2	2021 S3	No significant relation	No significant relation
C3	2021 S5	No significant relation	No significant relation

Note. – No data was collected.

### 3.7 Relations between CPS and digital literacy scores from 2019 to 2021

Correlation analysis was conducted to examine whether the CPS scores were correlated with the DL scores. The full sample of students completing both DL and CPS assessments in each wave was used in this analysis. As shown in Table 3.7, we found that students with higher CPS scores usually had higher DL scores. However, the statistical analysis indicated the strength of this association was only moderate, suggesting that DL and CPS are distinct competencies. Although both DL and CPS are subsets of 21<sup>st</sup> century skills, there is not much overlap in what the two constructs measure. Therefore, DL and CPS may require distinct educational support and pedagogy.

In 2019, DL was found to be more strongly correlated with cognitive process skills ( $r = 0.35$  in Cohort 2 and  $r = 0.40$  in Cohort 3, respectively) than social process skills ( $r = 0.19$  in Cohort 2 and  $r = 0.29$  in Cohort 3, respectively). In 2021, DL was correlated more strongly with social process skills ( $r = 0.23$  in Cohort 1 and  $r = 0.21$  in Cohort 2, respectively) than cognitive process skills ( $r = 0.19$  in Cohort 1 and  $r = 0.14$  in Cohort 2, respectively) in the younger age cohorts, whereas DL was correlated more strongly with cognitive process skills ( $r = 0.25$ )



than social process skills ( $r = 0.22$ ) in Cohort 3 Overall, the correlation between CPS and DL decreased in 2021 compared to 2019. A possible explanation for the decreased correlation is that the smaller sample sizes in 2021 lead to narrower ranges of CPS and DL scores.

Table 3.7  
Pearson Correlation Coefficients ( $r$ ) Between CPS and Digital Literacy

Cohort	CPS cognitive		CPS social	
	2019	2021	2019	2021
C1	–	0.19 **	–	0.23 **
C2	0.35 ***	0.14 **	0.19 ***	0.21 ***
C3	0.40 ***	0.25 ***	0.29 ***	0.22 ***

Note. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .  
– No data was collected.

### 3.8 Summary

In this chapter, we report on Hong Kong students' CPS performance and some related factors across the two waves. Our findings are summarized as follows.

- On average, the CPS test scores of both Cohorts 2 and 3 students in both domains in 2021 were lower than the scores in 2019. Primary students had similar CPS social scores to secondary students, and secondary students had better CPS cognitive performance than primary students.
- In both 2019 and 2021, students had better CPS social process skills compared to cognitive process skills in all three age cohorts.
- No gender difference was found for CPS social process skills, whereas girls outperformed boys in the cognitive domain of CPS in 2019 Cohort 2 and 2021 Cohort 3.
- ACAD-CAP scores of SES had some significant relationship with students' CPS performance in both waves, whereas HOME-RES scores of SES were not related to students' CPS performance. Specifically, in 2019, students in school with higher school-level ACAD-CAP scores had significantly better CPS performances in both social and cognitive domains in both Cohorts 2 and 3. In 2021, both individual- and school-level ACAD-CAP scores had a significantly positive association with the CPS social scores of Cohort 1 students.
- Regarding individuals' growth in CPS in the sample of common students, Cohort 2 students had similar CPS performances in the cognitive domain over time but regressed in their social process skills. Cohort 3 students generally regressed in both cognitive and social process skills on average over time.
- The correlations between the two CPS scores and DL scores in 2021 were generally smaller than the corresponding ones in 2019.

## 4. Students' digital technology use and their wellbeing from 2019 to 2021

### 4.1. Introduction

The rapid proliferation of digital technology use and its adoption by society have transformed how we interact with and relate to others formally and informally in environments in which digital technology has been pervasively integrated. As a result, our individual and social wellbeing are now closely linked to the state of our information environment and the digital competences that mediate our interaction with it (Floridi, 2014).

In conceptualizing the relationship between digital use and wellbeing, we adopted two important perspectives from Livingstone, Mascheroni, and Staksrud (2015): (1) The study of the wellbeing of citizens in the digital age should not be confined to what happens online; and (2) Digital technology use and practices present both *risks* and *opportunities*, but whether these result in harms and/or benefits depends on factors at multiple levels, including individual (e.g., digital competence), family (e.g., SES, parental restrictions, support), school (e.g., digital learning opportunities), and beyond.

To investigate students' wellbeing, the study collected data on physical activity and sleep, as well as data that may reveal adverse wellbeing, including symptoms indicative of mental health problems, Internet addiction, and online game addiction. To understand students' digital technology use and practices, we gathered data on students' digital technology use patterns at home and in school. We also investigated the extent to which students encountered problematic experiences (specifically having digital security problems and being cyberbullied) and/or engaged in problematic behaviors (specifically risky communications and cyberbullying others) online. In this chapter, we report the descriptive findings on these variables, while in-depth relational analyses are reported in the next chapter.

Sampled students in all cohorts participated in online surveys in both 2019 and 2021. However, as mentioned in previous chapters, only a portion of the sampled students participated in both waves of data collection. Table 4.1 shows the sample sizes of students surveyed in the two waves and the size of the matched sample.

Table 4.1  
Sample Sizes in the Student Survey by Cohort in 2019 and 2021

Cohort	Schools		Students		Matched
	2019	2021	2019	2021	
C1	18	12	736	449	248
C2			711	828	403
C3	14	11	581	606	281

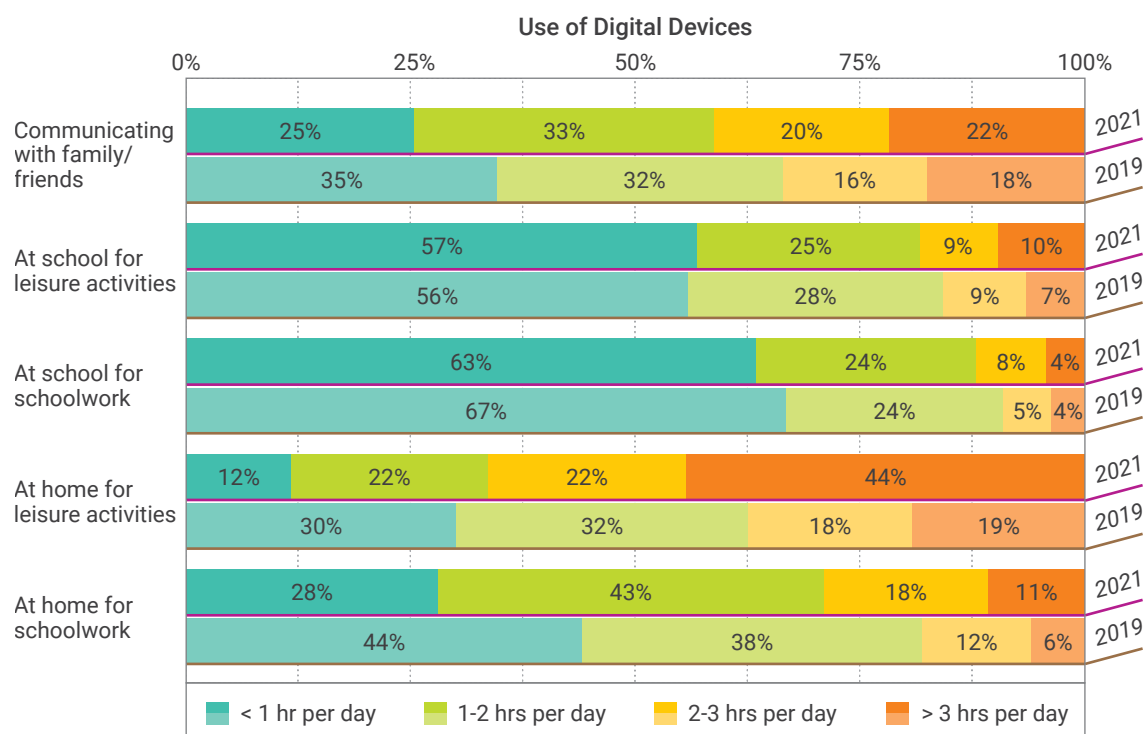
We compared the demographic characteristics (e.g., gender ratio, books at home, and language spoken at home) and wellbeing indicators (e.g., internet and game addiction) of the students in the three sub-samples, that is, students who participated only in 2019, those who participated only in 2021, and students in the matched sample (matched students in 2019 and 2021). We found that students who participated only in 2021 had similar demographic characteristics (e.g., gender ratio, books at home, language spoken at home), digital technology use and digital wellbeing compared to students in the matched sample. Although those who participated only in 2019 had fewer books at home than students in the matched sample, they were similar with respect to gender ratios, amounts of time spent using digital devices, and wellbeing status. It is thus reasonable to believe that the matched sample (who took part in both the 2019 and 2021 studies) was comparable to the full samples in the two respective years in terms of students' digital technology use and wellbeing. Hence, the data from the full samples collected at these two time points were used for the analyses reported in this chapter regarding students' digital technology use and wellbeing in 2019 and 2021, and the changes in between.

## 4.2 Hong Kong students' digital technology use

### 4.2.1. Students' digital technology use patterns

Students reported through the survey their time spent using digital devices per day regarding five main purposes: (1) communicating with family/friends, (2) at school for leisure activities, (3) at school for schoolwork, (4) at home for leisure activities, and (5) at home for schoolwork. [Figure 4.1](#) summarizes the students' daily usage of digital devices for all three cohorts in 2019 and 2021. In 2019, students used digital devices mostly for leisure activities at home and to communicate with others. In 2021, students spent even more time on digital devices at home for leisure activities and to communicate with others compared to 2019. The multiple school closures during the COVID-19 outbreak since 2020 meant that a lot of learning activities shifted to online mode. We thus see that in 2021, using digital devices for schoolwork at home has increased greatly compared to 2019. Although the use of digital technologies for all purposes has increased, the net time spent and increase in time spent using technologies at home for schoolwork per day was less than the corresponding figures for leisure activities at home per day.





**Figure 4.1.** Students' Use of Digital Devices at Home and in School per Day (All Three Cohorts) in 2019 and 2021.

In both 2019 and 2021, the older student cohorts spent significantly more time on digital devices at home for leisure activities than the younger cohorts (Figure 4.2). Students in all cohorts spent more time on digital devices at home for leisure activities and schoolwork in 2021 compared with 2019. While the time spent on digital devices at home for leisure was higher for the higher-grade cohorts in both waves, the difference between cohorts 2 and 3 students became smaller. On the other hand, the pattern of digital use at home for schoolwork had a different change pattern. Cohort 3 spent the least amount of time at home on digital schoolwork in 2019, but the most time on digital schoolwork in 2021 compared to the other two cohorts. This indicates that teachers were much more likely to assign digital schoolwork to the Cohort 3 students in 2021 than in 2019. Such change could be due to the need to prepare the S5 students for public examination, and digital schoolwork became the most viable mode for the assignment of schoolwork during the pandemic.

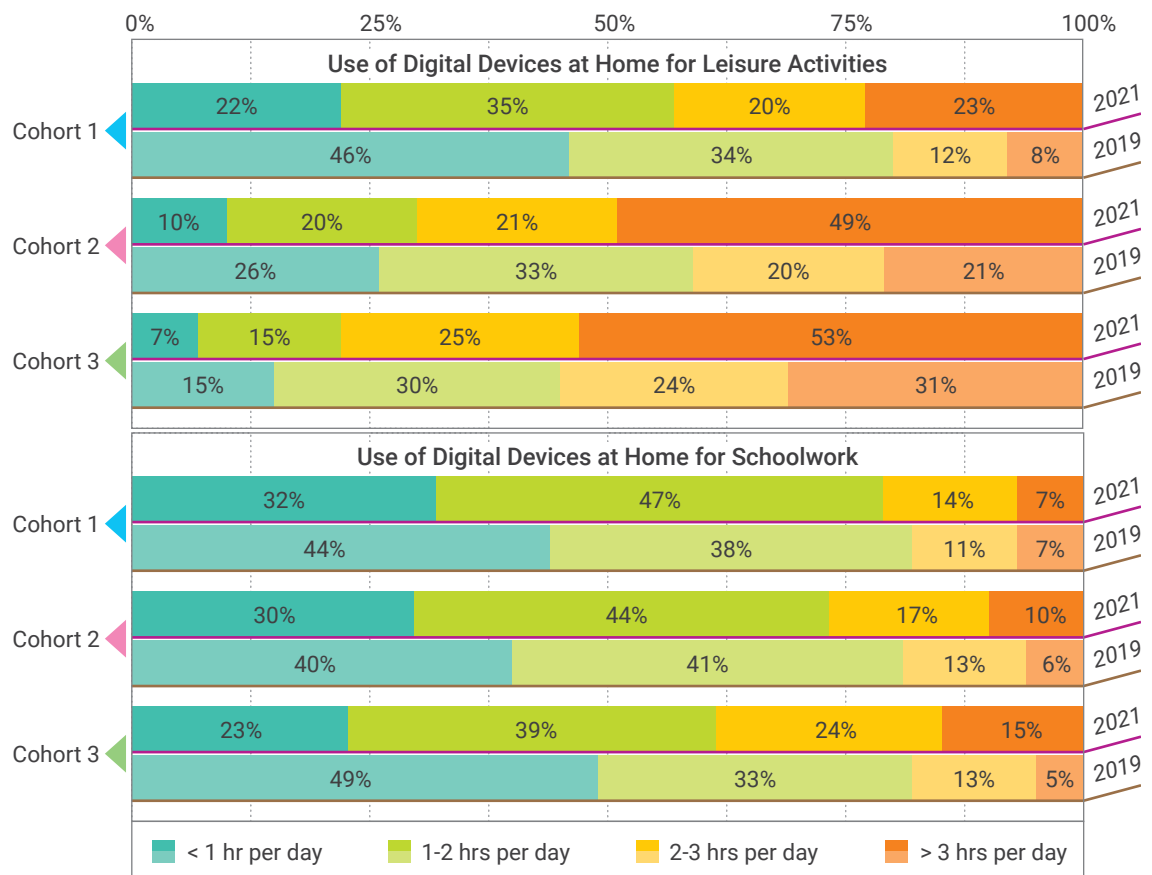


Figure 4.2. Students' Use of Digital Devices at Home per Day by Cohort in 2019 and 2021.

#### 4.2.2. Social networking and schoolwork were students' predominant online activities at home

Students were further asked how much time they spent on particular online activities at home (Figure 4.3a, Figure 4.3b and Figure 4.3c). Among the specified online activities, students in all cohorts spent most of their time chatting with friends and browsing social networking sites in both 2019 and 2021. Students in the older cohorts frequently discussed with classmates matters related to learning, searched for information/learning materials related to schoolwork and browsed the Internet without a particular purpose. Compared to 2019, cohort 1 students in 2021 spent more time chatting with friends, browsing the Internet without a particular purpose, browsing social networking sites, and discussing learning-related topics with classmates. Time spent writing a blog post or creating websites decreased. Cohort 2 students in 2021 spent more time chatting, social networking, browsing the Internet without a particular purpose, making charts/graphs, and discussing learning-related topics with teachers, but less time completing assignments and searching for information related to schoolwork compared to 2019. Cohort 3 students spent more time on all categories of online activities related to learning in 2021 compared to 2019, while they spent less time on social media.

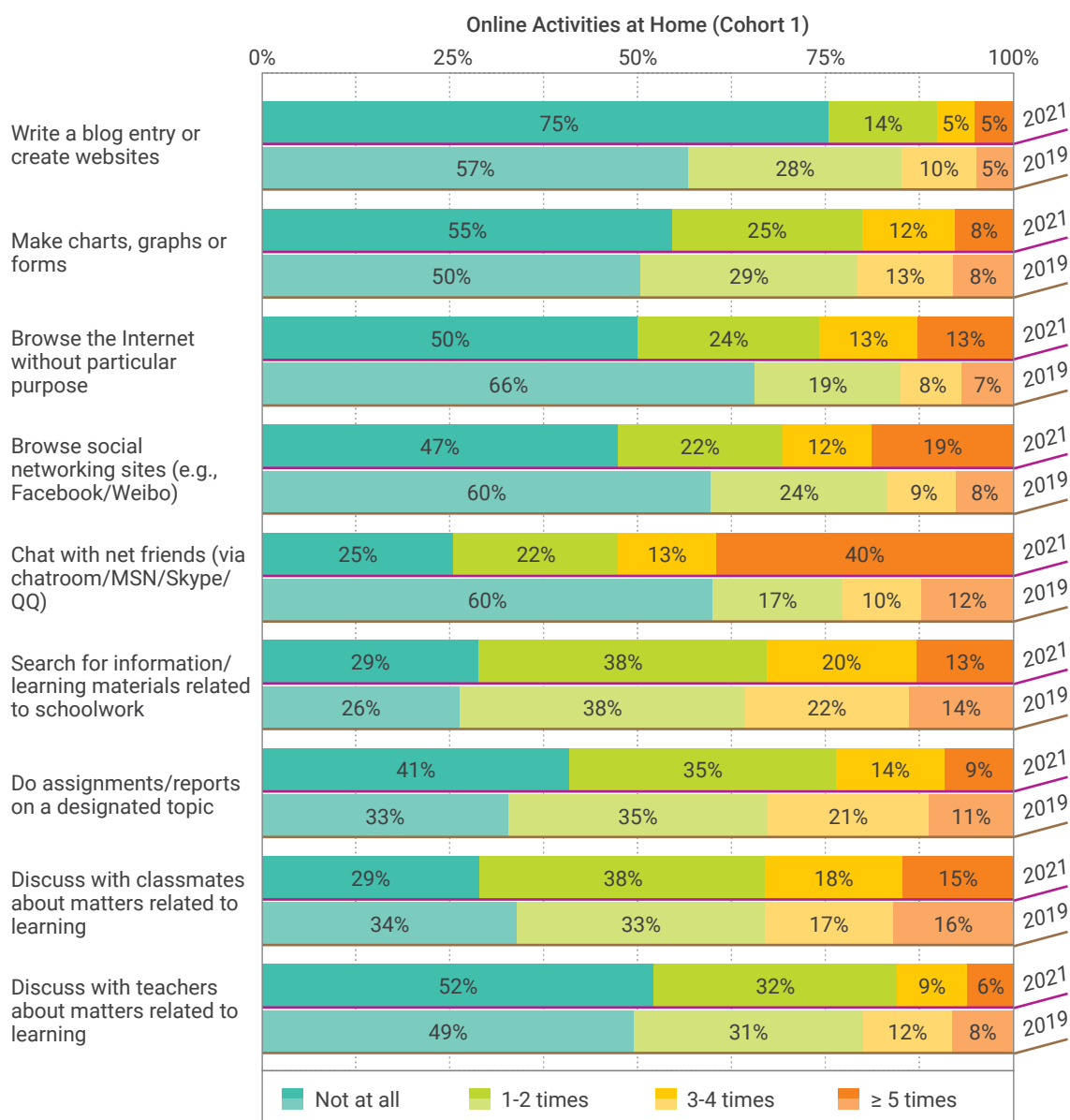


Figure 4.3a. Students' Online Activities at Home per Week (Cohort 1) in 2019 and 2021.

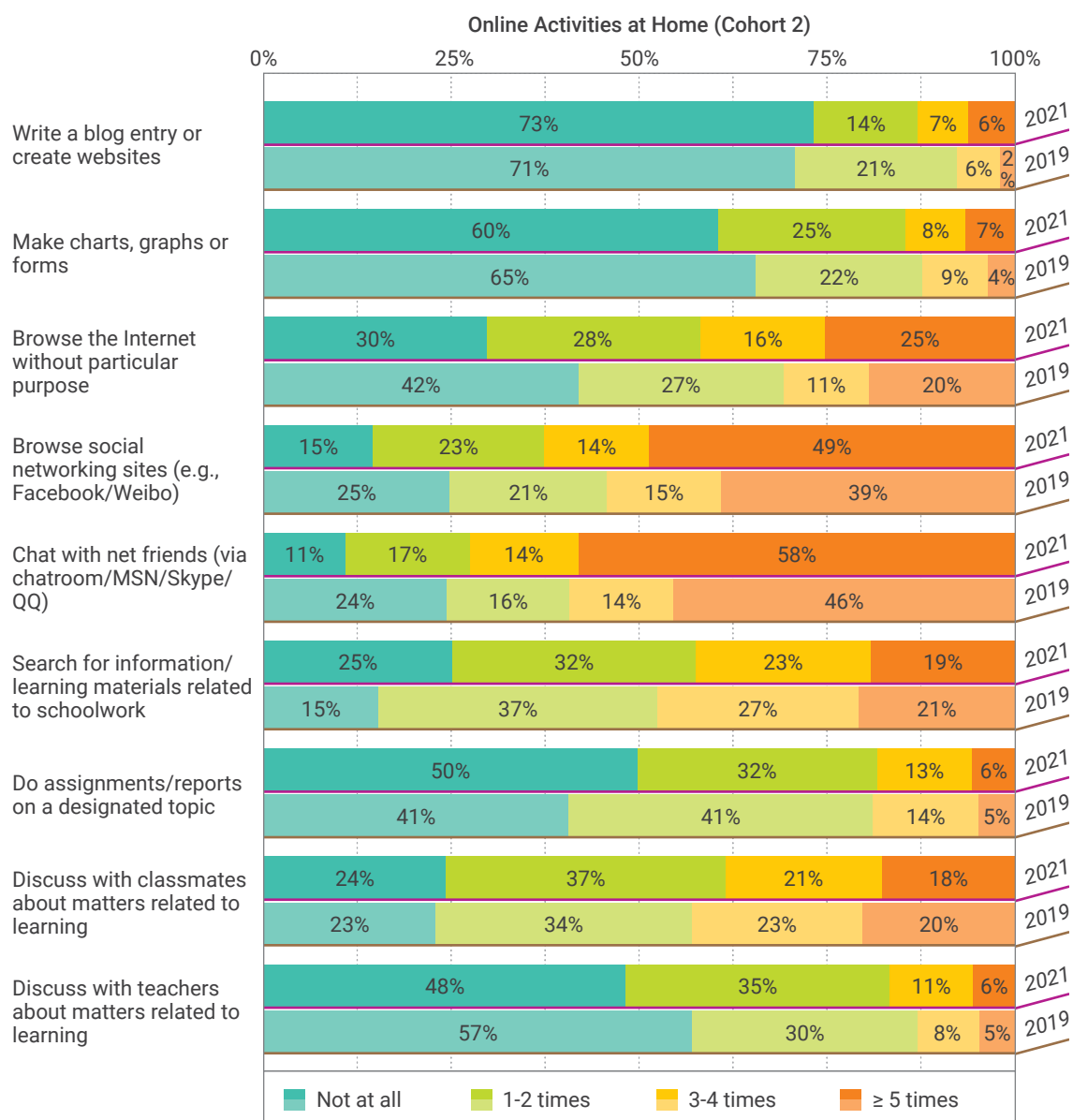


Figure 4.3b. Students' Online Activities at Home per Week (Cohort 2) in 2019 and 2021.



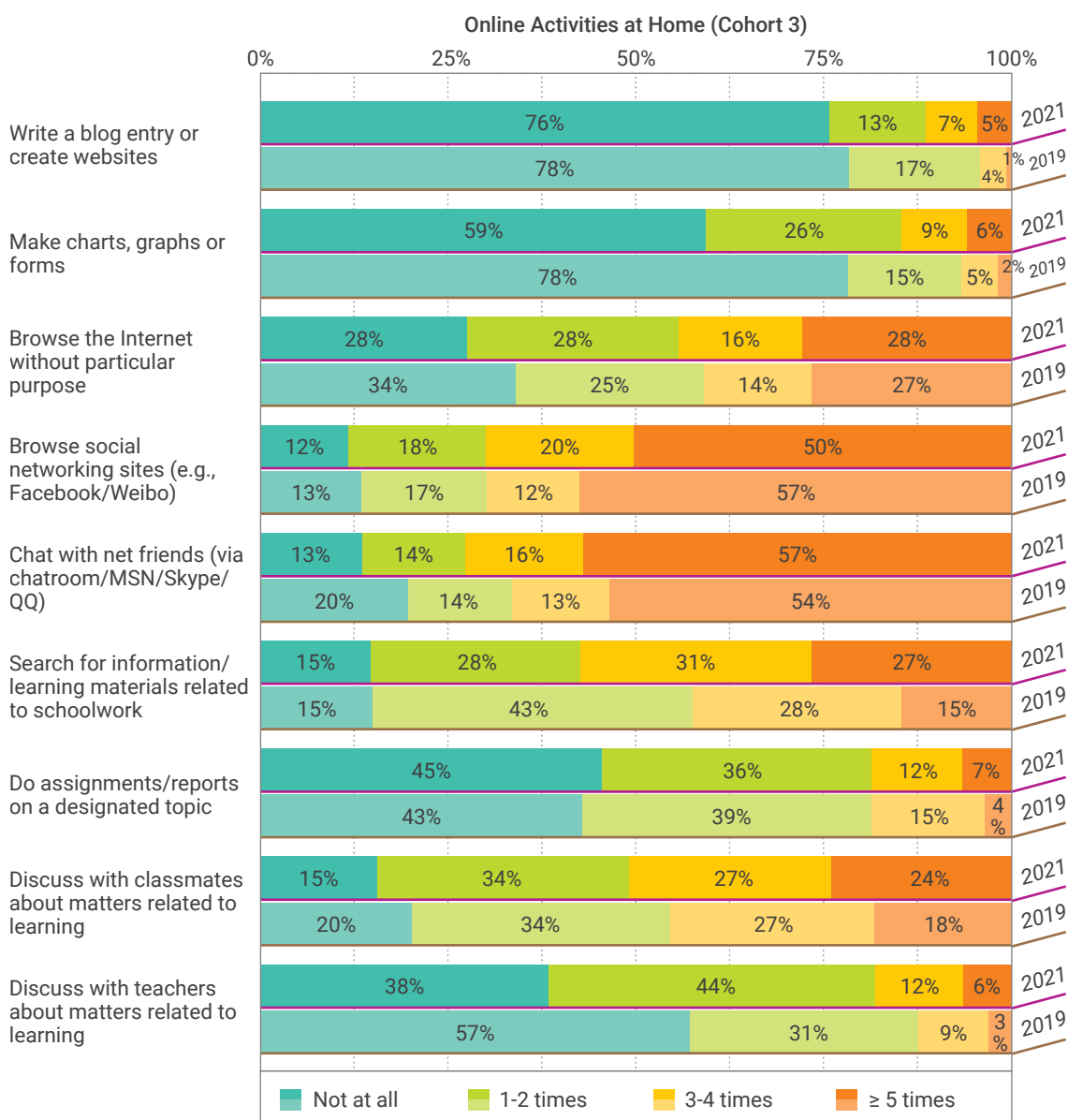


Figure 4.3c. Students' Online Activities at Home per Week (Cohort 3) in 2019 and 2021.

## 4.3 Students' online safety

### 4.3.1. Unauthorized use of personal information and computer viruses were the most common security problems

A set of five questions was adapted from *EU Kids Online* to understand the extent to which students encountered security problems when using digital devices online (Livingstone & Haddon, 2009). In 2019, students were asked if they *had ever* experienced any Internet safety issues (*yes*, *no* or *don't know*; listed in Figure 4.4). In 2021, the same questions were asked with a different reference time frame ("*in the last 12 months*" instead of "*had ever*") and only two response options (*yes* or *no*). Thus, it is not appropriate to directly compare the percentages

in the two waves. In both 2019 and 2021, the most common security problems for students were unauthorized use of personal information by others and computer viruses, but the latter dropped from the top security problem in 2019 to the second place in 2021. In 2019, the cohort reporting the highest percentage regarding a security problem differed across the security issue concerned. However, in 2021, a higher percentage of students in the younger cohort tended to report more security problems, with the exception of “lost money by being cheated,” for which cohort 2 reported the highest percentage (11%) compared to 8% in the other two cohorts. Previous experiences of online safety problems reported in 2019 were significantly positively related to recent (in the past 12 months) experiences of online safety problems reported in 2021 (Pearson  $r = 0.18$ ).

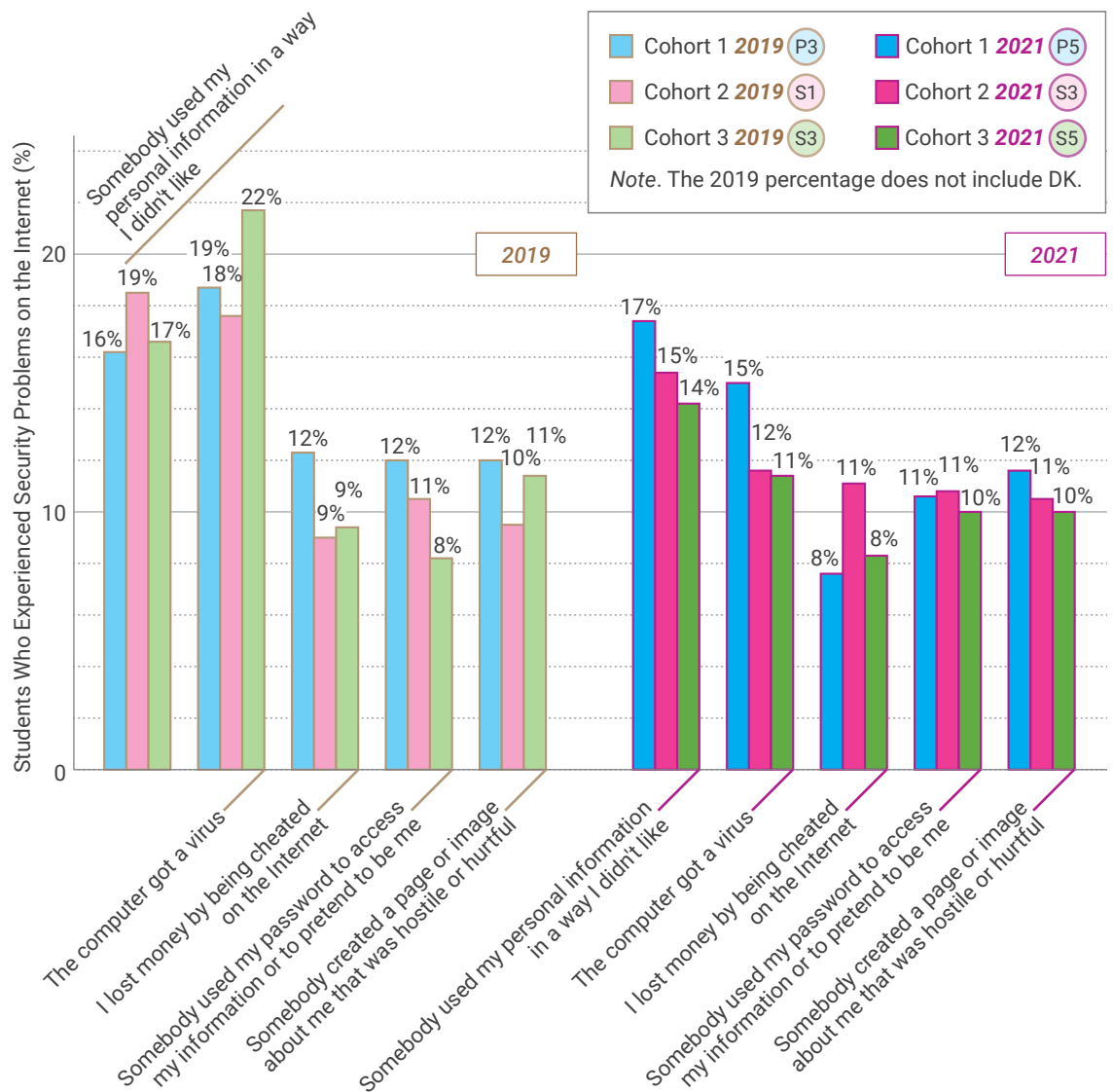


Figure 4.4. Percentage of Students Who Experienced Security Problems on the Internet by Cohort in 2019 and 2021.

### 4.3.2. Students engaging in risky online communications

Students may encounter online risks not only from being passive victims, but also from the activities for which they take active agency to initiate (Livingstone, Mascheroni & Staksrud, 2015). Four questions were adapted from the EU Kids Online study (Livingstone et al., 2011) to capture students' risky communications with online contacts in 2019. In 2021, the same questions were asked with a change time frame in one of the response categories ("*in the last 3 months*" instead of "*had ever*"). Thus, it is not appropriate to directly compare the percentage in the two waves. Figure 4.5 shows the percentage of students who reported engaging in different forms of risky communication online during the two waves of data collection. For all age cohorts in both waves of data collection, the most frequently reported risky behaviors were respectively 'looking for new friends online' and 'pretending to be older for online activities.' The least frequently reported risky behavior was 'sending personal information to strangers.' For the other three types of risky behavior, the older students reported a higher likelihood of engagement in 2019. However, the situation changed in 2021, with Cohort 2 reporting the highest likelihood and Cohort 1 the lowest. Apparently, Cohort 3 students became more cautious compared to their Cohort 2 counterparts over the two-year period.

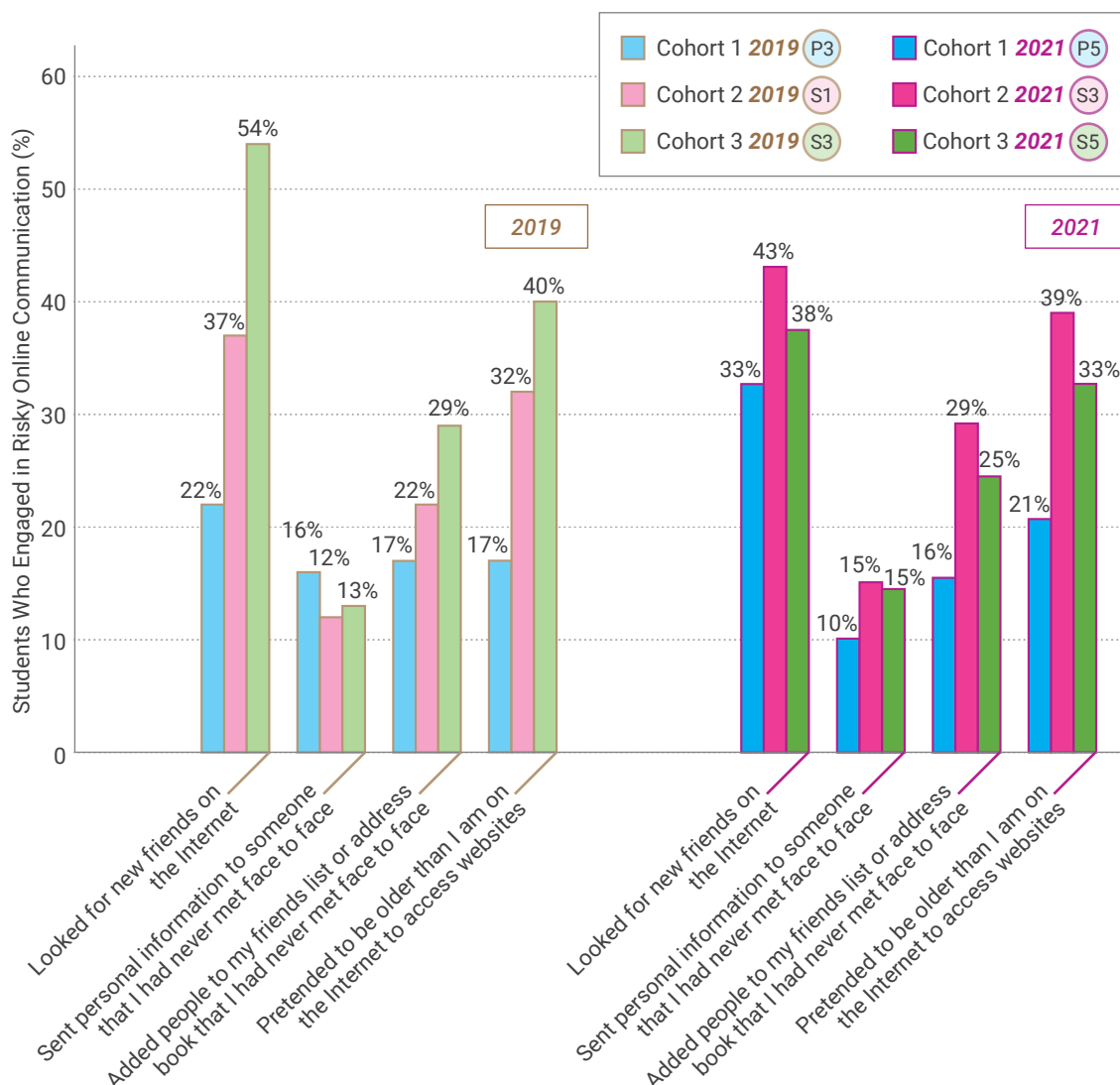


Figure 4.5. Percentage of Students Who Engaged in Risky Online Communication by Cohort in 2019 and 2021.

### 4.3.3. Prior cyberbullying experiences were associated with subsequent cyberbullying experiences

Twelve questions measuring cyberbullying perpetration and cybervictimization were adapted from an instrument validated in other cultural contexts (Shapka, Onditi, Collie, & Lapidot-Lefler, 2018). Students indicated whether they *had ever* cyberbullied someone (e.g., posted something mean about another person) or been a victim of cyberbullying themselves (e.g., rumors about the student were spread electronically) in 2019. In 2021, we asked the students about cyberbullying experiences *in the past 3 months*. In 2019, two thirds (65%) of all surveyed students reported no cyberbullying experiences. About a quarter of each cohort reported being a cyberbullying victim and a slightly lower percentage reported being a perpetrator (Figure 4.6). Among these students, almost half (48%) were both victims and perpetrators, indicating a strong correlation (Pearson  $r = 0.53$ ) between being a victim and a perpetrator. In 2021, around 73% of all surveyed students reported no cyberbullying experience in the past 3 months. Similar to the case in 2019, about 45% of those who reported cyberbullying experiences in 2021 were both victims and perpetrators. The correlation between being a victim and a perpetrator in 2021 was even stronger (Pearson  $r = 0.71$ ). In both 2019 and 2021, significantly more male than female students reported cyberbullying experiences. Previous cyberbullying experiences (reported in 2019) were significantly positively associated with subsequent cyberbullying experiences reported in 2021 (Pearson  $r = 0.17$  for perpetrators and  $r = 0.18$  for victims).

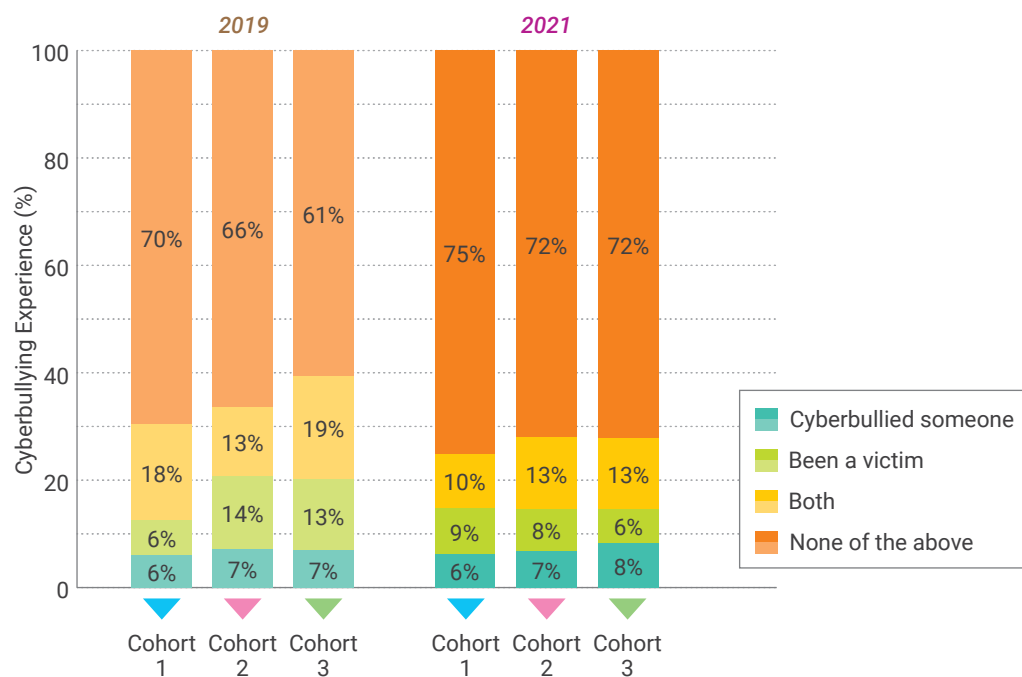


Figure 4.6. Percentage of Students Reporting at Least One Incident of Cyberbullying as Perpetrator or Victim in 2019 and 2021.

## 4.4 Hong Kong students' wellbeing

In this section, we report on findings related to students' wellbeing. Two of the constructs examined are related to (negative) digital wellbeing, i.e., threats to wellbeing due to digital technology use: Internet addiction and game addiction. In addition, we also investigated students' physical wellbeing (amount of physical activity and sleep) and mental wellbeing (the extent to which students reported symptoms of mental health problems).

### 4.4.1. Increasing cases of internet addiction during the pandemic

Internet addiction refers to “the frequent and uncontrolled use of the Internet to the extent that other aspects of the user's life are negatively affected” (Teo & Kam, 2014, p.624). We measured Internet addiction by adapting Young's (2016) Internet Addiction Test. It included questions that probed the extent to which students failed to cut down on time spent on the Internet, lost sleep due to nightly logons, and suffered in their schoolwork because of the amount of time spent online. Students gave responses on a scale from 0 to 4, which were then averaged. An average score higher than 2.5 is considered a threshold indicating a risk of addiction. The instrument was deemed appropriate for respondents aged 10 years and above. The Internet addiction items were thus administered to cohorts 2 and 3 students in 2019 and students in all three cohorts in 2021.

Figure 4.7 shows the cumulative frequencies of students' levels of Internet addiction in 2019 and 2021. In 2019, about 8% of cohort 2 and cohort 3 students showed symptoms of Internet addiction. In 2021, the corresponding percentages increased to 20% for cohorts 2 and 3. This implies that secondary school students showed more symptoms of Internet addiction after the outbreak of the pandemic. In addition, about 15% of P5 students showed symptoms of Internet addiction in 2021, which was much higher than the secondary students in 2019. There was no gender difference in Internet addiction for all cohorts in both 2019 and 2021.

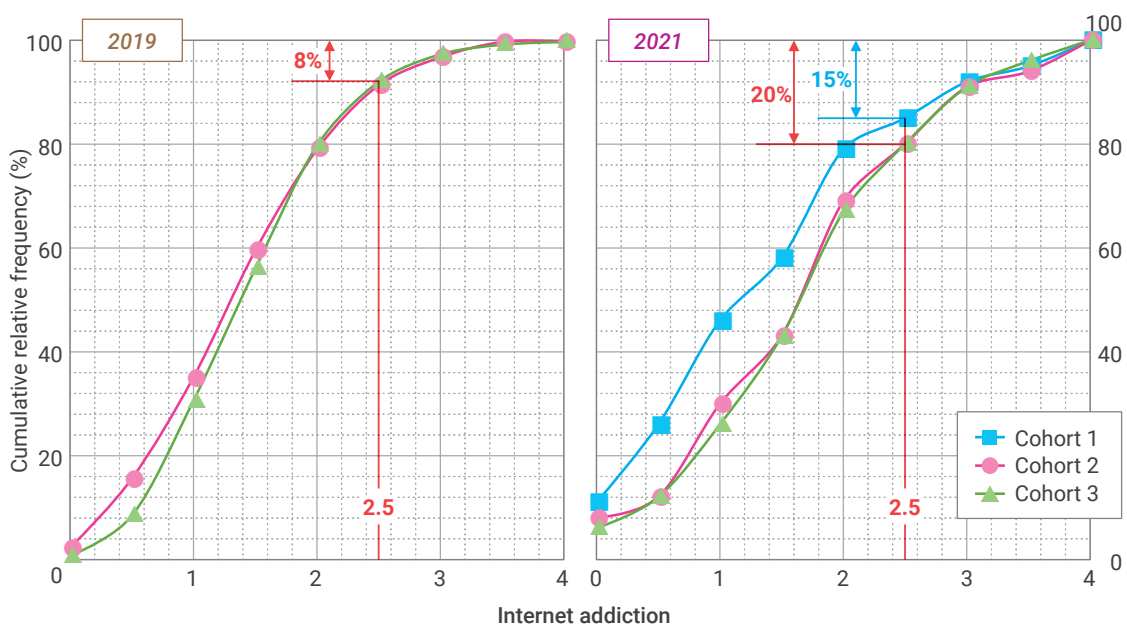


Figure 4.7. Cumulative Frequencies of Students' Level of Internet Addiction by Cohorts in 2019 and 2021.

#### 4.4.2. Digital game addiction remained stable and gender differences persisted

Students also responded to questions designed to capture game addiction (e.g., only thinking about playing a game, feeling miserable when not playing, and hiding how much time they spent playing). The questions were adapted from the Short Internet Gaming Disorder Scale (Lemmens et al., 2015). Students gave responses on a scale from 0 to 4, which were averaged to provide the Digital Game Addiction score. Based on Qin et al. (2020), a score higher than 2.56 indicates that the respondent is at risk of a disordered game. As shown in Figure 4.8, in 2019, about 7% of cohort 1 and cohort 2 students, and 4.2% of cohort 3 students showed symptoms of game addiction. In 2021, the corresponding percentages were around 8% for cohort 1 and cohort 2, and 4% for cohort 3. Thus, a significantly lower percentage of cohort 3 students reported game addiction symptoms than cohort 1 students in 2019 and 2021. Boys in all three cohorts showed higher levels of game addiction at both time points.

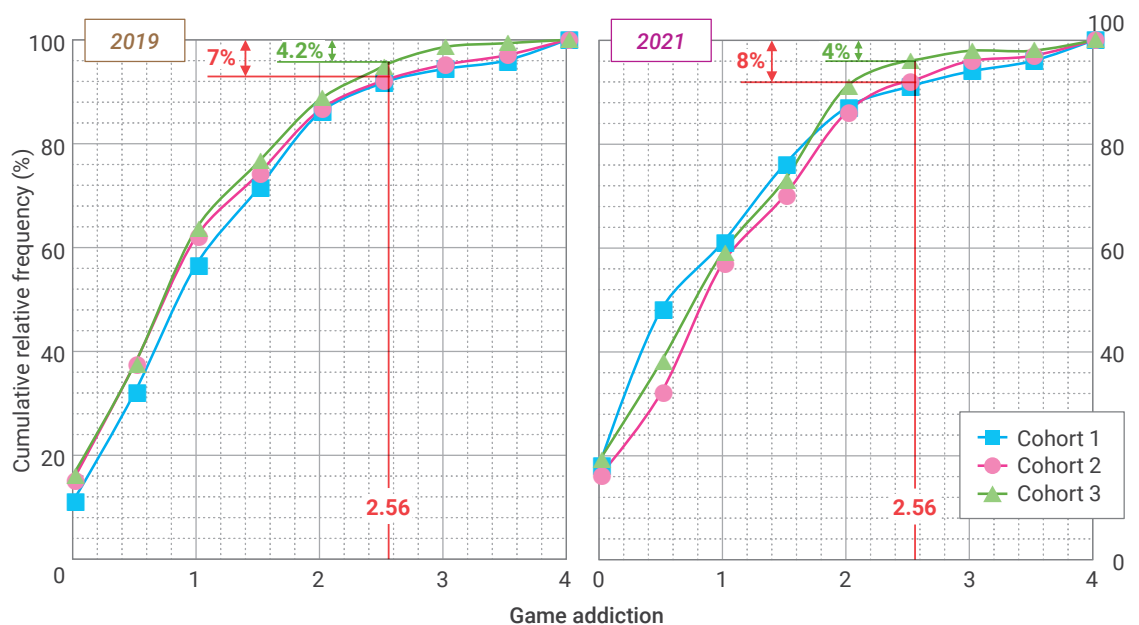


Figure 4.8. Cumulative Frequencies of Students' Digital Gaming Addiction by Cohorts in 2019 and 2021.

#### 4.4.3. Physical activity and sleep

Students in both 2019 and 2021 were asked to indicate how many hours per week they engaged in physical activity on a four-point scale (1 = less than one hour to 4 = more than 8 hours), and how much time they spent sleeping per night on a six-point scale (1 = less than 6 hours to 6 = more than 9 hours).

In 2019, students spent an average of 1-3 hours per week on physical activity, with no significant differences among the three cohorts. As shown in Figure 4.9, cohort 1 students were able to retain in 2021 a level of physical activities comparable to 2019. However, for the two older age cohorts, there is a significant increase in the percentage of students who had less than one hour of physical activity per week, at 39% and 45% for cohorts 2 and 3 respectively.

In both 2019 and 2021, students in cohort 1 reported sleeping the longest (average of 8 hours), followed by students in cohort 2 (average of 7 hours) and cohort 3 (average of 6 hours), with significant differences observed among the three cohorts. According to the American Academy of Sleep Medicine (AASM 2005), children aged 6 to 12 years should regularly sleep 9 to 12 hours per day, and adolescents aged 13 to 18 years should sleep 8 to 10 hours per day. Hence, in 2019, 53% of cohort 1 students had enough sleep, and the percentage decreased to 32% in 2021; 47% of cohort 2 students reported sufficient sleep in 2019 and decreased to only 27% in 2021. The percentage of cohort 3 students who had enough sleep decreased from 29% in 2019 to 15% in 2021.

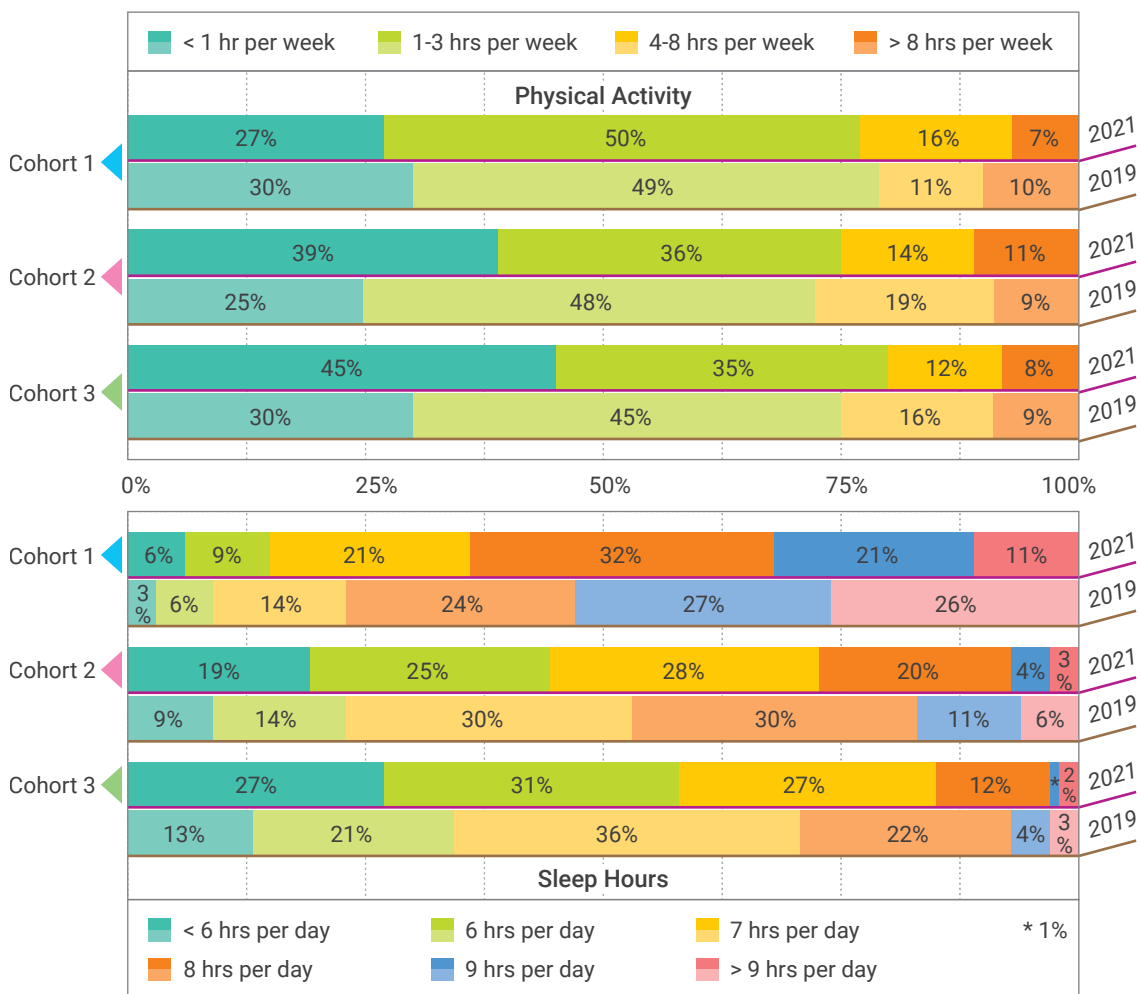


Figure 4.9. Frequencies of Students' Sleep (per Day) and Physical Activity per Week by cohort in 2019 and 2021.

#### 4.4.4. Mental health problems

Students were asked to respond to questions in the General Health Questionnaire (GHQ-12, Goldberg & Hillier, 1979), which is a popular and validated instrument measuring the current mental health status of the respondent. The students indicated whether they were able to concentrate on their work, felt constantly pressured, and whether they lost confidence in themselves. Each item was scored on a four-point scale (1 = less than usual to 4 = much more than usual). A total score of 22 to 24 is considered typical, scores above 27 suggest evidence of distress, and scores above 32 indicate severe mental health problems.



This instrument has been validated for respondents aged 11 and above. Thus, the GHQ-12 questions were administered to students in cohorts 2 and 3 in 2019 and to students in all three cohorts in 2021. Figure 4.10 indicates that around 6.2% of cohort 2 students and 9.5% of cohort 3 students reported symptoms indicative of severe mental health problems (a score higher than 32) in 2019. In contrast, the corresponding percentage increased to 13.5% and 17.9% for cohort 2 and 3 students in 2021, respectively. About 9.2% of cohort 1 students reported symptoms of severe mental health problems in 2021. Students in older cohorts reported lower levels of mental health than younger students in both 2019 and 2021, with significant differences across all cohorts.

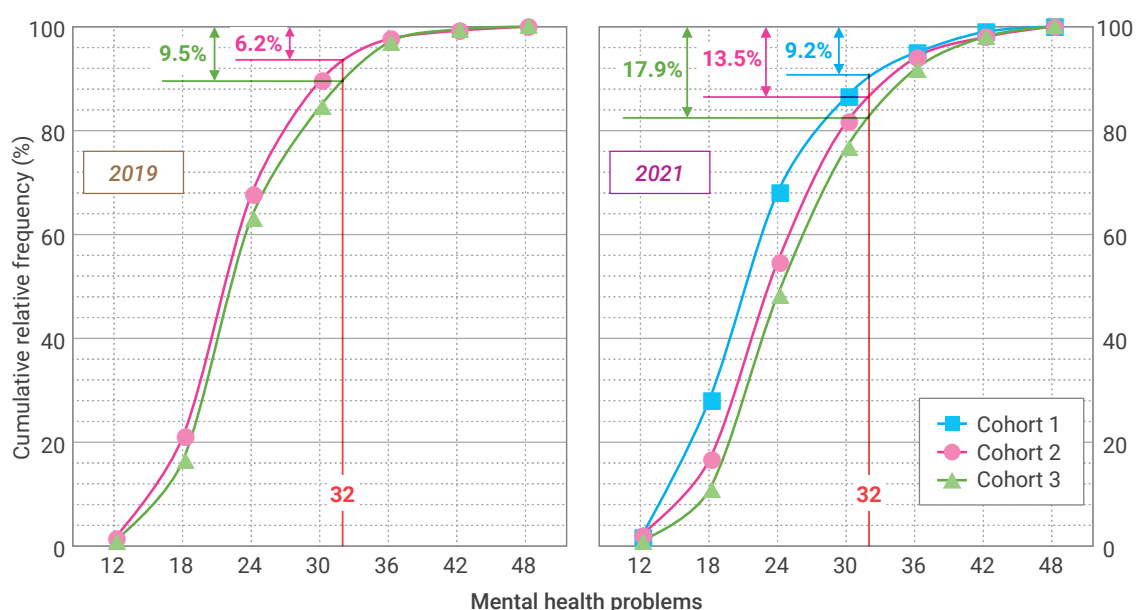


Figure 4.10. Cumulative Frequencies of Students' Mental Health Problems in 2019 and 2021.

## 4.5 Summary

To conclude, this chapter reports on Hong Kong students' digital technology use and digital wellness in 2019 and 2021. The findings are summarized as follows:

- Students in general spent more time on digital devices at home in 2021 than in 2019, whether for leisure activity or schoolwork.
- While the use of digital technologies for all purposes increased, the net time spent and the increase in time spent using technologies at home for leisure activities were much higher than other types of use.
- Unauthorized use of personal information and computer viruses were the most common security problems students encountered in both 2019 and 2021.
- The prior cyberbullying experience was associated with subsequent cyberbullying experiences.
- Increased percentages of students reported Internet addiction in 2021 compared to 2019. No gender difference was reported on Internet addiction.



- ◆ Younger student cohorts (i.e., Cohorts 1 and 2) were more prone to game addiction. A higher proportion of boys reported game addiction than girls.
- ◆ Older students reported more mental health problems than younger students in both 2019 and 2021. There was a very large increase in the percentage of students reporting symptoms of serious mental health problems in 2021 compared to 2019 for all age cohorts.
- ◆ Students in older cohorts (i.e., Cohort 2 and 3) spent less time on physical activity in 2021 than in 2019.

Due to the school closures during the COVID-19 pandemic, much of students' learning time shifted online. Digital technology used for schoolwork at home had become one of the most important channels for formal learning in 2021. The increased use of digital technologies could provide students with more opportunities to improve their digital literacy skills. However, it also poses more online risks such as Internet addiction and cyberbullying.

In parallel with increased time spent on digital devices and changed activity patterns, our findings also show worsened wellbeing experienced by students such as more Internet addiction and mental health problems reported in 2021 than in 2019. In the next chapter, we explore the extent to which students' uses of digital technology contributed to their wellbeing status, and whether there are factors that may protect students' wellbeing.

# 5. Digital literacy and students' wellbeing

## 5.1. Introduction

Digital technologies accord many benefits for students by facilitating instant access to information, rapid communication, and extensive social networking. The increased digital technology use, for example, provides students with opportunities to learn and practice their online self-protection capabilities, such as knowledge of data privacy and online security (Livingstone et al., 2019). However, the use of these technologies may also bring problems. For instance, students who spend more time in front of screens are more likely to encounter negative online experiences, such as security problems and risky online communication (Livingstone et al., 2019). Increased digital technology use has been found to associate positively with the experience of cyberbullying, either as a perpetrator or victim, or both (Lee & Shin, 2017; Yang et al., 2018). These negative online behaviors/experiences have been found to occur even at a young age (i.e., in children as young as 6 years old; OECD 2015) and can lead to maladaptive consequences such as sleep loss and psychological distress later in life (Aizenkot 2020; Saquib et al., 2017). Prolonged use of digital devices has also been shown to be a risk factor for Internet addiction (Aşut et al., 2019) and game addiction (Saquib et al., 2017), which in turn are associated with increased mental health problems (Ko et al., 2012).

However, not all students who encountered negative online experiences report feeling bothered or influenced afterward (Livingstone et al., 2011). A recent study showed that, on average, only a quarter of students who had negative online experiences reported being upset (Smahel et al., 2020). These findings suggest the presence of protective factors at the individual and contextual (e.g., family and school) levels, and that digital literacy (DL) serves as a crucial skill for accomplishing everyday tasks and for full participation in today's networked society (Carretero et al., 2017). While some studies suggest that digitally literate students may encounter more negative online experiences simply because they spend more time online than less digitally literate peers, it is generally expected that students with higher DL report fewer negative consequences of these negative online experiences because they have better knowledge of digital devices and better problem-solving skills when confronted with negative online experiences (der et al., 2014).

In this chapter, we discuss how students' DL is related to students' well-being. The first part of this chapter describes the associations between students' DL and various aspects of wellbeing by cohort in 2019 and 2021 respectively, using the full samples. We then present the results of two studies published from this project, both showing that DL may serve as a potential protective factor for student wellbeing. This chapter concludes with a summary of the findings and some recommendations.

## 5.2 Correlations between students' digital literacy and their wellbeing

Figure 5.1 presents the conceptual framework for the relations between students' DL, their reported mental health problems, and different aspects of digital wellbeing. Based on the findings from Livingstone, Mascheroni, and Staksrud's (2015), we investigated three categories of constructs related to students' wellbeing in the digital world in this study: adverse digital



wellbeing (i.e., Internet and game addiction; see 4.4.1 and 4.4.2 for details), online self-protection capacity (i.e., students' knowledge of data privacy and security measures), and negative online behavior and/or experiences (i.e., security problems, risky online communications, and cyberbullying; see 4.3 for details). All of the above-mentioned variables were measured through the student survey in 2019 and 2021. The mean scores for each of the variables were used for the analyses in this chapter. Students' mental health problems were assessed by the General Health Questionnaire (GHQ-12), and the total scores of the responses were used for the analysis (see 4.4.4 for details). Bivariate correlation analyses were performed to examine the relationships between DL, mental health problems and wellbeing.

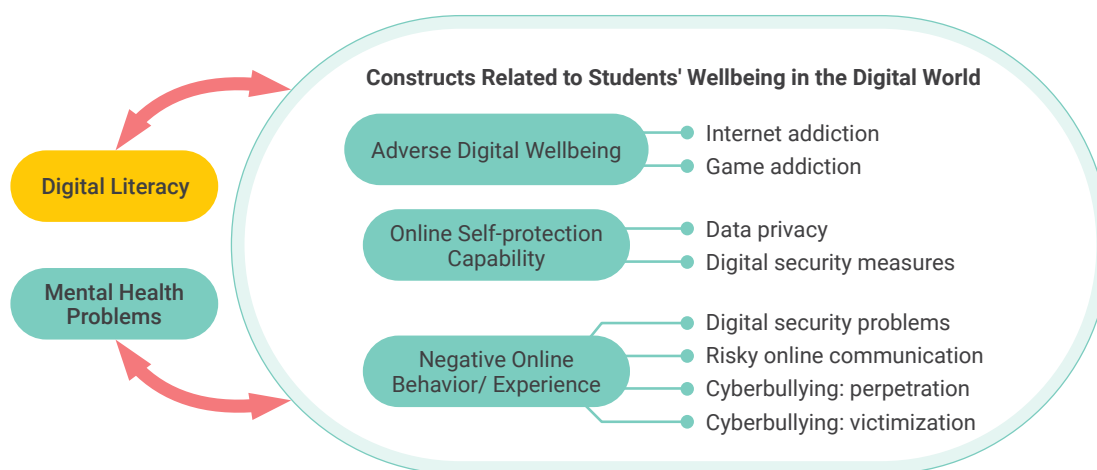


Figure 5.1. Conceptual Framework of the Relationships between DL, Mental Health Problems, and Constructs Associated with Wellbeing in the Digital World.

### 5.2.1. Digital literacy and wellbeing

Table 5.1 summarises the correlation coefficients between DL and each of the eight variables related to students' well-being in the digital world, shown in Figure 5.1 for each of the three 2019 and 2021 cohorts, respectively. It can be seen from the presented results that overall, DL serves as a strong protective factor on all the eight aspects investigated.

In terms of the adverse digital wellbeing studied, DL served as a protective factor for game addiction for cohorts 1 and 2 in both 2019 and 2021, as indicated by the statistically significant negative coefficient, showing that students with higher DL are less likely to report game addiction. There was no significant correlation for cohort 3 for game addiction, which was found to be low for this cohort in both waves of data collection. The relationship between DL and Internet addiction appears to be age-dependent. DL was negatively and significantly correlated with Internet addiction for Cohort 1 in 2021, thus serving as a protective factor for this cohort of students in 2021 (there is no data on Internet addiction for cohort 1 in 2019 as the instrument is not validated for children under age 10). The correlations were insignificant for cohort 2 in both waves and for cohort 3 in 2019. However, the correlation was positive and significant for cohort 3 in 2021. This apparent age-dependent relationship between DL and Internet addiction needs more in-depth investigations in future studies.

Regarding online self-protection capabilities, the significant positive correlations suggest that students who scored higher on DL tended to report higher awareness and capabilities in relation to data privacy issues for all three cohorts in both 2019 and 2021. There are similar positive significant relationships between DL scores and the ability to handle security issues for all three cohorts in 2021 but only for cohort 2 in 2019, possibly because the need to handle security issues escalated greatly for students in all three cohorts after the onset of the pandemic.

With regards to the four negative online behaviors/experiences, students who faced security problems in 2019 (cohorts 1 and 2) and 2021 (all three cohorts) as well as had risky online communication in 2019 (cohort 1) and 2021 (cohort 1 and 2) tended to score lower on DL. The significant negative correlations between DL and the two indicators of cyberbullying experiences suggest that students in cohorts 1 and 2 who had cyberbullying experiences (both for being a perpetrator or victim) tended to have lower DL scores in both 2019 and 2021. For students in cohort 3, lower DL scores were also related to more cyberbullying experiences in 2021.

Table 5.1  
Pearson Correlation Coefficients (*r*) between DL and Wellbeing

Aspect	Variable	Cohort 1		Cohort 2		Cohort 3	
		2019	2021	2019	2021	2019	2021
Adverse digital wellbeing	Internet addiction	-	-0.31***	0.00	-0.03	0.10	0.14**
	Game addiction	-0.27***	-0.35***	-0.19***	-0.28***	-0.02	-0.05
Online self-protection capabilities	Data privacy	0.26***	0.39***	0.35***	0.44***	0.36***	0.44***
	Digital security measures	0.07	0.21***	0.17**	0.21***	0.13	0.32***
Negative online behavior/experience	Digital security problems	-0.26***	-0.26***	-0.21***	-0.33***	-0.11	-0.23***
	Risky online communication	-0.28***	-0.16*	-0.10	-0.11*	0.00	-0.06
	Cyberbullying: perpetration	-0.28***	-0.23***	-0.2***	-0.26***	-0.07	-0.23***
	Cyberbullying: victimization	-0.29***	-0.25***	-0.13**	-0.23***	-0.06	-0.2***

Note. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$  (p-values were adjusted by Bonferroni correction); - not measured.

### 5.2.2. Students' mental health problems and digital wellbeing related factors

In addition to the relationships between DL and wellbeing, we also conducted correlation analysis on student-reported mental health problems and digital wellbeing related variables (Figure 5.1 and Table 5.2). Overall, the level of student-reported Internet addiction and game addiction was positively and significantly correlated with their reported mental health problems (the only exception being found for cohort 2 in 2021), indicating that students' mental health was adversely affected if they suffered from Internet and/or game addiction.

The correlation coefficients between student-reported mental health problems and their online self-protection capabilities related to security measures and data privacy were all insignificant. This indicates that these capabilities were not directly related to students' mental wellbeing.

Regarding the four negative online behaviors/experiences, the cyberbullying-related experiences appeared to have more serious ramifications on the students' mental health situation. Students' experiences of digital security problems and engagement in risky online behavior did not show a significant correlation with their reported mental health problems, except for cohort 3 in 2019, which were both positive. This may reflect that this cohort of students became more actively engaged in Internet use at that point in time. More investigations are needed to explore whether there is an age effect here.

The correlation coefficients between cyberbullying experiences (for being a perpetrator or a victim) and mental health problems were all positive, indicating that cyberbullying may contribute to mental health problems. However, the correlations were not significant for cohort 1 students. This indicates that this cohort of students may not be seriously disturbed by cyberbullying experience, perhaps because of their age, and because of the lower probability of encountering cyberbullying. There is evidence that cyberbullying victimization is likely to contribute more seriously to mental health problems as correlations for victimization were all higher than the respective correlations for perpetration. For victimization, all four coefficients (for cohorts 2 and 3 in 2019 and 2021) were statistically significant, while the coefficients for perpetration were only significant in 2019 for the two older cohorts.

Table 5.2  
Pearson Correlation Coefficients (*r*) between Mental Health Problems and Wellbeing

Aspect	Variable	Cohort 1		Cohort 2		Cohort 3	
		2019	2021	2019	2021	2019	2021
Adverse digital wellbeing	Internet addiction	-	0.36***	0.34***	0.23***	0.42***	0.29***
	Game addiction	-	0.26***	0.2***	0.09	0.19***	0.15**
Online self-protection capabilities	Data privacy	-	0.04	-0.01	0.03	-0.02	-0.02
	Digital security measures	-	-0.04	-0.12	-0.03	-0.13	-0.07
Negative online behavior/experience	Digital security problems	-	0.08	0.03	0.08	0.16*	0.06
	Risky online communication	-	0.10	0.07	0.06	0.25***	0.07
	Cyberbullying: perpetration	-	0.08	0.13**	0.09	0.15**	0.11
	Cyberbullying: victimization	-	0.13	0.17***	0.13**	0.24***	0.14**

Note. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$  (p-values were adjusted by Bonferroni correction); - not measured.

### 5.3 Study I: Students' digital literacy as a protective factor against game addiction

The purpose of Study I was to explore whether students with good DL (referred to as digital competence in Tso et al. (2022)) were better protected from the potential adverse effects of digital use and the risk of gaming addiction. The analyses were based on the full student sample of 2019 (valid  $N = 1956$ ; Primary = 690; Secondary = 1266). Multiple regression analyses with further mediation analyses were performed to investigate the association of DL with game addiction and mental health status in children and adolescents. In this paper, mental health status was reverse coded based on the GHQ-12 items (i.e., a higher score represented better mental health status).

The regression results presented in Figure 5.2 show that children and adolescents with better DL were less likely to develop gaming addiction ( $\beta = -0.144$ ,  $p < 0.0001$ ). DL was found to mediate the relationship between digital device usage time and gaming addiction. Specifically, although children and adolescents who spent more time on using digital device were more prone to game addiction ( $\beta = 0.21$ ,  $p < 0.0001$ ), more time spent on digital device use was also associated with higher DL ( $\beta = 0.23$ ,  $p < 0.0001$ ), which in turn predicted less gaming addiction ( $\beta = -0.20$ ,  $p < 0.0001$ ). The declined gaming addiction was, in turn, predictive of better mental health status ( $\beta = -0.26$ ,  $p < 0.0001$ ).

To conclude, DL is associated with less gaming addiction and could potentially lead to better mental wellness in children and adolescents by reducing the risks of gaming addiction. Education programs that promote DL are essential to maximizing the benefits of digital use and at the same time reducing the potential adverse effects of the inappropriate use of digital devices.

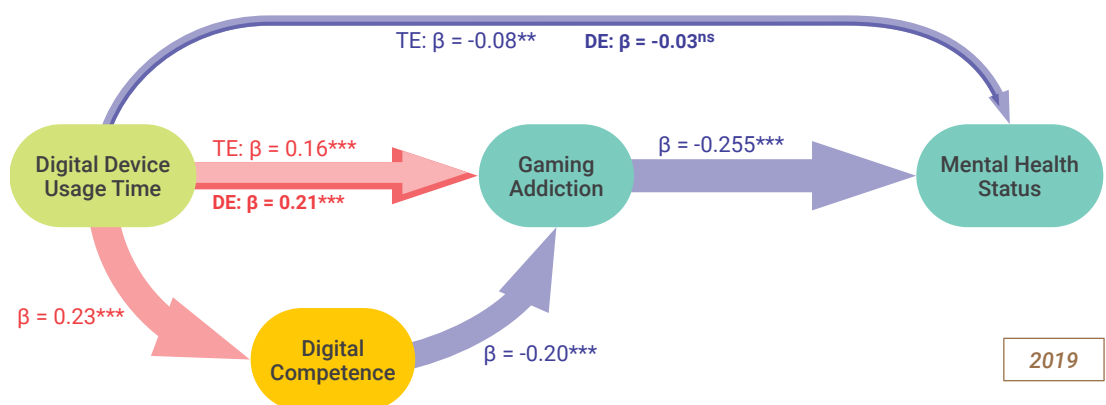


Figure 5.2. Relationship between Digital Device Usage Time, Gaming Addiction, Digital Competence (i.e., Digital Literacy), and Mental Health Status after Controlling for Gender and SES.

Mental health status was measured by the GHQ scale (reverse coded).

Standardized regression coefficient (beta) was used as the path coefficient.

TE: total effect. DE: direct effect. \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ , ns not significant.

(Adopted from Tso, W. W., Reichert, F., Law, N., Fu, K. W., de la Torre, J., Rao, N., ... & Ip, P. (2022). Digital competence as a protective factor against gaming addiction in children and adolescents: A cross-sectional study in Hong Kong. *The Lancet Regional Health-Western Pacific*, 20, 100382.)

Note. The analysis reported in this Study has not been performed for the full 2021 sample at the time of writing this report.

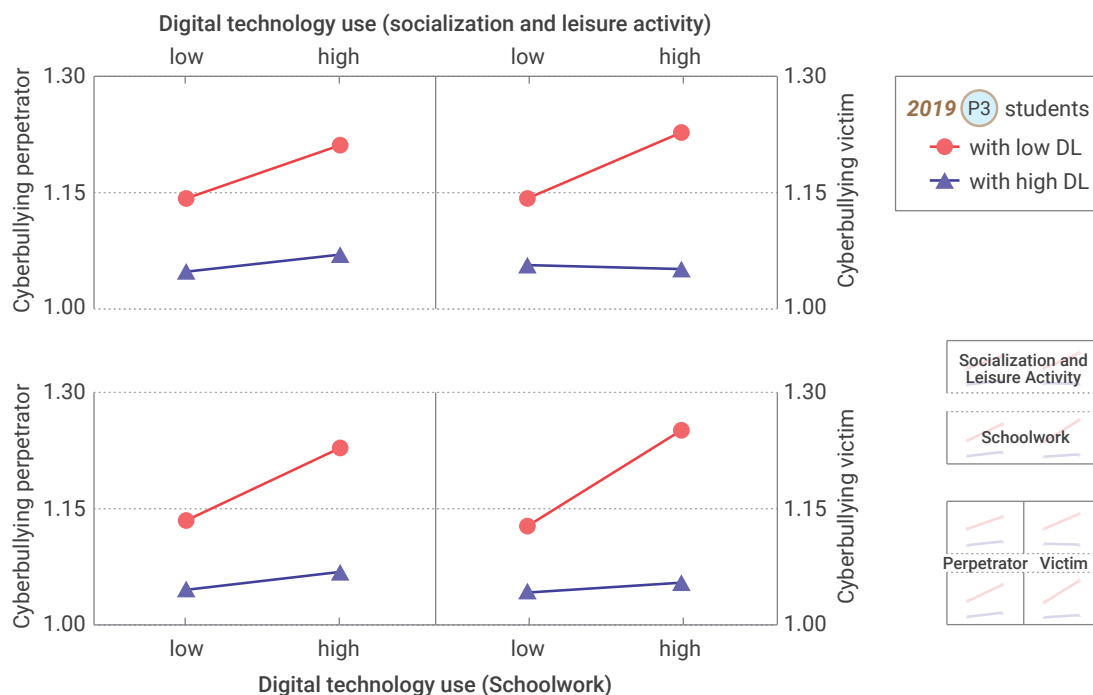
## 5.4 Study II: Students' digital literacy as a protective factor against cyberbullying

In Study II (Tao et al., 2022), we examined whether primary school students' probabilities of experiencing cyberbullying (perpetration and victimization) were related to their frequency of digital technology use and their levels of DL achievement. The analyses were based on the full sample of cohort 1 students in 2019 (valid  $N = 736$ ). Moderated regression analyses were conducted in SPSS PROCESS using listwise deletion; children's gender and socioeconomic status were used as control variables. In the moderation analyses, the independent variables were digital technology use for leisure activity and for schoolwork respectively. Cyberbullying experience (as perpetrator and as victim) was used as dependent variables. The students' DL scores were included as moderators in two separate regression models (one for perpetrator and one for victim). As the interaction effect of DL was detected, a simple slope analysis was conducted for two groups of students, one with high DL performance (those with DL scores  $\geq (\text{mean}+1\text{SD})$ ) and the other with low DL performance (those with DL score  $\leq (\text{mean}-1\text{SD})$ ) and shown in Figure 5.3.

The results in Figure 5.3 show that the more time children spent using digital devices (both for leisure and for schoolwork), the more likely they were to experience cyberbullying (both as perpetrators and as victims;  $r = 0.22-0.25$ ,  $ps < 0.001$ ). These positive associations were much stronger among children with low levels of DL (but only statistically significant for victims;  $B = -0.05$ ,  $p < 0.05$  for leisure and  $B = -0.06$ ,  $p < 0.01$  for schoolwork). This means that students with low DL were more likely to be victims of cyberbullying if they spent a lot of time online, either for leisure or for schoolwork. On the other hand, students with high DL were able to avoid becoming victims of cyberbullying even if they spent a lot of time online.

In summary, the results of this study suggest that even young children in Hong Kong have experienced cyberbullying. The more time they spent online (either for leisure or for schoolwork), the more likely they were to report cyberbullying experiences (being both perpetrators and victims). Notably, DL acts as a moderator between digital technology use and cyberbullying experiences (being a victim). Therefore, cyberbullying prevention programs should aim to improve children's DL as it can provide them with the necessary skills to avoid cyberbullying situations. Early prevention/intervention is recommended to include DL to reduce cyberbullying in primary school students.





**Figure 5.3.** This Figure Displays the Level of Cyberbullying (Left: Perpetrator, Right: Victim) as a Function of Digital Technology Use (Top: Socialization and Leisure Activity, Down: Schoolwork) at Low (Mean-1SD) and High (Mean+1SD) Levels of DL.

$p < 0.001$  for the two low DL paths for victim (two-tailed).

Adopted from Tao, S., Reichert, F., Law, N., & Rao, N. (in press) Digital technology use and cyberbullying among primary school children: Digital literacy and parental mediation as moderators. *Cyberpsychology, Behavior, and Social Networking*.

**Note.** The analysis has not been performed for the full 2021 sample at the time of writing the report.

## 5.5 Summary

This chapter reports on the relationship between students' DL, reported mental health problems and various aspects related to their digital wellbeing by cohort in 2019 and 2021. The analyses show that DL serves as a potential protective factor for student wellbeing. The findings are summarized as follows:

- Students who had higher DL scores were less likely to suffer from Internet and game addiction and had a lower probability of reporting the four negative online behaviors and/or experiences surveyed.
- Students with higher DL were more likely to develop better online self-protection capabilities (i.e., security measures and data privacy).
- Adverse digital wellbeing (Internet and game addiction) and cyberbullying experiences (perpetration and victimization) were two challenges to students' wellbeing that would negatively affect students' mental health.



- ◆ DL is associated with less game addiction, which potentially contributes to lowered risks to mental wellness associated with game addiction in children and adolescents.
- ◆ Even young children in Hong Kong have experienced cyberbullying. DL acts as a moderator between digital technology use and cyberbullying experiences (being a victim). Early prevention/intervention is recommended to include DL to reduce cyberbullying in childhood.

Overall, our findings indicate that education programs that promote DL are essential to maximize the benefits of digital use, while reducing the potential adverse effects of the inappropriate use of digital devices.

## 6. Students' online activities and digital literacy in a rapidly changing ecological context

### 6.1. Introduction

As mentioned in [Chapter 1](#), the present study aimed to investigate how the digital literacy competence of children and adolescents aged 9 to 17 develops and how their digital literacy competence affects their wellbeing. In designing this longitudinal panel study, the research team followed an ecological perspective (Bronfenbrenner, 1979, 2005) to consider factors at a broad societal level that may influence human development alongside individual and community factors. One potential exosystemic change that we hypothesized could occur within a short two-year period was the possibility of profound change in technology use at home, in schools and in the wider community. To measure the potential impact of macro-level contextual changes on students' digital competence development, the study recruited secondary 3 (S3) students in 2019 (i.e., Cohort 3) and in 2021 (i.e., Cohort 2) from the same schools, separated by two grade levels. Therefore, we can compare the digital competence and survey results of S3 students in 2019 and in 2021 at the same school.

The COVID-19 outbreak, which began in late January 2020 and had a devastating global impact on many fronts beyond health and the economy, was unexpected by the research team, requiring strict social distancing measures. The Hong Kong SAR government has mandated long periods of intermittent school suspension since the end of January 2020 (Education Bureau, 2020). The shifting of the learning mode from primarily face-to-face to fully online has greatly increased students' time spent on digital technology use, which is likely to have impacts on students' DL development.

In this chapter, we focus on S3 students' DL and their online activities at home and at school, as well as the relationships between these two parameters at the two different data collection time points (2019 and 2021). As these students attended the same grade at the same sampled schools, modelling these relationships allows us to understand how the socio-technological macro context influences the relationships between students' online activities and their DL before and after the pandemic. The first part of this chapter presents descriptive information on the students' online activities at home and at school for different purposes at both time points. This is followed by a report on the latent factor extraction from various online activities, and how these latent factors were associated with students' DL. In the second section, we present a person-centred approach to understanding how students' online activity patterns were associated with DL. In the final section, we summarize our findings.

### 6.2. S3 students' online activities and digital literacy competence in 2019 and 2021

Students responded to several questions in the survey to report on the time they spent per week on different online activities at home (1 = not at all; 2 = 1-2 times; 3 = 3-4 times; 4 = almost every day (2019)/5 times or more (2021)) and per month at school (1 = never; 2 = less



than once a month; 3 = at least once a month but not every week; 4 = at least once a week). As the research team made some minor changes to the online activity items to improve measurement in 2021, only the common items that were asked in both 2019 and 2021 are presented and analysed in this chapter. The percentage of responses for each of the frequency categories for online activities at home and at school can be found in [Table 6.1](#) and [Table 6.2](#), respectively.

Table 6.1

*Percentages of Students Reporting Different Frequencies of Engagement in Various Online Activities at Home per Week in 2019 and 2021*

	2019				2021			
	Not at all	1-2 times	3-4 times	Almost everyday	Not at all	1-2 times	3-4 times	5 times or more
Discuss with teachers about matters related to learning	57.1	30.5	9.3	3.1	38.3	43.5	11.8	6.4
Discuss with classmates about matters related to learning	20.1	34.4	27.2	18.2	15.5	33.6	26.9	24.0
Do assignments/reports on a designated topic	42.9	38.6	15.0	3.6	45.5	35.9	12.1	6.6
Search for information/learning materials related to schoolwork	15.0	42.5	27.9	14.6	14.6	27.9	30.8	26.6
Chat with net friends (via chatroom/MSN/Skype/QQ)	19.6	13.8	13.1	53.5	13.5	13.8	15.7	57.1
Browse social networking sites (e.g., Facebook/Weibo)	13.4	16.7	12.4	57.5	11.6	18.5	19.6	50.3
Browse the Internet without particular purpose	33.9	25.1	14.3	26.7	27.6	28.1	16.5	27.9
Write a blog entry	83.3	11.5	3.3	1.9	75.7	12.9	6.9	4.5
Make or use charts, graphs or forms	78.1	15.1	4.8	1.9	59.3	26.1	8.7	5.9
Create websites	89.2	7.6	2.6	0.7	75.7	12.9	6.9	4.5

On average, S3 students spent more time discussing with teachers about matters related to learning, chatting with net friends, and making charts, graphs or forms at home in 2021 than in 2019. The time students spent on browsing social networking sites (e.g., Facebook and Weibo) was less in 2021 compared to 2019. They spent similar amounts of time discussing with classmates about matters related to learning, doing assignments/ reports on a designated topic, searching for information related to schoolwork, writing a blog entry and creating websites.

Table 6.2  
Percentages of Students Reporting Different Frequencies of Engagement in Various Online Activities at School per Month in 2019 and 2021

	2019				2021			
	Never	Less than once a month	At least once a month but not every week	Less than once a week	Never	Less than once a month	At least once a month but not every week	Less than once a week
Preparing reports or essays	29.1	39.3	24.5	7.1	36.1	38.8	17.3	7.9
Giving presentations	31.4	45.5	19.8	3.3	39.0	44.9	11.9	4.2
Working with other students at your own school	22.4	36.6	28.4	12.6	30.0	40.6	20.0	9.4
Writing about your learning	54.0	26.9	13.8	5.3	52.3	26.9	13.4	7.4

In terms of learning activities at school, S3 students spent on average less time preparing reports or essays, giving presentations, and working with other students at their own school in 2021 compared to 2019. This could be due to the fact that students experienced several intermittent school suspensions in 2021, which reduced their overall time spent on learning activities in school.

## 6.3 The relation between online activities and DL competence

### 6.3.1. Online activity latent factors

To explore the relationship between students' online activities and DL performance, factor analyses and measurement invariance tests were conducted based on students' responses regarding online activities in both 2019 and 2021. Table 6.3 shows the resulting factors and the corresponding items. Two latent factors for online activities at home and one latent factor for online activities at school were extracted based on S3 students' responses. Specifically, learning activities at home include using digital technologies to communicate with teachers and classmates, searching online for information related to learning, and making or using charts, graphs, or forms. Leisure activities at home include online activities that are not related to schoolwork, such as browsing social networking sites, chatting with friends on social media, and browsing the Internet without a particular purpose. Finally, learning activities at school refer to preparing reports or essays, giving presentations, working with other students and writing about their own learning. Full metric measurement invariance was achieved for learning activities at home, and partial metric invariance was supported for leisure activities at home and learning activities at school between 2019 and 2021. We therefore believe that the three factors of online activities are comparable between 2019 and 2021.

Table 6.3

*Factor Analysis of Students' Online Activities in 2019 and 2021*

Factor Name	Items in the Survey
Learning activities at home	1. Discuss with teachers about matters related to learning
	2. Discuss with classmates about matters related to learning
	3. Do assignments/ reports on a designated topic
	4. Search for information/ learning materials related to schoolwork
	5. Make or use charts, graphs or forms
Leisure activities at home	1. Browse social networking sites (e.g., Facebook/ Weibo)
	2. Browse the Internet without particular purpose
	3. Chat with friends on social media (via WhatsApp/ Instagram/ WeChat)
Learning activities at school	1. Preparing reports or essays
	2. Giving presentations
	3. Working with other students at your own school
	4. Writing about your own learning

### 6.3.2. Structural equation models of the relations between students' online activities and digital literacy

Using the factors described above, we examined the relations between S3 students' online activities and DL performance in 2019 and 2021. Structural Equation Models (SEM) were constructed that included both the measurement model (i.e., factor analysis) and the structural model (i.e., the relations between factors and DL) to obtain an explicit assessment of measurement error and to estimate the latent (unobserved) variables (i.e., factors) via observed variables (i.e., the items). Figure 6.1 and Figure 6.2 shows the structural model and results for 2019 and 2021, respectively.

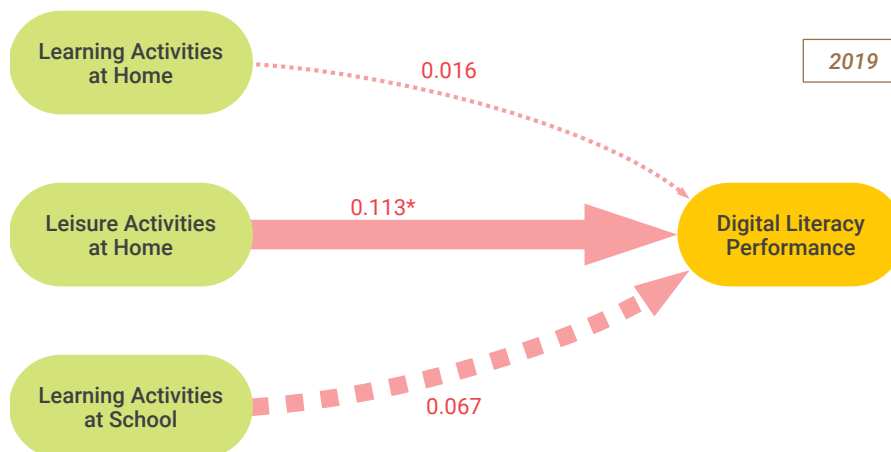


Figure 6.1. Structural Model of Students' Online Activities and Digital Literacy Performance in 2019.

Dash line = non-significant path. \*  $p < 0.05$ .

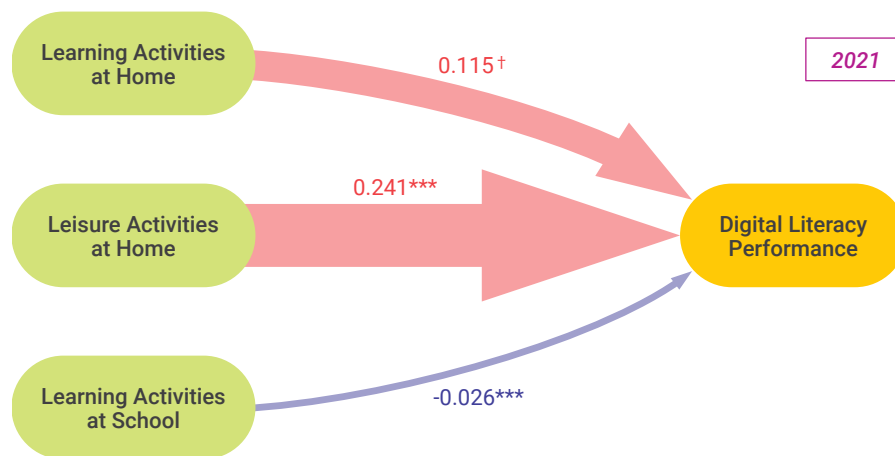


Figure 6.2. Structural Model of Students' Online Activities and Digital Literacy Performance in 2021.

\*\*\*  $p < 0.001$ ; +  $p < 0.10$ .

According to the SEM results, in 2019, students who spent more time on leisure activities at home performed better in DL assessment ( $\beta = 0.11$ ,  $p = 0.04$ ). Learning activities at home and at school were not predictive of students' DL performance. In 2021, students who spent more time on leisure activities at home performed better in DL assessment ( $\beta = 0.24$ ,  $p < .001$ ), and those who spent more time on learning activities at school performed worse in DL assessment ( $\beta = -0.26$ ,  $p < .001$ ). Those who spent more time on learning activities at home tended to perform better in the DL assessment, though the relationship is not statistically significant ( $\beta = 0.12$ ,  $p = 0.08$ ). These results indicate that the digital learning activities assigned to students at school were not conducive to DL development, whereas the more self-directed leisure activities at home appear to contribute positively to students' DL.

### 6.3.3. Latent profile analysis of the relations between students' online activity patterns and DL performance

To understand the relationships between students' online activities and DL performance from a holistic perspective of an individual's profile of engagement in the different categories of online activities, latent profile analyses were conducted using the factor scores of the above three factors, one for each wave of the data collected. In contrast to the traditional variable-centred approach (e.g., SEM) which focuses on the general relationships between individual variables, latent profile analysis is a person-centred approach that describes population heterogeneity in terms of differences between individuals in a set of behaviors or characteristics (for details, please refer to <https://www.theanalysisfactor.com/what-is-latent-class-analysis/>). In other words, each latent profile represents a subset of individuals characterised by a pattern of responses to a set of variables. Therefore, latent profiles derived from different online activities are conceptually meaningful and methodologically useful to understand students' online activity patterns and their relations to DL performance.

Factor scores of the three types of online activities (i.e., learning activities at home and at school and leisure activities at home) were subjected to a robust maximum likelihood estimation of latent profile analysis. The relations between online activity profiles and DL performance were examined by Wald chi-square tests (i.e., Bolck et al., 2004). As indicated in Figure 6.3, two profiles were obtained for S3 students' data in 2019 and four profiles for S3 students in 2021. In 2019, profile 1 students were characterised by low frequencies of learning activities (both at home and at school) and moderate frequency of leisure activities at home; profile 2 students were characterized by moderate frequencies of learning activities (at home and at school) and relatively high leisure activities at home. In 2021, students in profile 1 were characterised by a low frequency of learning activities (at home and at school) and moderate leisure activity at home; profile 2 students were characterised by moderate learning activities both at home and at school, and high frequencies of leisure activity at home; profile 3 contains students with moderate-to-high frequencies of learning activities both at home and at school, and high frequencies of leisure activity at home; profile 4 includes a small group of students who reported very high frequencies of engagement in all online activities.

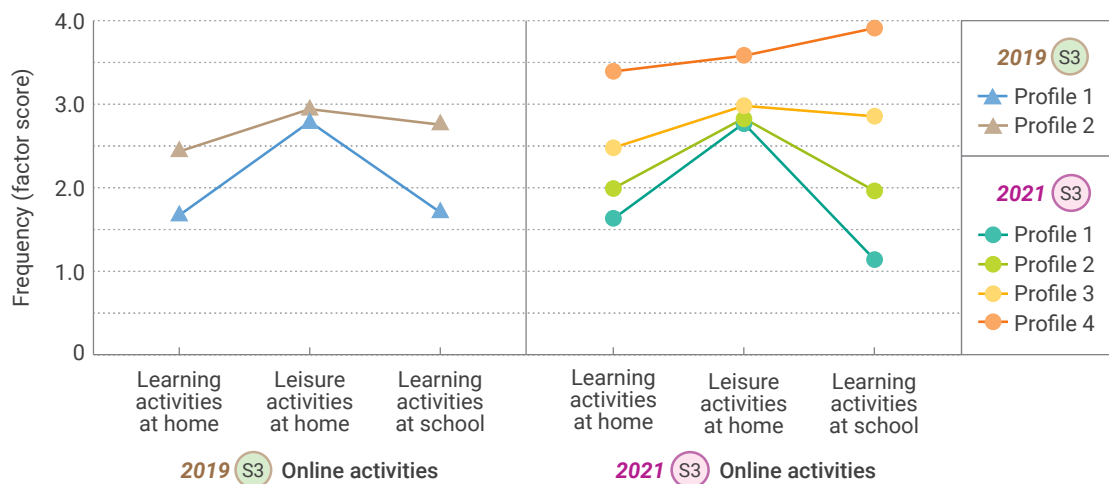


Figure 6.3. Frequency of Online Activities for Each of the Classified Profiles in 2019 and 2021.

Table 6.4 shows the comparison of DL scores across the online activity profiles in 2019 and 2021. In 2019, DL performance was not significantly different between profiles 1 and 2. In 2021, students in profile 2 had the highest DL score and were significantly higher than students in profile 3. The DL score of students in profile 1 was lower than the DL score of students in profile 2 and higher than those in profile 3 (but not significantly different). Students in profile 4 had the lowest DL score and were significantly lower than the other three profiles.

Table 6.4  
Mean, SD, and comparison of DL score among profiles in 2019 and 2021

DL score			
2019 S3	Mean (SD)	2021 S3	Mean (SD)
★ Profile 1	0.484 (0.045)	● Profile 1	1.149 (0.079)
		● Profile 2	1.316 (0.085)
★ Profile 2	0.603 (0.070)	● Profile 3	0.829 (0.148)
		● Profile 4	-0.155 (0.298)
2019 S3	Chi-square test	2021 S3	Chi-square test
		● Profile 1 vs. ● Profile 3	$X^2 = 3.70$
		● Profile 2 vs. ● Profile 3	$X^2 = 7.37^*$
		● Profile 3 vs. ● Profile 4	$X^2 = 8.55^*$
★ Profile 1 vs. ★ Profile 2	$X^2 = 1.73$	● Profile 1 vs. ● Profile 2	$X^2 = 1.93$
		● Profile 1 vs. ● Profile 4	$X^2 = 17.96^{***}$
		● Profile 2 vs. ● Profile 4	$X^2 = 22.63^{***}$

Note. \* adjusted  $p < 0.05$ , \*\*\* adjusted  $p < 0.001$ .

## 6.4 Summary

This chapter focuses on the relationships between S3 students' online activities at home and at school and their DL at two different time points (2019 and 2021). The key findings are summarized below.

- ◆ On average, S3 students spent more time discussing with teachers about matters related to learning, chatting with net friends, and making charts, graphs or forms at home, but less time browsing social networking sites in 2021 compared to 2019.
- ◆ The time spent on learning activities at school in general decreased in 2021.
- ◆ In both 2019 and 2021, students who spent more time on leisure activities at home performed better in DL assessment. Additionally, in 2021, students who spent more time on learning activities at school performed worse in DL assessment.
- ◆ In 2021, students with moderate learning activities both at home and at school and a high frequency of leisure activity at home scored highest in DL assessment.

In conclusion, students' online learning activities were closely related to their DL performance in both 2019 and 2021.



## 7. Conclusions and policy recommendations

Digital citizenship is conceptualized as the human capacity to leverage the potential of digital technologies to live and learn and to ensure their own wellbeing, as well as to exercise their responsibility to engage and participate in the globally networked world (Law et al., 2018). It has gained increasing attention in recent years as the use of digital technology has become essential for almost every aspect of life in the 21st century. Digital citizenship capacity is compared to reading and writing literacy as a fundamental skill in everyday life, for learning, wellbeing, and career development for children and adolescents. In this context, the Learning and Assessment for Digital Citizenship (eCitizen for short) project aimed to address the grand challenge of understanding and enhancing the development of digital citizenship as a multi-faceted human capacity within the diverse educational, social, cultural, and technological contexts in Hong Kong.

In this study, we have developed a theoretically robust and empirically grounded conceptual framework and instruments for measuring digital citizenship development from childhood to early adulthood, encompassing cognitive, metacognitive, social and affective learning outcomes important for personal and social well-being. A longitudinal cohort design with three age cohorts (8-10, 12-14, 15-17) was adopted in this project with the main data collection conducted in the second half of the 2018-2019 and 2020-2021 school years. This report summarises the research findings pertaining to the following four key research questions that were elaborated in [Chapter 1](#) in conjunction with the conceptual framework.

1. What levels of digital citizenship capacity did students reach and whether these were influenced by the students' family socioeconomic backgrounds?
2. Did students' digital citizenship capacity influence the extent to which students had experiences indicative of adverse wellbeing?
3. Whether and how did different uses of digital technology correlate with students' digital citizenship capacity?
4. What were the changes that took place between the two waves of data collection in 2019 and 2021? Which of the changes observed were likely to be related to the tsunamic social and schooling changes that took place due to the COVID-19 pandemic induced extended disruptions that started since February 2020?

To answer these questions for the three age cohorts at the two time points of data collection separated by a time gap of two years, this report is organized as follows:

- ◆ [Chapter 2](#) and [Chapter 3](#) reported on students' growth and development in digital citizenship capacity and the family factors that influenced them.
- ◆ [Chapter 4](#) reported on students' digital technology use and the overall status of different aspects of students' wellbeing.
- ◆ [Chapter 5](#) reported on the relationships between digital technology use, digital citizenship capacity and wellbeing.
- ◆ In [Chapter 6](#), we compared the online activities and DL skills of Secondary 3 students in 2019 and 2021 to explore how the COVID related disruptions changed students' learning lives and their DL development.

This final chapter summarises the main findings reported in the previous chapters and discusses the contributions of and implications arising from this study.

## 7.1 Students' digital citizenship capacity and their family socioeconomic background

### 7.1.1. Students' DL performance

The DL performance of students in all cohorts generally increased in 2021 compared to 2019. In both years, students in the older cohorts performed significantly better than those in the younger cohorts. No gender difference in DL performance was observed except for Cohort 2 students, and girls performed significantly better than their male peers in both 2019 and 2021.

While there were overall improvements in DL for all three age cohorts over time, the performance gap in DL also widened significantly for each of the cohorts. Moreover, for a small number of students in all three age cohorts, their DL scores actually decreased. This widened DL gap may likely have also contributed to a wider academic gap over the same period, particularly as DL proficiency could influence the extent to which students were able to learn effectively via online modes during the pandemic. Unfortunately, it was not within the scope of the present study to investigate whether students with lower DL were doubly disadvantaged in their academic development because of the need to move to the online mode of learning. This should be one of the priority areas for further research in order to address the challenges to education due to the COVID pandemic.

The DL performance gap has increased significantly within and between schools between 2019 and 2021, and this widening gap was even more acute at the secondary school level. In all three age cohorts, students in a couple of high performing schools were able to improve their DL greatly while maintaining a relatively small DL divide within the school. Unfortunately, the reverse was also observed in some other schools. In 2021, Cohort 1 (primary 5) students' DL performance in the best performing school was better than the DL performance of Cohort 2 (Secondary 3) students in several secondary schools. Cohort 3 students' DL performance in the lowest performing school in 2021 was poorer than the average DL performance of the Cohort 1 students. The widened DL performance gap poses a major challenge for the curriculum planning of schools and teachers and highlights the need for professional support to improve DL competence in disadvantaged groups.

Analyses based on the matched sample (students who participated in 2019 and 2021) indicated that on average, students in all three cohorts showed improvements in DL scores from 2019 to 2021. Those in cohorts 1 and 3 improved more than students in Cohort 2.

### 7.1.2. Students' DL performance and their family socioeconomic background

Two indices were used in this report to measure students' family socioeconomic background (SES): (1) academic social capital, computed based on parental education levels and the number of books at home, and (2) home resources, computed based on whether students have their own room, study desk, and a quiet place to study (only assessed in 2021). Results show that family SES indices were positively related to students' DL achievement, but only significant for the two younger cohorts. Academic social capital had a stronger positive correlation than home resources with students' DL scores and the extent of the DL growth between 2019

and 2021 (as measure through the increase in DL scores). Students who came from schools with higher mean SES performed better in DL, but an individual student's family SES had no relationship to his/her DL compared to their peers in the same school.

Students' access to large screen devices at home was found to be an important predictor of their DL performance in 2019 (Frank et al., 2020). In 2021, access to large screen devices at home was also positively associated with students' DL for all cohorts, especially for the two senior cohorts' students. Matched data from students who took part in both waves of data collection show that those who had no access to large screen devices in 2019 but had access in 2021 were able to catch up with their peers in terms of growth rate for all three cohorts. This underlines the crucial role that accesses to large screen devices at home plays in students' DL performance.

Detailed results on students' DL performance and its relations with students' family SES can be found in [Chapter 2](#).

### **7.1.3. Students' CPS performance**

CPS assessment was administered to students in cohorts 2 and 3 in 2019 and all three cohorts in 2021. In 2021, the CPS scores of students in cohorts 2 and 3 (in both social and cognitive domains) were moderately lower than in 2019. No significant differences were found in the social CPS scores across the two cohorts in 2019 and the three cohorts in 2021. However, Cohort 3 students had better CPS cognitive scores compared to Cohort 2 students in 2019, and secondary school students performed better in cognitive scores than primary school students in 2021.

No significant gender differences were observed for social CPS process skills in both 2019 and 2021. Girls in Cohort 2 significantly outperformed their male counterparts in the CPS cognitive domain in 2019, whereas in Cohort 3, girls had significantly better CPS cognitive performance than boys in 2021.

The matched students in Cohort 2 did not show significant changes in cognitive CPS skills but regressed in social skills from 2019 to 2021. For the matched Cohort 3 students, both cognitive and social skills regressed. The regressed CPS skills over the two years may reflect the consequences of reduced opportunities for students to engage in social interactions and collaborative learning due to the school suspension and social distancing measures. It is important for educators to seek ways to remedy students' lowered CPS skills, as well as explore how online learning can be organized to provide rich CPS learning opportunities. The extensive research on computer-supported collaborative learning (CSCL) could be a rich reference resource to draw on to address this important challenge.

### **7.1.4. Students' CPS performance and their family socioeconomic background**

Academic social capital score was positively associated with students' CPS performance in both waves, whereas home resources were not related to students' CPS performance. Specifically, students with higher academic social capital tended to perform better in both

social and cognitive process skills in 2019 (Cohort 2 and 3). In 2021, both individual- and school- level academic social capital scores were significantly and positively associated with the social CPS scores of students in Cohort 1.

Detailed results on students' CPS performance and its relations with students' family socioeconomic background can be found in [Chapter 3](#).

## 7.2 Students' digital citizenship capacity and wellbeing

Correlational analyses show that DL served as a protective factor for students' digital wellbeing and mental health. Specifically, students who had higher DL scores were more likely to report having better online self-protection capabilities (i.e., being more knowledgeable about digital security measures and how to safeguard their own data privacy). At the same time, they were less likely to suffer from adverse digital wellbeing (Internet and game addiction) and had a lower probability of reporting engagement in the four negative online behaviors and/or experiences surveyed: digital security problems, risky online communication, and cyberbullying experiences (perpetration and victimization). These negative online behaviors and/or experiences were found to be positively correlated with the students' probability of experiencing mental health problems.

One study published from this project found that DL was associated with less game addiction, which potentially contributes to lowered risks of associated mental wellness problems in children and adolescents. Another study published from this project found that even young children in Hong Kong have experienced cyberbullying, and DL served as a protective factor for those who spent a lot of time online from being a cyberbullying victim.

Students are now living in the digital age. They inevitably spend more time on digital devices, thus increasing their exposure to experiences that may have adverse effects on their digital wellbeing. An important implication of the current findings is that efforts need to be made to improve students' DL through early education and intervention programmes to protect them from negative digital wellbeing and associated mental health problems.

Detailed results on students' digital citizenship capacity and wellbeing can be found in [Chapter 5](#).

## 7.3. Students' digital technology use and their digital citizenship capacity

Access and use of digital technology by students and adults alike are inevitably influenced by external factors such as the socioeconomic context of the society they are in. Technologies (including Internet infrastructures, devices and software applications) and their adoption are advancing ever more rapidly such that different cohorts of children born at different times may have very different exposures and experiences when they were at the same age. The sampling design of the present study allowed us to explore how Secondary 3 students studying in the same schools but born two years apart (i.e., Cohort 3 students in 2019 and Cohort 2 students in 2021) may differ in their digital technology use experiences and digital literacy performance. As it turned out, the differences measured may not simply be a result of technological changes

over time, but of the mega scale changes resulting from the COVID pandemic. Moreover, a major consequence of the pandemic was the much increased pervasiveness and intensiveness of digital technology use. Our study was thus able to track how the social technological changes that took place during 2019 and 2021 affected the experiences and digital citizenship development of Secondary 3 students in Hong Kong.

Students' use of digital technology was conceptualized according to the factor analysis as learning activity at home/at school and leisure activity at home. Structural equation modelling shows that in both 2019 and 2021, students who spent more time on leisure activities at home performed better in DL assessment. In 2021 only, students who spent more time on learning activities at school performed worse in DL assessment.

Students' engagement in the different types of online activities is not totally independent. Instead, they often fall into different patterns of usage across different types of activities. We performed Latent Profile Analysis (LPA) to identify whether there are distinct clusters of digital technology usage among these S3 students. LPA revealed very different cluster structures for these two cohorts of students. The analysis found two distinct profiles for the S3 in 2019: Profile 1 was characterized by low amounts of time spent on online learning activities (both at home and at school) and moderate amounts of time on leisure activities at home; Profile 2 was characterized by moderate amounts of time spent on learning activities (at home and at school) and slightly higher amounts of time on leisure activities at home. No significant difference in DL performance was observed between these two profiles of students.

In contrast, LPA results for the cohort of S3 students in 2021 revealed four distinct profiles based on their online activities. It was found that for all four profiles, the amount of time spent on online learning at home was similar to that at school. Students belonging to Profiles 1, 2, and 3 spent similar (moderate) amounts of time on online leisure activities at home but differed in the amount of time they spent on online learning at home and at school. Profile 1 students spent very little time and the least amount of time studying online, which was very low whether at home or at school. Profile 2 students were characterised by spending moderate amounts of time on online learning, while Profile 3 students spent moderate-to-high amounts of online learning time. Profile 4 students constituted a relatively small group who reported very high frequencies of engagement in all online activities, for both learning and leisure.

The DL scores of students in Profile 1 were lower than those of Profile 2 students and higher than those in profile 3 (but not significantly different). Students in profile 4 had significantly lower DL scores compared to the other three profiles. The results suggest that neither a low nor an extremely high frequency of digital device use is helpful for DL development. Moreover, a moderate frequency of home and school learning activities and a high frequency of home leisure activities seem to foster DL performance.

Detailed results on students' online activity and digital literacy performance can be found in [Chapter 6](#).

## 7.4. Changes in students' digital technology use and wellbeing from 2019 to 2021

Changes in students' digital technology use and wellbeing were compared using the full student samples between 2019 and 2021. Regarding digital technology use, students in general spent more time on digital devices at home in 2021 than in 2019, whether for leisure activity or schoolwork. While the use of digital technologies for all purposes increased, the net time spent and the increase in time spent using technologies at home for leisure activities were much higher than other types of use.

Students' wellbeing was undermined over the two years. Specifically, the proportion of secondary students with Internet addiction rose from approximately 8% to 20% over the two years. Also, 15% of Cohort 1 students indicated they had Internet addiction in 2021. No gender difference was reported for Internet addiction.

Although no significant change in game addiction was found between 2019 and 2021, students in the younger cohorts seem to be more vulnerable to game addiction than Cohort 3 students. The study also found gender differences in game addiction: the proportion of boys reporting game addiction was much higher than that of girls across all three age cohorts in both 2019 and 2021.

Unauthorized use of personal information and computer viruses were the most common security problems reported by students in both 2019 and 2021. For all age cohorts in both waves of data collection, the most frequently reported risky behaviors were respectively 'looking for new friends online' and 'pretending to be older for online activities.' In 2019, about a quarter of each cohort reported having been a cyberbullying victim and a slightly lower percentage reported having been a perpetrator. In 2021, one in four participants reported experiencing cyberbullying, as perpetrators and/or victims, in the three months prior to data collection. In both years, about half of those reporting having such experiences (48% in 2019 and 45% in 2021) were both victims and perpetrators. Previous cyberbullying experiences reported in 2019 were positively associated with subsequent cyberbullying experiences reported in 2021.

Older students reported more mental health problems than younger students in both 2019 and 2021. There was a large increase in the percentage of students reporting symptoms of serious mental health problems in 2021 compared to 2019 for all age cohorts. Students in older cohorts (i.e., Cohort 2 and 3) spent less time on physical activity in 2021 than in 2019. In all three cohorts, less time was spent on sleep in 2021 compared to 2019.

Figure 7.1 provides a diagrammatic overview of the key findings summarized above.



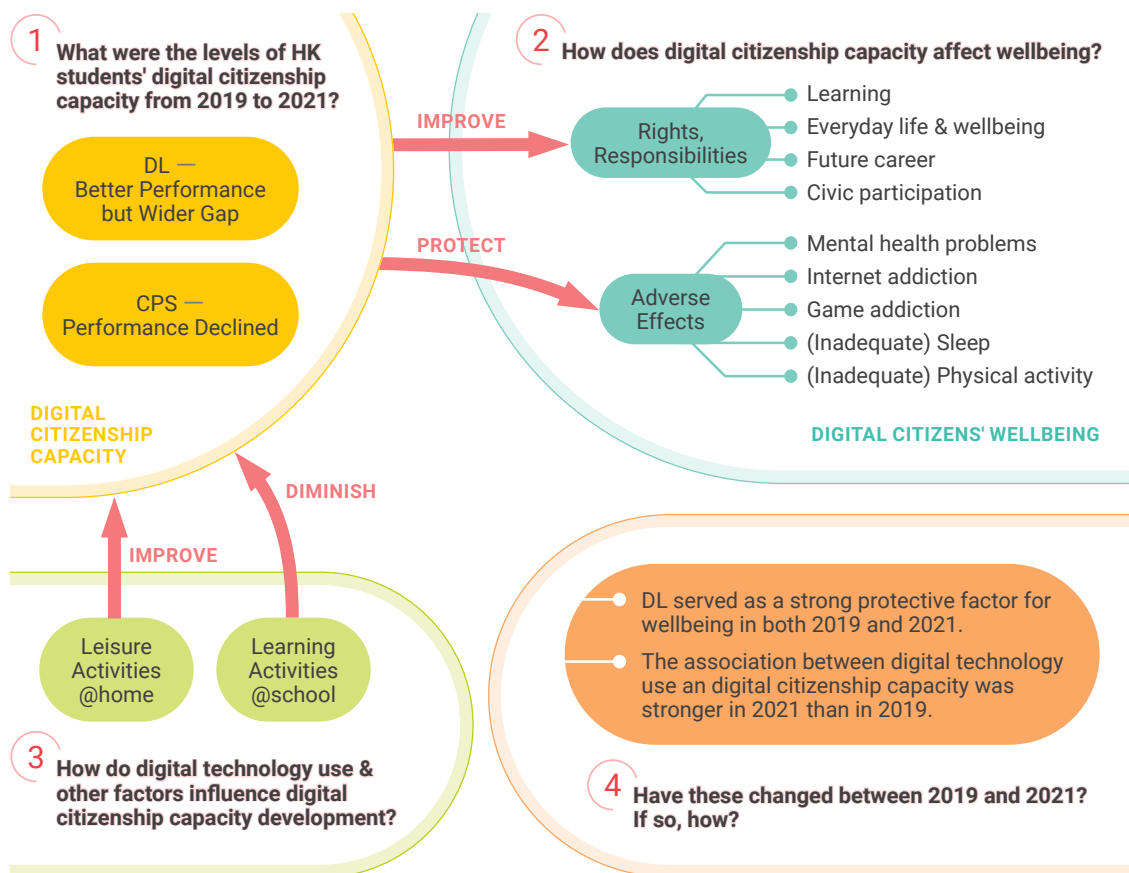


Figure 7.1. Overview of the Key Findings.

## 7.5. Policy recommendations

Fostering digital competence and ensuring students' wellbeing in the digital world are important educational outcome goals of school education in Hong Kong and in other parts of the world. The COVID-19 pandemic heightened the importance of digital means of communication and social connectivity in providing alternative means for individuals and societies to carry on with their everyday activities such as networking, formal and informal learning, digital commerce and transactions in diverse social, economic and political arenas. Our findings presented in this report show that the overall digital literacy of Hong Kong students across the primary and secondary grade levels has greatly improved during the period 2019 to 2021, greatly surpassing the achievement reached by students in a comparable age group in 2019. This is possibly due to the pervasive use of digital technology for learning and for leisure during the pandemic.

On the other hand, the DL divide also increased in 2021, even though a large majority of students already have large screen devices at home in 2021, which is extremely concerning. The positive relationship between students' digital competence and their socioeconomic background at the individual- and school- levels show that simply improving access to digital devices cannot solve the problem of widening DL divides. This increasing DL divide is expected to negatively impact students' academic learning and further exacerbate the overall learning divide among students. The deterioration of students' mental health and other conditions

affecting their wellbeing during the two-year period, possibly related to the stresses brought about by the pandemic are also of concern. DL was found to serve as a protective factor for students' wellbeing.

The theoretical framework as well as the tools and instruments developed through this project have significant implications and potential applications for policy, practice and research related to curriculum and pedagogy, parenting practices, family support, youth services, and in guiding the design of e-learning tools and resources. Based on our findings, we recommend the following policy priorities:

1. Digital competence as a core curriculum component should be integrated across the different Key Learning Areas throughout the K-12 curriculum.
2. Measures, including the provision of professional learning and curriculum innovation support should be provided to schools and teachers for the development of appropriate learning environments and school-based curriculum opportunities to foster students' digital competence and resilience.
3. Concerted efforts involving both educators and other community sectors such as youth and family support services are necessary to address the wellness challenges and the learning divides uncovered through this research.
4. Funding and policy support should be set up for research and development on digital citizenship education, including educating parents and professionals providing support to children, youth and families.



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## Website

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