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Extramural ICT factors impact adolescents' academic performance and well-being differently: Types of self-regulated learners also matter

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Abstract

Most studies have explored how information and communication technology (ICT) factors impact adolescents' schooling, but often ignore the potential influences on their well-being; no research has further scrutinized the moderating role of self-regulated learning (SRL) as a multi-dimensional combination, that is, different types of SRL learners. This cross-cultural study simultaneously scrutinized how distinct outside-of-school ICT factors influenced adolescents' digital reading and multi-dimensional well-being. It also took a person-centered approach to identify different types of SRL learners and examined whether the influences varied across the learner types. Data were based on 10,527 students in 308 schools from one East Asian region and one Western country participating in Programme for International

Implications for practice What is already known about this topic:
• ICT exerts profound influences on student learning;
• ICT impacts adolescents' well-being, but the results are inconclusive;
• The influences of ICT are complicated and dependent on many factors;
• Self-regulated learning plays a paramount role in digital reading and technology-involved behaviors.
What this paper adds:
• It simultaneously examined how outside-of-school ICT factors affected adolescents' digital reading and well-being;
• It adopted a person-centered approach to identifying types of self-regulated learners in the reading context;
• It explored whether and how the influences of ICT factors varied across different types of self-regulated learners;
• All the dynamics were unraveled from a West-East comparative perspective.
Implications for theory, policy, or practice:
• Considering distinct within-individual configurations of (meta-)cognition and motivation, subgroup-specific interventions for learning/well-being would be more effective than one-size-fits-all schemes;
• Parents are advised to strictly monitor their children's Internet use (e.g., intensity, devices and services) as well as to guide them for more meaningful and conducive activities;
• Schools and teachers should highly value ICT-integrated extracurricular learning by meticulously designing sessions and assignments, and also improving students' digital competence, to enhance students' academic and subjective well-being.

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Student Assessment (PISA) 2018. Multivariate multiple regression analysis revealed that overall, outside-of-school ICT factors impacted adolescents' digital reading and well-being differently, which also varied across cultures. Latent profile analysis detected culturally-mixed four profiles of SRL learners: High Profile (high in all indicators), Metacognitive Profile (in-between, optimal metacognition), Cognitive Profile (in-between, optimal cognition), and Low Profile (all low). It was the relatively weaker SRL learners in the East but the stronger SRL learners in the West that were particularly susceptible to the influences, either in a beneficial or detrimental way. Moreover, the cognitive, eudemonic, emotional and social dimensions of adolescents' well-being were all affected by ICT factors, without recurring trends in patterns. The findings provide implications to strictly monitor and guide adolescents' Internet use to enhance their academic and subjective well-being.

Keywords ICT factors · Digital reading · Well-being · Self-regulated learning · Cross-cultural study · PISA

1 Introduction

Ample evidence of the effects of information and communication technology (ICT) in education has been established, especially in (print or digital) reading, science, and mathematics (OECD, 2019a). However, prior studies that draw on international large-scale datasets, such as Programme for International Student Assessment (PISA), often ignore its potential influences on adolescents' well-being (Ma & Cheng, 2022), which is indispensable to their holistic development and could induce entrenched, detrimental implications for their later life without insufficient investments in this formative period (OECD, 2019b).

How ICT affects students' schooling or well-being depends on many factors, such as the types/purposes of technology use (e.g., Dienlin & Johannes, 2022; Hu et al., 2018; Liu et al., 2019) and the frequency/intensity of use (e.g., Gubbels et al., 2020; J. Ma & Cheng, 2022; Zhu & Li, 2022). Nevertheless, personal attributes like capabilities, dispositions and psychological functioning that may also intervene the relationships remain less-investigated (Castellacci & Tveito, 2018; Ma & Cheng, 2022). One potentially important attribute is users' competency in self-regulated learning (SRL). The fact that SRL has been corroborated to act a profound part in media and technology engagement (Uzun & Kilis, 2019; Zylka et al., 2015), academic attainment (Coiro & Dobler, 2007; Karlen, 2016) and well-being (Chu et al., 2020; Rodríguez et al., 2022), rationalizes it as a plausible source of variability in their interrelationships.

Further, no research has scrutinized the moderating role of SRL as a multi-dimensional combination, that is, different types of SRL learners. Theoretically, SRL's multi-dimensionality is underscored by its definition as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior" (Pintrich, 2000, p. 453). Empirically, researchers have asserted that learners develop SRL subskills via distinct trajectories (Karlen, 2016), which results in the differential configurations of components within individuals. A person-centered approach, in contrast to the usual variable-centered one, that identifies subgroups of SRL learners with similar behavior patterns, would inform researchers and practitioners of tailored interventions for specific types of learners (Chen et al., 2023a, b).

To fill those gaps, the current study, based on PISA 2018, simultaneously examined how a range of ICT factors affected adolescents' digital reading and well-being, and whether the relationships varied across different types of self-regulated learners.

2 Literature review

This section will first review how ICT factors impact academic performance (digital reading in particular) and well-being, respectively. It will then summarize the interrelationships of ICT factors, SRL, and academic performance/well-being. Considering that no studies have examined how the associations between ICT factors and schooling/well-being vary across different types of SRL learners, the subsequent review is limited to typologies of SRL learners and their associations with academic performance and well-being. This section concludes with the East–West cultural variations intervening the interrelationships of interest.

2.1 ICT and academic performance/digital reading

The relevant literature mainly focuses on outside-of-school ICT factors, which involve three categories: ICT availability at home, ICT use, and attitudes toward ICT. And inconsistent results between any of those factors and academic performance, have been reported (Courtney et al., 2022; Gubbels et al., 2020; Hu et al., 2018). Researchers have also pointed to several moderators to account for the inconsistencies, for example, countries/nationalities (e.g., Germany vs. China; Meng et al., 2019), subjects (e.g., reading, science and mathematics; Petko et al., 2017), grade levels (e.g., elementary vs. secondary school; Skryabin et al., 2015), types/purposes of ICT use (e.g., academic vs. social entertainment use; Hu et al., 2018; Petko et al., 2017; Skryabin et al., 2015), measures of ICT use (Hu et al., 2018; Petko et al., 2017), and frequency/intensity of ICT use (Gubbels et al., 2020; Ma & Cheng, 2022; Naumann & Sälzer, 2017; Papanastasiou et al., 2005; Rodrigues & Biagi, 2017; Zhu & Li, 2022).

Exclusive to digital reading, it is conceptually analogous to but much more complex than the print-based reading; it involves an individual's knowledge and expertise of print reading, and additional higher-level processing capabilities in the digital contexts (OECD, 2019a). As online reading requires an array of ICT skills, students with similar print-reading proficiencies, are inclined to perform better in the digital case if having more navigation experience (Lim & Jung, 2019).

Noticeably, mere access to ICT does not guarantee improved reading achievements; the utilization and perception of ICT matter more (Gubbels et al., 2020). For example, negative links between home ICT resources and reading scores were reported by Lee and Wu (2012), and Hu et al. (2018), but positive links were found if students used digital devices for meaningful online resources/information-seeking activities (Lee & Wu, 2012). Scholars also attempted to differentiate the influences of ICT use on digital reading based on purposes/types (chiefly for education or social entertainment), resulting in ambiguous findings (Gubbels et al., 2020). Recent endeavors, considering the frequency and intensity of ICT use, have somewhat alleviated these ambiguities. Specifically, Naumann and Sälzer (2017), Gubbels et al. (2020), and Zhu and Li (2022), by investigating into the adolescents in Germany, Netherlands, and Hong Kong, respectively, all claimed negatively quadratic, i.e., inverted U-shaped (mountain-shaped) curvilinear, relationships between various ICT uses and digital reading. Moderate use yielded maximum benefits, while both low and excessive use were associated with poorer digital reading. Regarding attitudes toward ICT, students with higher interest, autonomy, and competence in ICT tended to achieve higher digital reading scores, while those who primarily enjoyed social interactions in/about ICT demonstrated the opposite pattern (Hu et al., 2018; Xiao & Hew, 2022).

2.2 ICT and well-being

Being a positive subcategory of mental health, adolescents' well-being denotes "psychological, cognitive, material, social and physical functioning and capabilities that students need to live a happy and fulfilling life" (OECD, 2019b, p. 40). Despite its underlying multifaceted nature, well-being in the literature commonly embraces hedonic (emotional) well-being and eudemonic (evaluative) well-being: the former is affective, stressing short-term emotions, feelings of pleasure, or need fulfillment; whilst the latter is cognitive, emphasizing long-term self-evaluations, meanings, or self-esteem (Castellacci & Tveito, 2018; Dienlin & Johannes, 2022).

The interdisciplinary investigations into the effects of ICT on well-being encompass a wide range of literature that is fragmented and heterogeneous (Meier et al., 2020). As summarized in Castellacci and Tveito (2018), Internet may exert impacts on well-being through transforming the patterns of time consumption, providing access to an abundance of information, introducing novel digitally-mediated activities, and facilitating distinct communication channels. However, Dienlin and Johannes (2022) concluded in their recent meta-review that the overall influences of digital technologies on adolescents' well-being, though very small, tended to lean toward the negative side; in fact, extensive research has presented a conflicting combination of positive, neutral, and negative relationships with several meta-analyses failing to support a clear effect. Moreover, they contended that technology use was a stronger predictor of volatile, temporary hedonic well-being (e.g., positive and negative feelings), than of stable, robust eudemonic well-being (e.g., life satisfaction). Meanwhile, a large portion of the knowledge base has repeatedly confirmed the positivity that ICT contributed to boosting adolescents' social connectedness and school belonging (e.g., Liu et al., 2019; Ma & Cheng, 2022; McCahey et al., 2021; Meier et al., 2020; Wu et al., 2016). This is primarily due to the prevalent use of digital communication media (e.g., social networking sites) among young people (Dienlin & Johannes, 2022; Liu et al., 2019; Meier et al., 2020).

The scholarship suggests that how ICT impacts adolescents' well-being is more complicated than a globally linear effect (Dienlin & Johannes, 2022). Those effects may vary contingent on the populations (Ma & Cheng, 2022), measures of ICT (e.g., single vs. composite indicators; Dienlin & Johannes, 2022), types of technology use (e.g., social and active vs. procrastination and passive; Dienlin & Johannes, 2022), kinds of online activities (e.g., interaction, self-presentation, recreation and content consumption on social media; D. Liu et al., 2019) and so forth. The effects could also be non-linear (Dienlin & Johannes, 2022). For example, Przybylski and Weinstein (2017) found that adolescents who used digital technologies at low and high intensity reported slightly lower life satisfaction than those who used them moderately. Likewise, J. Ma and Cheng (2022), exploiting the PISA 2018 database, revealed similar inverted U-shaped relationships between 15-year-old students' home ICT use for schoolwork and their social, emotional, and eudemonic well-being in several developed countries/regions.

2.3 ICT, SRL, academic performance/digital reading and well-being

2.3.1 Variable-centered approaches to SRL

SRL, digital reading and well-being SRL plays a paramount role in digital reading (Chen et al., 2021). Inevitably, compelling evidence has shown the salient contributions of (meta-)cognition, the SRL component, to digital reading (Coiro & Dobler, 2007; Lee & Wu, 2013; Lim & Jung, 2019). As classic SRL theorists such as Pintrich (2000) typically centralize "cognition, behavior and motivation" in successful SRL orchestration, the positivity of the motivation component, which propels learners to actively adopt strategies for self-regulation, is also accumulating. Motivation often encompasses intrinsic and extrinsic motives for learning, as well as the ability to persist in learning despite encountering obstacles (Karlen, 2016). Specifically, intrinsic motivation for reading (e.g., interest, enjoyment; Ma et al., 2021) and reading self-concept (Chen et al., 2021; Ma et al., 2022) have been affirmed to benefit digital reading.

Regarding the effects of SRL on well-being, a general trend could be depicted, as summed up in Rodríguez and colleagues' (Rodríguez et al., 2022) systematic review, that better SRL abilities (e.g., more strategic in setting goals and planning) are often associated with learners' well-being such as pleasant feelings and greater life satisfaction. This applies to the reading scenario in which the more self-regulated students tend to better self-control their attention, and sustain favorable reading behaviors with autonomy; achievement of goals would in turn bring a strong sense of fulfilment and joyful emotions (Chu et al., 2020).

ICT and SRL SRL plays a role in users' technology involvement (e.g., Uzun & Kilis, 2019), digital competencies (e.g., Anthonysamy et al., 2020) and attitudes toward

ICT-aided learning (e.g., Huang et al., 2021). Specifically, the stronger self-regulated students tend to demonstrate less Internet-use misconducts (Uzun & Kilis, 2019), as they demonstrate better inhibitory control, resist instant gratification from non-academic media activities (Gaudreau et al., 2014), sustain attention with less instant messaging during class (Wei et al., 2012), and mitigate smartphone obsessions (Van Deursen et al., 2015). Moreover, SRL is positively associated with online users' digital literacy (Anthonysamy et al., 2020). Digital literacy requires effective self-regulation (Greene et al., 2014) and SRL, particularly the (meta-)cognition component, facilitates the acquisition of such literacy (Zylka et al., 2015). Simultaneously, the motivation component of SRL, namely the enjoyment of learning, drives learners to seek and acquire information through digital devices/services for intrinsic rewards and to integrate ICT for academic purposes (Huang et al., 2021).

2.3.2 Person-centered approaches to SRL

Most SRL-based studies use variable-centered approaches, assuming that the sampled subjects are homogeneous regarding their causal dynamics; conversely, a person-centered approach considers individuals as the primary unit of analysis, viewing them as a functioning wholeness of combined characteristics (Bergman, 2001). In reality, the SRL components themselves interact, and several rather than a single of them function in task execution (Broadbent & Fuller-Tyszkiewicz, 2018). A person-centered approach that classifies subgroups of SRL learners with similar behavior patterns, therefore, would better fit the real situations (Chen et al., 2023b).

Several studies have deployed person-centered approaches, such as clustering, latent profile analysis (LPA) and latent class analysis (LCA) to explore different profiles/clusters (i.e., subgroups/types) of SRL learners in various contexts. Whilst all of them have examined how different learner types correlated to academic performance/well-being, no studies have included the types as a moderator in predictor-outcome relationships, which enables the estimation of distinct regression parameters across the subgroups. Detecting such evidence of moderation provides additional insights into the characteristics of individuals within the subgroups, in contrast to conventional regressions where the moderators are not person-centered (Arch, 2021). The following literature review, however, is limited to typologies of self-regulated learners and their associations with academic performance and well-being.

Typologies of self-regulated learners Through quantifying SRL in the amounts, frequencies or extents of subscales typically conceptualized from mixture models of (meta-)cognitive, social-behavioral regulation, and motivational factors, researchers have generally identified three to five such subgroups, totaling four sets of classification.

One classification is to trichotomize respondents with high, average and low scores on all SRL subscales as high, moderate and low SRL learners, respectively (e.g., Abar & Loken, 2010; Vanslambrouck et al., 2019). Another partitions the in-between subgroup in trichotomy classification into two or three with optimal features on certain SRL indicators (e.g., Broadbent & Fuller-Tyszkiewicz, 2018; Chon

& Shin, 2019; Karlen, 2016). A third mode of classification involves identifying one subgroup with the highest scores on all SRL indicators, and another two or three with flexible combinations of higher and lower indicators (e.g., Chen et al., 2019; Dörrenbächer & Perels, 2016). The fourth classification is differentiated from the previous ones by the fact that none of its subgroups contain uniformly high or low SRL scores (e.g., Liu et al., 2014). For clarity of demonstration, the classification is summarized in Table 1.

Types of self-regulated learners, academic performance and well-being A conclusion about the SRL types with coherent levels of all indicators is that the higher-quantity SRL learners are likely to have higher academic performance, for instance, the SRL subgroups under the trichotomy classification (e.g., Abar & Loken, 2010; Vanslambrouck et al., 2019). However, the quality of SRL strategies may also be profoundly important to learning autonomy and performance (Karlen, 2016; Vanslambrouck et al., 2019). Chen et al. (2019), for example, reported that compensatory/memorization-based learners of English frequently used strategies, but mostly lower-level cognitive ones, and performed worse than their peers who adopted higher-order metacognitive strategies.

The limited literature has also indicated that stronger SRL learners (i.e., higher-quantity/quality SRL subskills) tend to have better well-being. For example, Liu et al. (2014) detected four clusters of college English learners in reference to six SRL indicators of motivation and (meta-)cognitive regulation: the highest, moderate, low and very low SRL learners; the two adaptive subgroups showed higher need satisfaction, but not in the way that each subgroup was significantly differentiable with one another.

2.4 Roles of East–West cultures

Cultural variations, particularly the East-versus-West dynamics, further intervene the intricate interrelationships of ICT factors, SRL, and academic performance/well-being. It is suggested that countries/regions matter with respect to how digital technologies affect schooling (Meng et al., 2019) or well-being (Ma & Cheng, 2022). In particular, research pertaining to well-being has been strongly biased toward the Western context where adolescents prefer to use Facebook, YouTube and snapchat, in contrast to the markedly disparate services popular in other cultures (e.g., WeChat and WhatsApp in East Asia); the ensuing consequences are assumed to be different (Dienlin & Johannes, 2022). Next, recognizing SRL being context-sensitive (Chen et al., 2023a), researchers have repeatedly found that memorization, a self-regulatory strategy claimed to be maladaptive to learning in Western societies, seems not so harmful for East Asian students (Chiu et al., 2007; Xu et al., 2021). Plus, their fiercely competitive schooling systems and the high stakes of performance render the latter extrinsically motivated to learn (Chiu et al., 2007); and social comparisons often lead to them under-estimating themselves (Xu et al., 2021), becoming emotionally vulnerable (OECD, 2019b), and/or withdrawing from self-regulation efforts

Table 1 Typical classification of self-regulated learners

Classification	Description	Example studies
1	Trichotomizes respondents into three groups: high, moderate, and low SRL learners based on SRL subscale scores	Abar and Loken (2010); Vanslambrouck et al., (2019)
2	Extends the trichotomy classification by further dividing the moderate group into two or three subgroups based on optimal SRL subscales	Broadbent and Fuller-Tyszkiewicz (2018); Chon and Shin (2019); Karlen (2016)
3	Identifies one subgroup with the highest scores on all SRL subscales and two or three additional subgroups with flexible combinations of higher and lower scores on these subscales	Chen et al., (2019); Dörrenbächer and Perels (2016)
4	Differentiates subgroups based on variations in SRL scores across different subscales	Liu et al., (2014)

(Wang & Peck, 2013). By comparison, Western students – whose cultures assign higher value to happiness – develop more positive attitudes toward learning and their own capabilities, though in the end, such attitudes do not resonate very closely with their academic outcomes, including in reading (Chen et al., 2021).

2.5 The present study

As a lacunae filler, this East–West, cross-cultural study concurrently explored the influences of extramural ICT factors on adolescents' digital reading and well-being; it also adopted a person-centered approach to identify different types of SRL learners, and examined whether the influential patterns of ICT varied across them. For ease of effect comparisons, the major research questions are organized as below, with the conceptual framework shown in Fig. 1.

(1) What are the latent profiles of adolescents' SRL? Any East–West differences?
(2) How do extramural ICT factors affect adolescents' digital reading and well-being overall? And whether the relationships vary across different types of self-regulated learners? Any East–West differences?

3 Method

3.1 Participants

This study adopted the open-access PISA 2018 dataset. PISA assesses the capabilities of 15-year-olds' applying the knowledge of reading, science and mathematics to life occasions every three years; aiming reading as the core subject, the 2018 round tested it primarily through simulated online reading, and thus estimated students' digital reading literacy (DRL) indeed (OECD, 2019a). To draw a full picture of how students acquired their academic accomplishments, reading in particular, questionnaires to elicit their learning experiences were distributed to students, teachers,

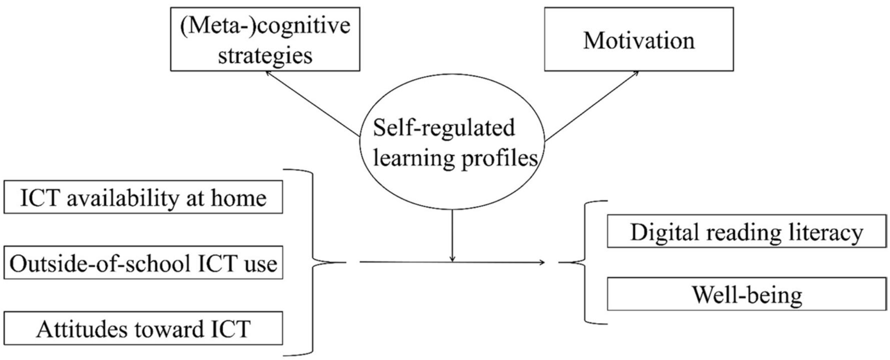

Fig. 1 Conceptual framework of the study

principals, and parents in a required or optional mode. Since the ICT factors were derived from the optional ICT Familiarity Questionnaire, we had to guarantee that the countries/regions we included had taken it. We finally selected Hong Kong (Confucian East) and the USA (English-speaking West) as the Eastern and Western representatives, respectively, grounded on the basic dichotomous categorization of cultures (i.e., collectivistic East vs. individualistic West) as well as the fined-grained cultural groupings of "West European, English-speaking, Latin American, East European, South Asian, Confucian influenced, and African and Middle Eastern" (Schwartz, 2006, p. 137). Meanwhile, both systems are developed economies and achieved comparable reading results (top 20 in PISA 2018 rankings).

In the PISA 2018 assessment, a two-stage stratified sampling method was utilized: initially, schools were chosen from each participating country/region based on the number of 15-year-old students they had, with a minimum requirement of 150; subsequently, within each selected school, 35 students at this specific age were randomly chosen to participate (OECD, 2019c). To address any potential sampling bias, survey weights were incorporated into the dataset to ensure accurate representation for each individual student (OECD, 2019c). Our final sample totaled 10,527 students (girls 48.79%) from 308 schools, with 5,689 students (girls 48.51%) from 144 schools in Hong Kong, and 4,838 students (girls 49.11%) from 164 schools in the USA.

3.2 Measures

Extramural ICT factors Three categories of factors were examined: ICT availability at home, outside-of-school ICT use, and attitudes toward ICT, totaling seven variables.

ICT availability at home (labeled as "ICTHOME") was computed as the sum of 11 digital devices (e.g., computer, smartphone) available at home, ranging from 0 to 11.

The types of use involved outside-of-school ICT use for social entertainment ("ENTUSE") and outside-of-school ICT use for schoolwork ("HOMESCH"). The former use, based on 13 items, related to entertainment (e.g., games), social (e.g., chatting online, using social networks), information seeking (e.g., reading news, obtaining practical information), and other leisure activities (e.g., downloading and uploading music and videos); while the latter, through 12 items, elicited information about respondents' digital integration for schoolwork activities (e.g., following up lessons, using emails or social networks to communicate with teachers and classmates). Students responded to the two types of use on a five-point Likert scale from 1 (never or hardly ever) to 5 (every day), and both index variables were standardized across OECD economies, with a mean of 0 and standard deviation of 1 (OECD, 2019c). A positive value denoted above OECD mean while a negative one was below it.

Four attitudinal factors were scrutinized: interest in ICT ("INTICT"; 6 items, e.g., "I forget about time when I'm using digital devices"), perceived ICT competence ("COMPICT"; 5 items, e.g., "I feel comfortable using digital devices that I am less familiar with”), perceived autonomy related to ICT use (“AUTICT”; 5 items, e.g., “If I need new software, I install it by myself”), and enjoyment of social interaction in/about ICT (“SOIAICT”; 5 items, e.g., “To learn something new about digital devices, I like to talk about them with my friends”). Students answered all items on a four-point Likert scale from 1 (strongly disagree) to 4 (strongly agree), and all were index variables standardized across OECD economies, with a mean of 0 and standard deviation of 1 (OECD, 2019c).

Digital reading literacy DRL assessment simulated the Internet reading mode in which the test takers clicked embedded hyperlinks, scrolled through continuous/non-continuous webpages, and selected useful materials from multiple dynamic/static documents. Three key abilities were measured, specifically, to locate, access and retrieve information (25% scoring), to understand, integrate and infer from texts (45%), and to evaluate and reflect on the quality as well as credibility of sources (30%); the test scores were standardized on a scale with a mean of 500 and standard deviation of 100 (OECD, 2019a). PISA aimed to guarantee the validity of reading assessments across diverse countries/languages, by strategies such as translation and back-translation of materials, expert review and adaptation, cognitive labs and field trials, and item response theory (IRT) analysis (OECD, 2019c). Despite that every student took a limited number of test items, ten plausible values, which were imputed scores through psychometric modelling, made it possible for country-level performance comparisons (OECD, 2019c). And it will not bias the results to randomly select one plausible value to represent a student’s DRL when working with a large-scale dataset (OECD, 2009). In our study, the first plausible value was settled for each student.

Well-being The cognitive, eudemonic, emotional and social dimensions of well-being were differentiated in the questionnaire.

Life satisfaction (“LIFESTS”) was operationalized as the cognitive aspect by asking the students to rate (0–10) on the item “Overall, how satisfied are you with your life as a whole these days?”.

Meaning in life (“EUDMO”; 3 items, e.g., “My life has clear meaning or purpose”) was the eudemonic dimension, measuring students’ sense of meaning and purpose in life through four-point scale from strongly disagree to strongly agree.

Positive feelings (“SWBP”) denoted the emotional well-being, for which students were asked how frequently they normally felt “happy”, “joyful” and “cheerful” (3 items) on a four-point scale ranging from never to always.

The social component was school belonging (“BELONG”), for which students answered 6 items (e.g., “I made friends easily at school”) to measure their sense of school relatedness on a four-point scale from 1 (strongly agree) to 4 (strongly disagree). For ease of interpretation, the responses were reverse coded so that a higher composite index meant stronger sense of school belonging.

Except life satisfaction, all the well-being constructs were combined index variables whose average was 0 and standard deviation was 1 across OECD economies (OECD, 2019c).

Self-regulated learning Three (meta-)cognitive strategies were assessed: understanding and remembering ("UNDREM"), summarizing ("METASUM"), and assessing credibility ("METASPAM"). To build each strategy index, students responded to 5 or 6 items that rated how useful this strategy was on a specific reading scenario, on a six-point scale from 1 (not useful at all) to 6 (very useful). An UNDREM item sample is "I read the text aloud to another person". Reading experts also assessed the usefulness of the strategies. Students who aligned more closely with the experts' ratings received higher scores, indicating a higher level of (meta-)cognitive awareness.

Two motivation constructs were covered, that is, reading enjoyment ("JOY") and reading self-concept ("SCOMP"). Responses to the 5-item enjoyment (e.g., "Reading is one of my favorite hobbies") and 3-item self-concept (e.g., "I am a good reader") were indicated on a four-point scale ranging from 1 (strongly disagree) to 4 (strongly agree).

These five index variables were all standardized across OECD economies, with a mean of 0 and standard deviation of 1 (OECD, 2019c).

Control variables As many studies have shown that gender and socio-economic status often significantly impact ICT factors (e.g., Hu et al., 2018), SRL (e.g., Chen et al., 2021), well-being (e.g., OECD, 2019b), and DRL (e.g., Lim & Jung, 2019), gender ("Gender", 1 = girl, 0 = boy) and the index of economic, social and cultural status ("ESCS") were included as covariates in relevant models.

Most survey constructs were derived variables based on IRT scaling from several items, and validated by PISA (OECD, 2019c); the scale reliabilities (calculating Cronbach's alpha coefficient) of those variables are extracted from PISA 2018 Technical Report, and reported in Table 2. Furthermore, to achieve validity and comparability of the constructs across different countries, a rigorous and closely monitored procedure involving translation and standardized administration was implemented; for each item and scale, analyses on the invariance of item parameters across countries and languages within a country were conducted (OECD, 2019c).

3.3 Data analysis

To address **RQ1**, LPA was used to classify individuals according to their (meta-)cognitive strategy use and reading motivation, totaling five SRL indicators. LPA, as a person-centered approach, refers to methods used to uncover hidden subgroups within data by estimating the likelihood of individuals belonging to distinct groups (Ferguson et al., 2019). Following Ferguson et al.'s (2019) primer on conducting LPA in M*plus*, we performed a three-step analysis. Step One – data inspection – included screening cases, handling missing values, and checking statistical assumptions. In Step Two, plausible, competing LPA models of one to five/six profiles were iteratively run (see also Masyn, 2013). In Step Three, we evaluated the LPA models to identify the one with the best fit and acceptable theoretical interpretability. Each model was compared against the previous one

Table 2 Scale reliabilities of the derived variables for the two educational systems

	Hong Kong	the USA
Extramural ICT factors		
ENTUSE	0.838	0.839
HOMESCH	0.942	0.921
INTICT	0.818	0.804
COMPICT	0.849	0.851
AUTICT	0.917	0.868
SOIAICT	0.893	0.871
Well-being		
EUDMO	0.907	0.893
SWBP	0.860	0.847
BELONG	0.771	0.843
Self-regulated learning		
JOY	0.813	0.871
SCOMP	0.836	0.849

Notes. *ENTUSE* outside-of-school ICT use for social entertainment, *HOMESCH* outside-of-school ICT use for schoolwork, *INTICT* interest in ICT, *COMPICT* perceived ICT competence, *AUTICT* perceived autonomy related to ICT use, *SOIAICT* enjoyment of social interaction in/about ICT, *EUDMO* meaning in life, *SWBP* positive feelings, *BELONG* school belonging, *JOY* reading enjoyment, *SCOMP* reading self-concept

using Akaike's information criterion (AIC), the Bayesian information criterion (BIC), and sample-adjusted BIC (SaBIC), lower values of which implied better model fit (Masyn, 2013). In addition, we utilized the Lo-Mendell Ruben test (LMRT) and bootstrapped likelihood ratio test (BLRT) to compare the likelihood ratio of each model against its previous counterpart; significant results suggested that addition of one profile statistically improved model discrimination (Lo, 2001; Masyn, 2013). Another criterion was entropy, which measured classification uncertainty in each model's partitioning of observations into subgroups; higher values represented better classification results, and a common threshold of 0.80 (range: 0–1) indicated satisfactory performance (Tein et al., 2013). We also checked each profile's size, and if its membership comprised less than 5% of the full sample, it was removed from further consideration as presumptively spurious/non-representative (Masyn, 2013). It was necessary to compromise between relatively sound criteria performance and model parsimony, because increased model complexity – and the addition of more profiles – caused AIC, BIC, and SaBIC values to keep decreasing, and made LMRT and BLRT significant (Ferguson et al., 2019).

Following the LPA that decided the best profiling model with individuals classified to each profile of the greatest likelihood, we reported the sub-profile descriptive statistics of the five continuous SRL variables and further quantified their mean differences with multiple-group analysis. That is, we conducted an omnibus Wald Test ("MODEL TEST" in M*plus*) to first check whether significance was reached among the profile mean differences, and if so, pairwise comparisons were warranted as a post-hoc test.

To address **RQ2**, multivariate multiple regression (MMR) analysis was performed with multiple response variables and a set of predictor variables (Johnson & Wichern, 2007). To establish each model, the five outcome variables (i.e., DRL, and four well-being constructs) were regressed on the seven input variables (i.e., ICT availability, two types of ICT use, and four ICT attitudes), controlling for gender and socio-economic status. The multiple-group method was adopted with the identical MMR modeling applied to all students and each profile, respectively, so as to unveil how the ICT factors impacted students' DRL and well-being in general, and for each type of SRL learners.

In our initial case screening, we removed cases who were not instructed and tested in the heritage language (non-Chinese ones for Hong Kong), and cases with over half of the five SRL indicators missing (for Hong Kong and the USA). The two territorial datasets shared the same analytical schemes, i.e., LPA, multiple-group mean comparisons, and multiple-group MMR, with M*plus* 8.3 (Muthén & Muthén, 1998–2019); full information maximum likelihood (FIML) tackled the random missing values and all models used maximum likelihood estimator with robust standard errors (MLR). Survey weights were included for each student to correct for bias from stratified sampling.

The whole process of data analysis is illustrated in Fig. 2.

4 Results

4.1 Descriptive statistics of and bivariate correlations between study variables

The descriptive statistics of the study variables separately for the two territories and their bivariate correlations for the whole sampled population are shown in Appendix

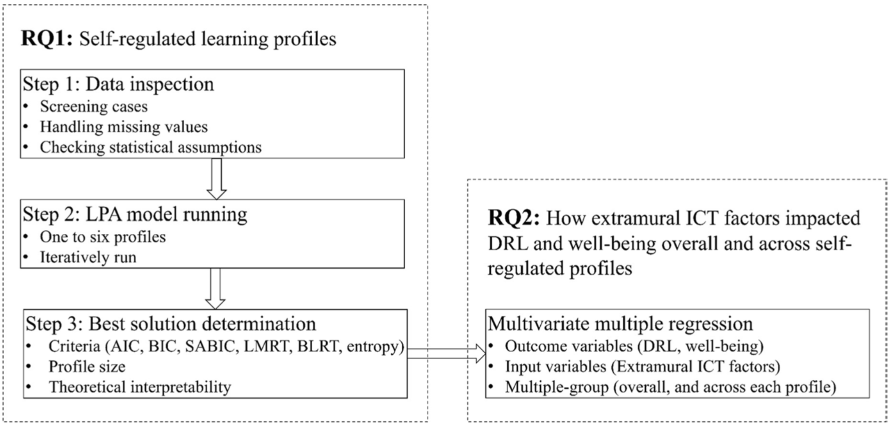

Fig. 2 Illustrative process of data analysis

Table 6. East–West disparities were not obvious except in standardized index variables such as ICT use for social entertainment, perceived competence and autonomy in ICT, meaning in life, and SRL components.

Most correlations reached significance ($p < 0.05$) with a few exceptions, and none were highly correlated ($r < 0.8$; Cohen, 1988). The skewness of all variables fell between -2 to + 2 and the kurtosis varied between -7 to + 7, indicating acceptable normal distributions (Byrne, 2010; Hair et al., 2010).

4.2 RQ1: What are the latent profiles of adolescents' SRL? Any East–West differences?

Table 3 exhibits the LPA model-fit indices of one to six profiles for both territories, accompanied by elbow plots of their information criteria (AIC, BIC, and SaBIC) in Fig. 3. Note that we determined the best solution with integrated considerations of the criteria performance, model parsimony, profile size, and theoretical interpretability. In both cases, the significant LMR and BLRT suggested that model fit improved significantly with profile addition; the values of AIC, BIC, and SaBIC decreased sharply and began to flatten around four-profile models. We then inspected the adjacent three-, four-, and five-profile models as potentially optimal solution. For Hong Kong, we first excluded the five-profile model because of its spurious memberships (< 5% of sampled population). Compared with the three-profile model, the four-profile one detected another qualitatively different profile which featured stronger metacognition. Confirmed by its great classification certainty (entropy: 0.848), the four-profile model was then retained as the best. For the USA, the three-profile model did not demonstrate satisfactory classification performance (entropy: 0.668). Also, compared with the four-profile model, the five-profile one neither showed sizable decreases in information criteria nor identified qualitatively different profile. The four-profile model therefore served as the optimal solution.

Table 4 demonstrates the sub-profile descriptive statistics of the five SRL indicators and their comparisons, with profile-specific means intuitively illustrated in Fig. 4. Intriguingly, both economies contained one profile with the significantly lowest/lower means, and another profile with the significantly highest scores, on all SRL indicators. The two profiles were, therefore, named Low Profile and High Profile, respectively. Meanwhile, of the two in-between profiles, one featured significantly higher scores on the two cognitive strategies, while the other had significantly better metacognitive strategy. These two profiles were then named Cognitive Profile and Metacognitive Profile, respectively. The members were not evenly, but also not sharply disproportionately, distributed among the profiles for both economies. In Hong Kong, Low Profile (31.52%) and High Profile (31.19%) occupied the comparably largest portions of students, whilst the USA allocated the most to High Profile (38.29%).

As seen from the table, a culturally independent phenomenon emerged that the between-profile mean differences were significantly differentiable ($p < 0.05$) on the (meta-)cognitive strategies, but not in the case with the motivation component.

Table 3 Relative model-fit indices of latent profile analysis of one to six profiles

	Profile	Nfp	LL	AIC	BIC	SaBIC	Entropy	Smallest	LMR p	BLRT p
Hong Kong (n = 5,444)	1	10	−37122.81	74265.62	74331.64	74299.87	1.000			
	2	16	−35214.38	70460.76	70566.40	70515.56	0.838	47.13%	< 0.001	< 0.001
	3	22	−34715.51	69475.03	69620.28	69550.37	0.848	29.63%	< 0.001	< 0.001
	4	**28**	**−34119.96**	**68295.92**	**68480.78**	**68391.80**	**0.848**	**16.04%**	**< 0.001**	**< 0.001**
	5	34	−33926.76	67921.53	68146.00	68037.96	0.844	3.66%	< 0.001	< 0.001
	6	40	−33627.23	67334.47	67598.56	67471.45	0.823	4.04%	1.000[1]	1.000[1]
USA (n = 4,657)	1	10	−32762.39	65544.79	65609.25	65577.47	1.000			
	2	16	−31333.85	62699.69	62802.83	62751.99	0.815	32.30%	< 0.001	< 0.001
	3	22	−31021.84	62087.67	62229.49	62159.58	0.668	25.90%	< 0.001	< 0.001
	4	**28**	**−30672.42**	**61400.83**	**61581.32**	**61492.35**	**0.803**	**12.80%**	**< 0.001**	**< 0.001**
	5	34	−30537.30	61142.60	61361.77	61253.73	0.734	11.90%	< 0.001	< 0.001
	6	40	−30383.03	60846.05	61103.90	60976.79	0.852	7.60%	< 0.001	< 0.001

Notes. The profile model in bold was selected as the best solution; *Nfp* number of free parameters, *LL* Log-likelihood, *AIC* Akaike's information criterion, BIC Bayesian information criterion, *SABIC* sample-adjusted BIC, *LMRT* Lo-Mendell Ruben likelihood ratio test, *BLRT* bootstrapped likelihood ratio test

[1]The likelihood ratio tests did not terminate normally because the log-likelihood values for the model were smaller than those of the previous one

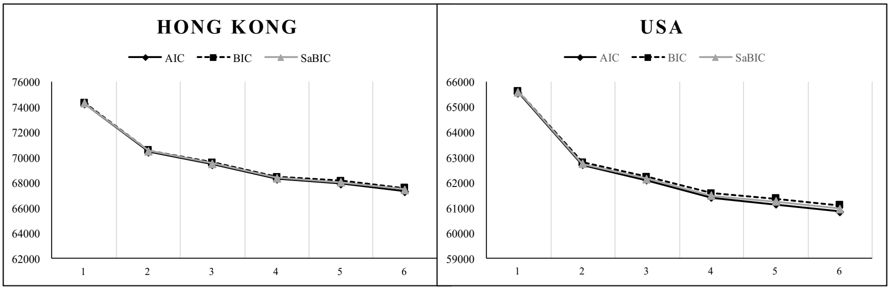

Fig. 3 Elbow plots of information criteria of one to six profiles**.** *Notes*. AIC = Akaike's information criterion; BIC = Bayesian information criterion; SABIC = sample-adjusted BIC

The sub-profile descriptive statistics of ICT factors, DRL and well-being as well as their mean comparisons across profiles, are also manifested in Table 4. A few intricacies arose in the Hong Kong dataset. For instance, the four profiles significantly varied on DRL ($p < 0.05$) with their means ranked in the same order as the SRL strategy of assessing credibility, but the differences were not significantly distinguishable on the well-being attributes. Plus, Low Profile consistently showed the significantly highest means on ICT home availability (M = 7.88, SD = 2.55), ICT use for social entertainment (M = 0.28, SD = 1.43), enjoyment of social interaction in/about ICT (M = 0.28, SD = 1.00), but the significantly lowest on perceived autonomy in ICT (M = 0.19, SD = 0.95). Compared with Hong Kong, more bilateral significant differences in the USA were detected on ICT factors and well-being variables; nevertheless, no strong patterns could be observed except that Cognitive Profile reported the significantly highest/higher means on well-being: life satisfaction (M = 6.87, SD = 2.57), meaning in life (M = 0.22, SD = 1.02), positive feelings (M = −0.05, SD = 1.02), and school belonging (M = −0.20, SD = 0.98).

4.3 RQ2: How do extramural ICT factors affect adolescents' digital reading and well-being overall? And whether the relationships vary across different types of self-regulated learners? Any East–West differences?

Table 5 summarizes the results of multiple-group MMR for all students and each profile in the two territories. For brevity, only paths under scrutiny (excluding gender and socio-economic status) are reported, with standardized coefficients for interpretation because of their comparability on the same metrics. Also, only significant paths ($p < 0.05$) are presented, and absolute coefficients (β) reaching 0.10 (small magnitude; Cohen, 1988) are brought to particular attention for their potentially greater policy implications.

4.3.1 ICT availability at home

Concerning ICT availability at home, for Hong Kong, it exerted a small to medium-sized negative effect on DRL overall (β = −0.17, SE = 0.02, $p < 0.001$) with similarities across profiles, but generally showed insignificance on well-being overall and

Table 4 Descriptive statistics of, and comparisons among, the profiles

	Hong Kong (n=5,444)	Low Profile (31.52%)	Metacognitive Profile (16.04%)	Cognitive Profile (21.25%)	High Profile (31.19%)	
		M (SD)	M (SD)	M (SD)	M (SD)	Ranking[1]
SRL	UNDREM	-1.00 (0.81)$_{234}$	-0.45 (0.84)$_{134}$	-0.07 (0.86)$_{124}$	0.30 (0.83)$_{123}$	L<M<C<H
	METASUM	-1.55 (0.33)$_{234}$	-1.30 (0.45)$_{134}$	0.10 (0.51)$_{124}$	0.37 (0.52)$_{123}$	L<M<C<H
	METASPAM	-1.19 (0.39)$_{234}$	0.74 (0.50)$_{134}$	-0.80 (0.50)$_{124}$	0.93 (0.46)$_{123}$	L<C<M<H
	JOY	0.04 (0.82)$_{234}$	0.28 (0.84)$_{14}$	0.28 (0.87)$_{14}$	0.59 (0.87)$_{123}$	L<M=C<H
	SCOMP	-0.42 (0.99)$_{234}$	-0.29 (0.87)$_{14}$	-0.24 (0.84)$_{14}$	-0.05 (0.88)$_{123}$	L<M=C<H
Extramural ICT	ICTHOME	7.88 (2.55)$_{234}$	7.60 (2.01)$_{1}$	7.64 (2.10)$_{1}$	7.48 (1.85)$_{1}$	
	ENTUSE	0.28 (1.43)$_{234}$	0.18 (0.88)$_{14}$	0.14 (0.89)$_{1}$	0.08 (0.64)$_{12}$	
	HOMESCH	0.20 (1.28)	0.13 (0.81)	0.14 (0.85)	0.08 (0.58)	
	INTICT	0.01 (1.09)	-0.06 (0.82)	0.03 (0.89)	0.07 (0.82)	
	COMPICT	-0.09 (0.94)	-0.05 (0.77)	-0.10 (0.79)	-0.08 (0.72)	
	AUTICT	0.19 (0.95)$_{234}$	0.27 (0.87)$_{14}$	0.29 (0.88)$_{14}$	0.39 (0.86)$_{123}$	
	SOIAICT	0.28 (1.00)$_{234}$	0.11 (0.87)$_{14}$	0.09 (0.86)$_{12}$	-0.07 (0.82)$_{12}$	
Outcomes	DRL	466.10 (91.75)$_{234}$	534.52 (85.44)$_{134}$	528.74 (87.49)$_{124}$	586.00 (74.38)$_{123}$	
	LIFESTS	6.29 (2.49)	6.21 (2.16)	6.31 (2.07)	6.30 (2.04)	
	EUDMO	0.02 (0.97)$_{4}$	-0.03 (0.97)	0.02 (0.92)$_{4}$	-0.10 (0.90)$_{13}$	
	SWBP	-0.09 (1.01)	-0.04 (0.92)	-0.02 (0.90)	-0.02 (0.88)	
	BELONG	-0.46 (0.72)$_{34}$	-0.40 (0.68)	-0.38 (0.70)$_{1}$	-0.35 (0.64)$_{1}$	
	USA (n=4,657)	Low Profile (19.20%)	Metacognitive Profile (12.80%)	Cognitive Profile (29.72%)	High Profile (38.29%)	
		M (SD)	M (SD)	M (SD)	M (SD)	Ranking[1]
SRL	UNDREM	-0.97 (0.81)$_{234}$	-0.53 (0.85)$_{134}$	0.08 (0.88)$_{124}$	0.42 (0.85)$_{123}$	L<M<C<H
	METASUM	-1.47 (0.40)$_{234}$	-1.06 (0.54)$_{134}$	0.37 (0.56)$_{124}$	0.65 (0.52)$_{123}$	L<M<C<H
	METASPAM	-1.15 (0.40)$_{234}$	0.67 (0.49)$_{134}$	-0.75 (0.48)$_{124}$	0.89 (0.46)$_{123}$	L<C<M<H
	JOY	-0.50 (0.95)$_{34}$	-0.39 (1.08)$_{34}$	-0.13 (0.99)$_{124}$	0.27 (1.10)$_{123}$	L=M<C<H
	SCOMP	-0.07 (1.02)$_{234}$	0.10 (0.98)$_{14}$	0.15 (0.92)$_{14}$	0.55 (0.97)$_{123}$	L<M=C<H
Extramural ICT	ICTHOME	8.57 (2.46)$_{3}$	8.42 (2.19)$_{4}$	8.30 (2.12)$_{1}$	8.57 (1.84)$_{2}$	
	ENTUSE	-0.01 (1.52)	-0.01 (1.03)	-0.01 (1.03)	-0.06 (0.71)	
	HOMESCH	0.30 (1.28)	0.16 (1.11)	0.25 (1.01)	0.23 (0.74)	
	INTICT	-0.11 (1.12)$_{234}$	0.10 (1.02)$_{1}$	0.08 (0.95)$_{1}$	0.18 (0.84)$_{1}$	
	COMPICT	0.05 (0.99)$_{24}$	0.18 (0.96)$_{13}$	0.07 (0.89)$_{24}$	0.19 (0.92)$_{13}$	
	AUTICT	-0.06 (1.04)$_{34}$	-0.02 (1.02)$_{3}$	-0.14 (0.95)$_{124}$	0.03 (0.96)$_{13}$	
	SOIAICT	0.20 (1.05)$_{34}$	0.11 (1.03)$_{4}$	0.04 (0.97)$_{4}$	-0.06 (0.94)$_{123}$	
Outcomes	DRL	425.243 (86.18)$_{234}$	488.739 (94.93)$_{14}$	484.660 (93.54)$_{14}$	571.584 (90.46)$_{123}$	
	LIFESTS	6.93 (2.70)$_{24}$	6.57 (2.66)$_{13}$	6.87 (2.57)$_{24}$	6.67 (2.43)$_{13}$	
	EUDMO	0.20 (1.01)$_{24}$	0.02 (1.06)$_{13}$	0.22 (1.02)$_{24}$	0.03 (1.04)$_{13}$	
	SWBP	-0.15 (1.07)$_{3}$	-0.25 (1.05)$_{3}$	-0.05 (1.02)$_{124}$	-0.14 (0.96)$_{3}$	
	BELONG	-0.23 (1.02)$_{2}$	-0.36 (0.92)$_{134}$	-0.20 (0.98)$_{2}$	-0.23 (0.95)$_{2}$	

Notes. *UNDREM* understanding and remembering, *METASUM* summarizing, *METASPAM* assessing credibility, *JOY* reading enjoyment, *SCOMP* reading self-concept, *ICTHOME* ICT availability at home, *ENTUSE* outside-of-school ICT use for social entertainment, *HOMESCH* outside-of-school ICT use for schoolwork, *INTICT* interest in ICT, *COMPICT* perceived ICT competence, *AUTICT* perceived autonomy related to ICT use, *SOIAICT* enjoyment of social interaction in/about ICT, *DRL* digital reading literacy, *LIFESTS* life satisfaction, *EUDMO* meaning in life, *SWBP* positive feelings, *BELONG* school belonging

Subscripts 1–4 (Low, Metacognitive, Cognitive, and High Profiles, respectively) indicate statistically significant differences ($p<0.05$) compared with the other profiles

[1]Ranking was based on significant ($p<0.05$) mean differences between profiles, indicated by the initials of their names; equal signs denote insignificance

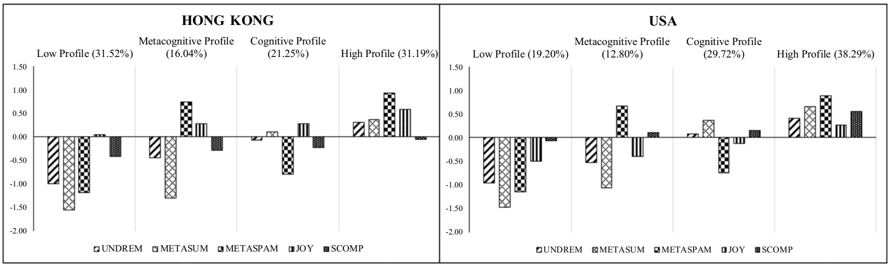

Fig. 4 Mean comparisons of self-regulated learning across profiles. *Notes.* UNDREM = understanding and remembering; METASUM = summarizing; METASPAM = assessing credibility; JOY = reading enjoyment; SCOMP = reading self-concept. Positive values indicate above the means across OECD economies while negative values are below OECD means

for each profile. For the USA overall, the effect on DRL was akin to Hong Kong's ($\beta = -0.11$, SE = 0.02, $p < 0.001$) but weak positive effects ($\beta < 0.10$, $p < 0.05$) were detected on every well-being construct; however, only Cognitive and High Profiles roughly resembled those effects.

4.3.2 Outside-of-school ICT use

Involving the outside-of-school ICT use, in Hong Kong, the subtype use for social entertainment had null, and generally negligible effects on DRL and well-being, respectively, for the overall and each profile of students; while no effects were found of the use for schoolwork on DRL, small to negligible positive effects ($\beta < 0.10$, $p < 0.05$) were present on all well-being constructs except positive feelings overall and particularly for Metacognitive Profile. In the USA, marginal negativity was revealed for both types of use on DRL; whereas the effects of the use for social entertainment on well-being were negligibly negative, the use for schoolwork positively influenced each well-being component at an approximately small magnitude ($\beta = 0.10$, $p < 0.001$) with salient benefits for High Profile ($0.10 < \beta < 0.20$, $p < 0.001$).

4.3.3 Attitudes toward ICT

With reference to the attitudes toward ICT, whether in Hong Kong or the USA, while adolescents' interest, perceived competence and autonomy in ICT impacted DRL positively for overall and/or at least two profiles at around small magnitudes ($\beta = 0.10$, $p < 0.05$), their enjoyment of social interaction in/about ICT exerted small to medium-sized negative effects ($-0.30 < \beta < -0.10$, $p < 0.01$) on DRL overall and invariably across profiles. In the case of well-being, for Hong Kong adolescents, the negative effects of interest in ICT were more obvious for Low Profile (meaning in life: $\beta = -0.12$, SE = 0.04, $p < 0.001$; school belonging: $\beta = -0.11$, SE = 0.04, $p < 0.01$), and for Cognitive Profile (life satisfaction: $\beta = -0.11$, SE = 0.04, $p < 0.01$; meaning in life: $\beta = -0.10$, SE = 0.04, $p < 0.05$). And despite the very limited impacts of perceived autonomy in ICT, students' perceived competence and enjoyment of

Table 5 Results of multivariate multiple regression analysis predicting digital reading and well-being

Hong Kong		DRL		LIFESTS		EUDMO		SWBP		BELONG	
		β	SE	β	SE	β	SE	β	SE	β	SE
ICTHOME	All	-0.17***	0.02							-0.05***	0.02
	Low-P	-0.17***	0.03							-0.06*	0.03
	Meta-P	-0.10*	0.05								
	Cog-P	-0.17***	0.04								
	High-P	-0.11***	0.03								
ENTUSE	All										
	Low-P										
	Meta-P							0.10*	0.05		
	Cog-P										
	High-P							0.08**	0.03		
HOMESCH	All			0.05*	0.02	0.09***	0.02			0.04*	0.02
	Low-P					0.09*	0.04				
	Meta-P			0.09*	0.04	0.15***	0.04			0.10*	0.04
	Cog-P										
	High-P			0.07*	0.03	0.09**	0.03				
INTICT	All			-0.07***	0.02	-0.07***	0.02				
	Low-P	0.05**	0.02			-0.12***	0.04			-0.11**	0.04
	Meta-P										
	Cog-P	0.14***	0.04	-0.11**	0.04	-0.10*	0.04				
	High-P			-0.10**	0.04						
COMPICT	All	0.06**	0.02			0.07**	0.02	0.09***	0.02	0.06*	0.02
	Low-P					0.10*	0.05	0.12*	0.05	0.12*	0.05
	Meta-P	0.11*	0.05					0.14**	0.05		
	Cog-P	0.08*	0.04			0.13**	0.05				
	High-P										
AUTICT	All	0.16***	0.02					0.04*	0.02	0.06**	0.02
	Low-P	0.12***	0.04								
	Meta-P										
	Cog-P	0.14***	0.03	0.09*	0.04			0.09*	0.04		
	High-P	0.12***	0.03								
SOIAICT	All	-0.21***	0.02	0.10***	0.02	0.15***	0.02	0.06**	0.02	0.09***	0.02
	Low-P	-0.15***	0.04	0.10*	0.04	0.21***	0.04			0.16***	0.05
	Meta-P	-0.16***	0.05	0.16***	0.05	0.15**	0.05			0.15**	0.05
	Cog-P	-0.21***	0.04								
	High-P	-0.10**	0.03	0.11***	0.04	0.12***	0.04				

Table 5 (continued)

USA		DRL		LIFESTS		EUDMO		SWBP		BELONG	
		β	SE	β	SE	β	SE	β	SE	β	SE
ICTHOME	All	**-0.11*****	**0.02**	0.08***	0.02	0.07***	0.02	0.04*	0.02	0.05***	0.02
	Low-P										
	Meta-P										
	Cog-P	**-0.14*****	**0.03**	**0.10****	**0.03**	**0.10****	**0.03**			0.07*	0.03
	High-P	**-0.11*****	**0.03**	0.07*	0.03	0.06*	0.03			0.08**	0.03
ENTUSE	All	-0.06**	0.02							-0.04*	0.02
	Low-P										
	Meta-P										
	Cog-P									-0.07*	0.04
	High-P			**-0.11*****	**0.03**						
HOMESCH	All	-0.06***	0.02	0.09***	0.02	**0.11*****	**0.02**	0.08***	0.02	0.08***	0.02
	Low-P										
	Meta-P	**-0.14****	**0.05**			**0.16****	**0.06**				
	Cog-P					0.09**	0.04				
	High-P			**0.11*****	**0.03**	**0.12*****	**0.03**	**0.10*****	**0.03**	**0.13*****	**0.03**
INTICT	All	**0.12*****	**0.02**								
	Low-P										
	Meta-P	**0.12***	**0.05**								
	Cog-P	**0.13*****	**0.04**							**0.10****	**0.04**
	High-P										
COMPICT	All	0.06**	0.02	**0.10*****	**0.02**	**0.13*****	**0.03**	**0.12*****	**0.02**	**0.19*****	**0.02**
	Low-P	**0.16****	**0.05**			**0.24*****	**0.07**			**0.18****	**0.06**
	Meta-P	**0.18*****	**0.05**					**0.16****	**0.06**	**0.20*****	**0.06**
	Cog-P					**0.10***	**0.04**	0.09*	0.04	**0.14****	**0.04**
	High-P			**0.15*****	**0.04**	**0.13*****	**0.04**	**0.14*****	**0.03**	**0.24*****	**0.04**
AUTICT	All	**0.14*****	**0.02**	**-0.15*****	**0.02**	**-0.12*****	**0.02**	**-0.13*****	**0.02**	-0.07**	0.02
	Low-P	**0.10***	**0.05**								
	Meta-P							**-0.16****	**0.06**		
	Cog-P	**0.10***	**0.04**	**-0.16*****	**0.04**	**-0.11***	**0.04**	-0.09*	0.04	**-0.12****	**0.04**
	High-P	**0.21*****	**0.03**	**-0.21*****	**0.03**	**-0.15*****	**0.04**	**-0.18*****	**0.03**	**-0.14*****	**0.04**
SOIAICT	All	**-0.21*****	**0.02**			0.05*	0.02	0.05*	0.02		
	Low-P	**-0.21*****	**0.05**								
	Meta-P	**-0.18*****	**0.05**								
	Cog-P	**-0.17*****	**0.04**								
	High-P	**-0.15*****	**0.03**					0.08*	0.03		

Notes. *ICTHOME* ICT availability at home, *ENTUSE* outside-of-school ICT use for social entertainment, *HOMESCH* outside-of-school ICT use for schoolwork, *INTICT* interest in ICT, *COMPICT* perceived ICT competence, *AUTICT* perceived autonomy related to ICT use, *SOIAICT* enjoyment of social interaction in/about ICT, *DRL* digital reading literacy, *LIFESTS* life satisfaction, *EUDMO* meaning in life, *SWBP* positive feelings, *BELONG* school belonging

Only significant path results are reported; absolute path coefficients (β) which reach 0.10 are shown in bold

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

social interaction in/about ICT, especially the latter, turned out conducive to well-being in a nearly all-round manner. A distinct picture, however, emerged from the USA scenario. Specifically, students' interest in ICT and enjoyment of social interaction in/about ICT imposed indiscernible influences on well-being; the uniform positivity of perceived competency on all well-being constructs at small to medium-sized magnitudes ($0.10 < \beta < 0.20$, $p < 0.001$) was in stark contrast to the negativity of perceived autonomy at similar strengths, the trends of which were perfectly reflected in High Profile.

5 Discussion

5.1 Self-regulated learning profiles (RQ1)

This study identified culturally-mixed four profiles of SRL learners: High Profile (all high indicators), Metacognitive Profile (in-between, optimal metacognition), Cognitive Profile (in-between, optimal cognition), and Low Profile (all low). It belonged to the second classification reviewed above that partitioned the in-between subgroup in the trichotomy classification into two with optimal features on certain SRL indicators (e.g., Broadbent & Fuller-Tyszkiewicz, 2018; Chon & Shin, 2019; Karlen, 2016; Ning & Downing, 2015).

Another intriguing finding about the profiling solutions was that students from high, in-between and low profiles manifested descending levels of digital reading. Such confirmed prominence of SRL in digital reading could be re-affirmed by the unique complexities and sophistication that have accompanied the online self-regulated reading (Coiro, 2021). For example, an interactive ensemble of self-regulatory strategies is intermingled with frequent physical movements of the input devices; recursive self-regulated processes with reading choices swiftly alternate through the juxtaposed and yet segmented digital spaces by skillful flipping back and forth (Coiro & Dobler, 2007). Moreover, online readers need to flexibly shift from wide-range navigation and text positioning (fast surface reading) to reflective, critical meaning construction (slow deep reading), indicative of more active control and regulation of comprehension for extra cognitive loads (Minguela et al., 2015).

5.2 Influences of extramural ICT factors on digital reading and well-being (RQ2)

5.2.1 ICT availability at home

Our study disclosed that overall, home ICT access was detrimental to adolescents' digital reading with other variables held constant, whether in the East or West, which echoes previous PISA-based findings (e.g., Hu et al., 2018; Lee & Wu, 2012). It is agreed that excessive ICT resources at home will distract students from academic learning, and displace their time for recreational reading (Gubbels et al., 2020; Hu et al., 2018; Lee & Wu, 2012; Naumann & Sälzer, 2017).

Alternatively, Internet as a multi-functional tool, can provide diversified information flows and create avenues for socially, leisurely oriented activities, which to a large extent, would improve students' well-being (Castellacci & Tveito, 2018). The benefits, however, were primarily witnessed in the West, which might be explained by the fact that, the Western adolescents, compared with the East Asian counterparts pressured by school workloads, enjoyed more out-of-school Internet hours for more online exploration (OECD, 2021). And those from Cognitive and High Profiles seemed to be exceptionally susceptible to the influences either in a detrimental or favorable manner. The raison d'être could be, in conjunction with the sub-profile finding that they often were significantly higher reading achievers, that such cohorts of students may have more frequently resorted to the virtual "getaway" to buffer against the escalating intensity of competing with their academic rivals (OECD, 2021).

5.2.2 Outside-of-school ICT use

The use for social entertainment was found to exert no effects, or no substantial harm on digital reading or well-being, regardless of the cultures and types of SRL learners. This phenomenon, we speculate, might arise from heterogeneous relations, with measures of specific use acting the dominant part. The literature indicated, for instance, that differential sets of subtypes of use could alter the influential patterns on reading (Hu et al., 2018; Petko et al., 2017), and that online information-seeking activities and social activities predicted reading in opposite directions via the mechanism of metacognitive knowledge (Lee & Wu, 2013). By the same token, whether ICT use was gauged by single or composite indicators, and what subtypes of use were scrutinized, would impact differently on well-being (Dienlin & Johannes, 2022). And our study operationalized ICT use through a composite measure encompassing information seeking, socialization and entertainment, which could have obscured the trends for both digital reading and well-being.

As for the use for schoolwork, how it affected adolescents' digital reading closely resembled that with the use for social entertainment, which was probably a compromised outcome from distinct frequencies of use. Note that Zhu and Li (2022), also employing the PISA 2018 dataset, reported the inverted U-shaped relationship, which peaked at the 50 percentile, between this ICT usage and Hong Kong adolescents' digital reading. Moderate use could benefit the students most by extending the classroom with lessons and materials shared online and also scaffolding student learning with (a)synchronous communications with teachers and classmates (Zhu & Li, 2022). The intensive use, however, may reflect users' inefficient management of online tools/resources (Gubbels et al., 2020), or the status that low achievers needed to frequently visit the sites to compensate for their unsatisfactory performance (Hu et al., 2018). On the other hand, it is fascinating to identify the discernable positivity this academic use contributed to students' multi-dimensional well-being, in line with the extant evidence (Ma & Cheng, 2022), and this was particularly so for members from Metacognitive and High Profiles. When ICT was integrated into extracurricular learning, for example, blogs or social media to release virtual sessions, and wikis to organize discussions and reflection, would supplement formal learning with social feedback, boosting their sense of accomplishment and school belonging; this also worked as a self-regulation process whereby students took responsibility for their learning (Kitsantas, 2013). And stronger SRL learners, especially those exceling in metacognition such as self-monitoring, task strategies, and self-evaluation, would arrive at an advantage (Kitsantas, 2013).

5.2.3 Attitudes toward ICT

In terms of the underlying attitudes, the culturally general finding was that adolescents' interest, perceived competence and autonomy in ICT positively predicted digital reading, congruent with prior evidence pertaining to reading in either form (Hu et al., 2018; Lee & Wu, 2012; Petko et al., 2017; Xiao & Hew, 2022). This further confirms that these self-determined motives may potently underpin students' acceptance and engagement of technologies (Goldhammer et al., 2017; Huang et al., 2021), thus facilitating optimal conditions to enhance their academic attainment (Goldhammer et al., 2017).

Enjoyment of social interactions in/about ICT, though, was culturally-invariantly harmful to digital reading. Recall that the U-shaped relationship between this disposition and Hong Kong students' digital reading in Zhu and Li (2022) peaked at the 1 percentile, meaning that only the lowest extent would not interfere with students' schooling. In contrast to the possible sacrifice of time for learning and Internet problematic behaviors, social interactions in/about ICT could bring feelings of connectedness and improvement of well-being by means of sharing relevant knowledge, skills and experiences (Zhu & Li, 2022). But the benefits were apparent only for East Asian adolescents in our study. This divergence may be rooted in the cultural values and educational systems. Specifically, folks in the Western individualism culture are independent from others but still actively seek interpersonal connections, the skills of which are then sharpened through prolonged and varied interactions (Ogihara & Uchida, 2014). The East Asian adolescents are, on one hand, often caught in burdensome schoolwork and discouraged from non-academic activities (OECD, 2021), and on the other, driven by palpable desires for belonging to social communities, peer group as a notable instance (Chiu et al., 2016); technology enabled or focused socialization may therefore become an outlet for their intense emotions to be satisfied.

Students' perceived competence in ICT was another prominent contributor to their well-being, generalizable to the two cultures and extra salient for High Profile in the West. Those who have higher ICT competence or self-efficacy are more likely to feel the ease of technologies, integrate them into tasks, and persevere when encountering setbacks (Huang et al., 2021). Also, digital competence can preserve students' well-being (e.g., lower academic burnout and anxiety) by alleviating their cognitive loads and elevating their engagement in online environments (Wang et al., 2021). Versatile self-regulation could definitely produce synergistic benefits by simultaneously promoting students' digital competence (Zylka et al., 2015) and well-being (Rodríguez et al., 2022). The reason why High Profile in the East did not show this pattern could be that those students, also the highest academic performers, might spend enormous time on schooling without much room for unrestricted digital undertakings (Chung et al., 2019).

Adolescents' interest in ICT for the East (especially Low and Cognitive Profiles) and perceived autonomy in ICT for the West (especially Metacognitive and High Profiles) were detected to be major negative predictors of their well-being. The explanations for the negativity, however, might not be identical. Researchers have found that students with higher interest and enjoyment in ICT involvement had greater likelihood of frequently using social communication (Areepattamannil & Khine, 2017); for the relatively weaker SRL profiles in the East, also the lower achievers, could prefer appealing media-related activities for instant gratification to challenging and unenjoyable schoolwork (Uzun & Kilis, 2019). For the relatively stronger SRL profiles in the West, also the higher achievers, may not feel schooling overly demanding. But as they intensively used ICT and felt autonomous, they would still suffer from Internet misconducts such as multitasking and addictive tendency (Uzun & Kilis, 2019), which could also be impactful to those less self-regulated counterparts in the East.

6 Conclusion

This was the first cross-cultural study to have simultaneously scrutinized how distinct outside-of-school ICT factors influenced adolescents' digital reading and multidimensional well-being. It was also an initiative to take a person-centered approach to identify types of self-regulated learners and examined whether the influences differed across the learner types. It could make valuable contributions to the scholastic intersections between technologies and education.

Several important findings are summarized. First, there existed culturally-mixed four profiles of SRL learners: High Profile (all high indicators), Metacognitive Profile (in-between, optimal metacognition), Cognitive Profile (in-between, optimal cognition), and Low Profile (all low).

Second, ICT factors impacted adolescents' digital reading and well-being differently, which also varied across cultures. Generally, ICT availability at home was culturally invariantly detrimental to digital reading, but not to well-being, with Western students even showing benefits. Home ICT use for social entertainment and schoolwork exerted no effects or no substantial harm on digital reading or well-being. Interest, perceived competence and autonomy in ICT positively, while enjoyment of social interactions in/about ICT negatively, predicted digital reading; while the other three attitudes impacted well-being differently, perceived competence in ICT showed culturally general benefits, especially for the West.

Third, the influential patterns differed across types of SRL learners. It was the relatively weaker SRL learners in the East but the stronger SRL learners in the West that were particularly susceptible to the influences, either in a favorable or detrimental way.

Fourth, the cognitive, eudemonic, emotional and social dimensions of adolescents' well-being were all affected by ICT factors, without recurring bias in patterns.

Several feasible implications could be drawn from the current study. For one, considering that many ICT factors such as home ICT resources affected student learning and well-being differently, it is advisable for parents to strictly monitor their children's Internet use (e.g., intensity, devices and services) as well as to guide them for more meaningful and conducive activities, so as to maximize the benefits of technologies. Next, the schools and teachers should place heightened value on ICT-integrated extracurricular learning by meticulously designing sessions and assignments, and also improving students' digital competence, as a promising avenue to enhance students' academic and mental well-being. Policymakers should consider investing in programs that enhance students' digital competence and now also artificial intelligence capabilities, ensuring that they develop the necessary skills to navigate and utilize technology effectively. Integrating digital/artificial intelligence literacy into the curriculum and providing professional development opportunities for teachers can be crucial steps in this direction. More importantly, since students demonstrated distinct within-individual configurations of (meta-) cognition and motivation, subgroup-specific tailored interventions for learning/well-being would be more effective than one-size-fits-all schemes.

This study possesses several limitations that should be acknowledged. Firstly, the inclusion of composite measures of ICT use may have obscured the specific trends and nuances of different types of ICT activities. Subsequent research endeavors could consider delineating various activities and also collecting objective measures, such as log data from digital devices, to provide a more comprehensive understanding of ICT use patterns. Secondly, the study's sample was limited to only two territories, which may constrain the generalizability of the results to other cultural contexts. Future efforts should involve the inclusion of additional countries or regions to achieve more robust and diverse conclusions regarding the relationship between ICT factors and educational outcomes. Furthermore, the utilization of cross-sectional data in the study precludes making causal inferences. To better comprehend the complex dynamics at play, future research could adopt multi-method approaches, such as experimental designs and longitudinal tracking, to examine the causal effects and temporal relationships between ICT use, student outcomes, and well-being.

Appendix

Table 6 Descriptive statistics of, and bivariate correlations between study variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	ICTHOME	/																		
2	ENTUSE	0.14**	/																	
3	HOMESCH	0.18**	0.51**	/																
4	INTICT	0.05**	0.34**	0.23**	/															
5	COMPICT	0.11**	0.33**	0.23**	0.52**	/														
6	AUTICT	0.11**	0.33**	0.21**	0.47**	0.65**	/													
7	SOIAICT	0.10**	0.35**	0.31**	0.38**	0.46**	0.51**	/												
8	DRL	0.07**	−0.03	−0.03	0.16**	0.12**	0.13**	−0.12**	/											
9	LIFESTS	0.14**	0.03	0.09**	−0.01	0.05**	−0.02	0.05**	−0.05**	/										
10	EUDMO	0.10**	0.04*	0.11**	0.02	0.08**	0.00	0.07**	−0.12**	0.53**	/									
11	SWBP	0.10**	0.06**	0.11**	0.05**	0.09**	0.01	0.07**	−0.02	0.56**	0.48**	/								
12	BELONG	0.11**	0.06**	0.10**	0.07**	0.16**	0.08**	0.07**	0.00	0.38**	0.38**	0.41**	/							
13	UNDREM	−0.00	0.01	0.03	0.07**	0.04*	0.01	−0.05**	0.33**	0.02	−0.01	0.04	0.04*	/						
14	METASUM	−0.00	−0.04*	0.00	0.07**	0.01	−0.01	−0.11**	0.41**	−0.01	−0.02	0.03	0.02	0.48**	/					
15	METASPAM	0.04*	−0.03*	−0.05**	0.10**	0.07**	0.06**	−0.08**	0.49**	−0.05**	−0.10**	−0.03	−0.02	0.29**	0.36**	/				
16	JOY	−0.02	−0.06**	0.07**	−0.02	−0.02	−0.03	−0.06**	0.32**	−0.04**	−0.02	−0.00	−0.08**	0.20**	0.22**	0.18**	/			
17	SCOMP	0.10***	0.07**	0.07**	0.15**	0.21**	0.18**	0.01	0.35**	0.05**	0.08**	0.08**	0.11**	0.12**	0.16**	0.19**	0.38**	/		
18	Gender	−0.07**	−0.15**	0.01	−0.01	−0.13**	−0.22**	−0.23**	0.10**	−0.11**	−0.02	−0.02	−0.08**	0.09**	0.15**	0.05**	0.24**	0.01	/	
19	ESCS	0.45**	0.11**	0.18**	0.13**	0.13**	0.13**	0.03	0.35**	0.11**	0.05**	0.11**	0.12**	0.15**	0.16**	0.25**	0.14**	0.26**	−0.02	/
	Skewness	−0.95	0.90	0.32	0.38	0.24	0.42	0.27	−0.12	−0.71	−0.07	−0.14	1.18	−0.07	−0.42	−0.08	0.02	0.11	0.02	−0.41
	Kurtosis	0.83	6.68	2.84	1.62	0.16	0.28	0.55	−0.38	−0.20	−0.57	−0.84	2.57	−1.06	−1.01	−1.35	0.41	−0.40	−2.00	−0.15
HK	M	7.67	0.17	0.14	0.02	−0.08	0.28	0.11	527.09	6.28	−0.03	−0.04	−0.40	−0.32	−0.57	−0.15	0.30	−0.25	0.49	−0.59
	SD	2.18	1.03	0.94	0.93	0.82	0.90	0.91	97.26	2.22	0.94	0.93	0.69	0.99	0.98	1.06	0.88	0.92	0.50	1.00

Table 6 (continued)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
USA	M	8.47	−0.03	0.23	0.08	0.12	−0.05	0.04	508.77	6.76	0.12	−0.14	−0.24	−0.06	−0.04	0.00	−0.07	0.26	0.50	0.12
	SD	2.10	1.03	0.98	0.96	0.93	0.98	0.98	106.72	2.55	1.04	1.01	0.97	1.00	1.00	1.00	1.08	1.00	0.50	1.02

Notes. *ICTHOME* ICT availability at home, *ENTUSE* outside-of-school ICT use for social entertainment, *HOMESCH* outside-of-school ICT use for schoolwork, *INTICT* interest in ICT, *COMPICT* perceived ICT competence, *AUTICT* perceived autonomy related to ICT use, *SOIAICT* enjoyment of social interaction in/about ICT, *DRL* digital reading literacy, *LIFESTS* life satisfaction, *EUDMO* meaning in life, *SWBP* positive feelings, *BELONG* school belonging, *UNDREM* understanding and remembering, *METASUM* summarizing, *METASPAM* assessing credibility, *JOY* reading enjoyment, *SCOMP* reading self-concept

Gender: 1 = girl, 0 = boy; $*p < 0.05$, $**p < 0.01$

Author's contribution Jiangping Chen: Conceptualization, Methodology, Formal analysis, Data curation, Writing—Original draft, Writing—Review & editing.

Chin-Hsi Lin: Conceptualization, Methodology, Writing—Review & editing, Supervision.

Gaowei Chen: Methodology, Review & editing.

Data availability The datasets generated during and/or analyzed during the current study are retrieved from the open-access Programme for International Student Assessment (PISA) 2018 via the official website https://www.oecd.org/pisa/data/2018database/.

Declarations

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