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Youth wellbeing, digital use and digital literacy: Evidence from PISA 2022

Research Report

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Contents

Abstract

What is this report about?

This report explores the nature of the relationship between digital use and youth wellbeing by examining how the frequency of engaging in different digital activities is linked to various aspects of youth wellbeing. Additionally, it investigates the links between digital literacy, digital use and youth wellbeing.

What did we do?

Using data from the Programme for International Student Assessment (PISA) 2022, we examined the strength of relationships between six types of digital activities and seven aspects of youth wellbeing. The digital activities included time spent accessing informational materials, browsing social media and playing video games. Rather than focusing on a single wellbeing outcome, we examined multiple aspects of youth wellbeing—life satisfaction, affect, perceived competence, interpersonal and physical wellbeing—to identify which are most affected by different types of digital activity. The methods employed were descriptive statistics followed by country-level fixed effects regression models. In the second part of the study, we explored the relationship between students' digital literacy—measured by their self-reported competency in using digital resources and their practices when engaging with online information—and their digital use and wellbeing.

What did we find?

We found evidence supporting all types of associations—positive, negative, and no association, underscoring the complexity of these relationships. Positive relationships were primarily observed in instrumental use, while negative associations were noted with social media browsing, gaming, and Internet use, though the extent varied. On gender differences, social media browsing was negatively associated with girls' body image perceptions and life satisfaction, but not boys'. Among the wellbeing aspects examined, the frequency of experiencing psychosomatic symptoms was most consistently and negatively associated with digital use, regardless of purpose or gender. For girls, the negative link between psychosomatic symptoms and social media browsing was close to two-thirds as strong as the correlation between being bullied and psychosomatic symptoms; for boys, it was slightly more than half. Our research also suggests that digital literacy alone may not be sufficient to mitigate the potential negative impacts of digital use and to motivate beneficial allocation of screen activities, even though it may marginally enhance wellbeing.

What are the implications?

Firstly, the mixed associations between digital activities and youth wellbeing highlight the need for purpose-specific guidance on youth digital use. Secondly, the differential impacts of social media on girls suggest that policy guidance and interventions should be gender specific. Thirdly, the consistent negative link between psychosomatic symptoms and digital use warrants further investigation and closer monitoring. Finally, young people may need additional skills—such as online resilience—to better protect themselves in the digital world, as digital literacy alone may not be sufficient to ensure beneficial use of time online or to mitigate possible negative impacts.

1. Introduction

Young people today supposedly grow up as “digital natives” as they become familiar with digital technologies early in life (Prensky, 2009). Using digital technologies in and outside of school is an integral part of their lives. According to data from the Programme for International Student Assessment (PISA), in 2022, 15-year-olds across various countries spent an average of 3.8 hours[1] online daily outside of school on weekdays, and almost 5.2 hours daily online on weekends. Digital technologies can be a great resource for students, e.g., allowing them to learn more about topics encountered in school and connect with friends. However, digital technologies also carry risks. Young people may invest less time into schoolwork and physical activity, and they may be exposed to violent or antisocial content or even experience cyberbullying. Accordingly, concerns have been raised about how the use of digital technologies may affect the wellbeing and academic functioning of young people (OECD, 2018a).

The effects of using digital technologies have been studied for some time, but recent reviews highlight that much is still to be learned (e.g., Fumagalli et al., 2024; Hietajarvi et al., 2022; Vissenberg et al., 2022). Research uncovered relationships between digital use and students’ academic performance, academic engagement, and school-related wellbeing. Statistically speaking, the average effects seem to be small, but highly heterogenous. Heterogeneity suggests that digital use can have detrimental, beneficial or no effects depending on the individual. Whether digital use is adaptive or maladaptive for wellbeing is likely to depend on various factors such as the type of use, the extent of use and the characteristics of the user (see Salmela-Aro & Motti-Stefanidi, 2022), e.g., age and users’ personality, with research still unfolding. Additionally, the current debate also centres on the practical significance of these pieces of empirical evidence (for a summary, see Pearson, 2025).

According to England’s Department of Health & Social Care (DHSC) and the Department of Education (DfE), “Keeping children and young people safe online is also an important way to protect their mental health” (DHSC & DfE, 2018, p.17). One factor that could protect youth wellbeing in the digital world is digital literacy (Vissenberg et al., 2022). Digital literacy can be defined as “the ability to access, manage, understand, integrate, communicate, evaluate, and create information safely and appropriately through digital technologies” (Law et al., 2018, p.6). Several empirical studies, though limited, have indicated that digital literacy can promote and protect wellbeing by increasing individuals' confidence to navigate digital environments effectively (Mayiwar et al., 2024), fostering online resilience (Pan et al., 2024), protecting them from false information (Sirlin et al., 2021), and helping them resource useful information to promote their wellbeing (Rivadeneira et al., 2023).

However, as concluded in Vissenberg et al. (2022), there is a limited number of studies focusing on the protective role of digital literacy and more empirical evidence is needed to understand its role for digital use and wellbeing. Accordingly, researchers have been urged to conduct more detailed research to untangle the impacts of digital use by looking at,

[1] Our own calculation; weighted using senate weights. The standard errors for the mean estimates are 0.62 for weekdays and 0.65 for weekends.

among others, specific user characteristics, such as gender (Orben, 2020, p.412) and age (Fumagalli et al., 2024, p.125), specific aspects of wellbeing outcome (ibid, p.126), and by moving beyond the "singular focus on screen time" (Odgers & Jensen, 2020, p.344) to consider the different purposes of digital use (Santos et al., 2023, p.17).

This research followed such recommendations. In this paper, we examined the association between time spent on various *types* of non-school related digital activities and several aspects of youth wellbeing. We also analysed these by gender to further our understanding on the heterogeneous nature of these relationships. Additionally, we analysed the role of digital literacy in relation to digital use and wellbeing with the aim to contribute to the emerging body of empirical research. To achieve this, we utilised data from PISA, a large-scale international assessment of 15-year-olds conducted by the Organisation for Economic Co-operation and Development (OECD) every three years since 2000. Our study focused on the 2022 cycle, which included questions on Information and Communications Technology use and competence, various aspects of wellbeing, as well as students' background characteristics.

Specifically, the key research questions we sought to answer are:

Research question 1: What is the association between digital use and youth wellbeing? How does the relationship vary depending on the types of use, the extent of use, the aspects of wellbeing considered, and gender?

Research question 2: What role does digital literacy play in protecting youth wellbeing in the digital world?

This paper is structured as follows. Section 2 synthesises the literature on young people's digital use, the multidimensional aspects of youth wellbeing, and the interaction between digital use and wellbeing, including the potential role of digital literacy in these relationships. Section 3 elaborates on our research questions. Section 4 provides an overview of the data and their summary statistics. Sections 5 and 6 outline the methods employed to answer these research questions and present the results, respectively. Finally, Section 7 discusses the overall findings and their implications, and concludes.

2. Literature review

2.1 Digital use

Participation in the digital world is enabled by Information and Communication Technologies (ICT). ICT can be defined as a "diverse set of technological tools and resources used to transmit, store, create, share or exchange information." (UNESCO Institute for Statistics, n.d.). These include computers, the Internet, live broadcasting technologies such as radio and television, recorded broadcasting technologies such as podcasting and audio/video players, and telephony. The terms ICT, digital technologies and digital media are often used interchangeably (Stavropoulos et al., 2022). "Digital" refers to any signal or data expressed as a series of digits 0 and 1. For the remainder of this report, "digital technology" will be used to describe any technological tool or resource that enables young people to participate in the digital world. We will use the term, "digital use" to mean participation in the digital world, similar to how the term "digital engagement" was defined in Hietjarvi et al. (2022). This can

be understood as “a broad concept of digital participation, which is not dependent on a specific technological device, platform, or tool” (p.102).

Digital technologies can be used for various purposes, and these can be broadly grouped into hedonic, instrumental, and social interaction motives (Senkbeil et al., 2016; Senkbeil & Ihme, 2017; also see Stavropoulos et al., 2022). Instrumental aspects include information seeking and learning/work-related motives, i.e., uses based on real-life needs in domains such as education, employment, and health. Hedonic motives include entertainment and “escapism” aspects, including using digital technologies to play digital games and watch audio-visual recordings for amusement, enjoyment, and escaping the real world. Lastly, social interaction aspects mostly relate to using online communities and networks (also known as social medias) to generate and distribute information, opinions and interests for social exchange and self-presentation. Note that the three aspects are not mutually exclusive; a young person could for instance use social networks to seek information on something they are learning in school, or they may play a multiplayer digital game to socialise. But in general, these three aspects seem to capture the main purposes of use relatively well.

The use of digital technologies is common among children and adolescents. According to an Ofcom (2024a) report, 100% of 12 to 15-year-olds in the UK went online in 2023 (p.9), 96% owned a mobile phone (p.10), 94% played online games, 92% were on at least one social media platform, and 81% watched YouTube (Ofcom, 2024b). Screen time data provides insights into the extent of usage. The same report for 2019 (Ofcom, 2020) indicated that boys aged 12 to 15 years in the UK spent about 14.5 hours gaming per week, which was twice as long as girls of the same age spent gaming online. Boys were also more likely to report difficulty controlling their screen time and being bullied via online gaming (ibid, p.23). However, girls were more likely to report experiencing “nasty or hurtful” interaction online (Ofcom 2024a, p.5).

2.2 Wellbeing

The concept of wellbeing, and the wellbeing of school-aged children and young people in particular, has only relatively recently become a focus in contemporary research (see McLellan & Steward, 2015). Even though interest has grown rapidly in the last couple of decades, this tended to focus on wellbeing of adults. However, the recent decline in wellbeing and happiness of young people globally (Moose & Bhargawa, 2024) is starting to receive much public attention.

There is no agreed definition of wellbeing and several terms with different meanings are often used interchangeably, such as “happiness” and “life satisfaction”. A further issue is that conceptualisations differ between disciplines. Arguably, the discipline of psychology is in the best position for conceptualising wellbeing given that its focus on the scientific study of the human mind (McLellan & Steward, 2015). Positive psychology, which is concerned with building positive qualities (Seligman & Csikszentmihalyi, 2000), contributed much to the conceptualisation of wellbeing. Drawing on theories from positive psychology as well as other disciplines, McLellan and Steward (2015) developed a conceptualisation of children’s and young people’s perceptions of their wellbeing in the school context. Their

conceptualisation has been adopted in the current study as it is suitable to the age group and context being studied.

The conceptualisation includes several dimensions related to hedonic (i.e., “feeling well”) and eudaimonic (i.e., “functioning well”) aspects of wellbeing (McLellan & Steward, 2015). These are life satisfaction, affect, perceived competence and interpersonal wellbeing (also see McLellan, 2019). As the name suggests, life satisfaction captures how satisfied an individual is with their life. Affect relates to subjective feelings and emotions. For instance, negative emotions include worry and boredom. Perceived competence is a eudaimonic aspect of wellbeing which captures positive functioning, including feeling that one is doing well and can deal with problems. Interpersonal wellbeing captures social aspects such as feeling cared for and being treated fairly.

As the current study draws on the PISA 2022 data, it is important to consider their wellbeing framework as well. Here, youth wellbeing is defined as “the quality of students' lives and their standard of living” (OECD, 2023, p.272). It is argued that wellbeing is a “multi-dimensional construct with both objective material components and subjective psychological facets” (p.272). This conceptualisation is not dissimilar from those by McLellan and Steward (2015). Both recognise that wellbeing is a multi-dimensional concept comprising hedonic and eudaimonic aspects which include but are not limited to life satisfaction. Specifically, both include aspects related to affect, interpersonal (or social) wellbeing, and perceived competence (or self-efficacy), while also highlighting the need to consider wellbeing inside and outside of school.

The frameworks differ in their focus on objective indicators and physical wellbeing, which are not emphasised by McLellan and Steward (2015). Although the wellbeing measure developed by McLellan and Steward (2015) includes the item “I feel healthy”, indicating that physical health is part of wellbeing, it does not take prominence in their conceptualisation. In contrast, the PISA 2022 questionnaire included several items on physical wellbeing. These are of interest here as previous research has found associations between screen time and physical wellbeing (Stiglic & Viner, 2019).

Youth wellbeing is on a declining trajectory globally (Marquez et al., 2024, p.77-80). PISA data shows that between 2015 and 2022, the average life satisfaction of 15-year-olds decreased in 39 out 45 participating countries (ibid, p.77-80)[2]. Among European countries, the UK has the lowest average life satisfaction score (The Children’s Society, 2024, p.44). One in four 15-year-olds in the UK scored below the midpoint of the life satisfaction scale and were thus considered to have low life satisfaction (ibid, p.44).

When looking across six areas of wellbeing — schoolwork, appearance, family, friends, school, and life as a whole — children were least happy with their appearance and most happy with their family (ibid, p.15). In addition, the Understanding Society survey suggested that wellbeing of 10- to 15-year-olds declined across many dimensions from 2009 to 2021. In 2021, children were on average less happy with their friends, appearance, school,

[2] The exceptions were Hungary, and five other East Asian countries – Hong Kong, Macao, Japan, South Korea and Taiwan.

schoolwork and life compared to twelve years earlier (ibid, p.16-18). More recently, girls have reported being significantly less happy with life, family, appearance and school than boys, as their satisfaction in these areas plummeted while boys' satisfaction remained relatively stable over the same period (ibid, p.19-21).

Amongst other reasons, the decline in youth wellbeing has been attributed to the potentially negative impact of social media and Internet use (DHSC & DfE, 2018). Importantly, older children (13 to 15-year-olds) were significantly less happy with their life overall than younger children (10 to 12-year-olds; DfE, 2019). This is relevant because the transition from childhood to adulthood is a crucial period in young people's lives. Understanding how wellbeing amongst this age group can be enhanced and protected is thus particularly important.

2.3 Digital use and wellbeing

Collectively, the large body of literature showed that digital technology use does not seem to be inherently adaptive or maladaptive. Its relationship with wellbeing tends to be heterogeneous across individuals, depending, for example, on their characteristics, extent of use, and types of use. These aspects often interact, creating a complex interplay.

Characteristics. Heterogeneous relationships have been found across groups of young people, depending on their characteristics such as gender, age, and personality traits. Girls' wellbeing was typically more negatively affected by increased use of social media and the Internet than boys' (Twenge & Farley, 2021; or see reviews by Azem et al., 2023; Fumagalli et al., 2024; Hilty et al., 2023; Liu et al., 2022; Santos et al., 2023), whereas boys tended to have different experiences with gaming (Hilty et al., 2023, p.7; Su et al., 2020). The relationship between digital use and wellbeing also varied by age, depending on the child's development stage. Orben et al. (2022) found that the most sensitive age window for social media impacts was 11-13 for girls, and 14-15 for boys, with the strongest negative association between social media use and life satisfaction among younger adolescents (10-15 years). Similarly, Hancock et al. (2022) concluded that social media use was associated with higher rates of depression among adolescents but not college-age students (p.203). On personality traits, individuals with a higher tendency to procrastinate, high neuroticism, low conscientiousness (resulting in a high likelihood of overuse), and those who placed high importance on social media tended to experience diminished wellbeing from digital media consumption (Liebherr et al., 2025, p.7).

Extent of use. Furthermore, the associations can also vary depending on the usage duration, specifically the relationship might be non-monotonic, i.e., wellbeing is not always increasing or decreasing as time spent increases. Przybylski and Weinstein (2017) first proposed the "Goldilocks theory", suggesting that there may be a "just right" amount of digital screen time for mental wellbeing. Using a sample of English adolescents, their analyses showed that the relationship of various digital activities (e.g., watching TV, gaming, using computer for Internet and smartphones for social networking) and wellbeing can be best explained by a quadratic function. For instance, those who spent two to three hours daily on gaming was associated with higher wellbeing than those who did not game, gamed fewer hours or gamed excessively (p.207). But the optimal level varied depending on the

activity (p.208-209). The quadratic relationships between digital media use and psychological wellbeing have also been replicated in other studies (see, Fumagalli et al., 2024; Hilty et al., 2023, p.4-5, for reviews). However, the non-monotonic effects may not be consistently present in all age groups and for all gender (see Fumagalli et al., 2024 for a summary).

Type of use. Many research papers tended to focus on "screen time" without differentiating between purposes of use (Nett, 2025, p.8). When distinctions were made, most research tend to focus on time spent digital gaming and social networking (Hietajarvi et al., 2022, p.103). However, a longitudinal study by Sanders et al. (2019) examined the link between five types of digital activity — social, passive, interaction, educational, or other—and various psychological outcomes (e.g., social and emotional functioning) of children aged 11-14. They concluded that while more screen time was associated with worse outcomes, the effects varied depending on the type of screen time. For instance, passive and interactive screen time (e.g., watching TV and gaming, respectively) had negative associations, but no negative link was found for educational screen time (e.g., using computer for schoolwork). Even within the same purpose of usage, how young people engage digitally matters. Research has mostly focused on passive (i.e., without interaction) and active (i.e., reacting or interacting) use of social media, where passive use tended to have detrimental effects on wellbeing, but not active use (Hilty et al., 2023, p.7; Meier & Krause, 2022, p.170-171 for a review of studies). In recent years, the literature has extended this passive-active dichotomy to consider more nuances, e.g., social network size, and their interactions with users' personality traits, e.g., susceptibility to envy (Orben et al., 2024; Shaw et al., 2022; Valkenburg et al., 2022; Verduyn et al., 2022).

Next to being heterogeneous, the literature also indicated that relationships between digital use and wellbeing were likely bi-directional, where the state of wellbeing also influences digital use. However, a review by Fumagalli et al. (2024, p.122) concluded that recent larger-scale longitudinal research had produced highly variable findings. Similarly, Tang et al. (2021, p.4, 9 & 12) concluded that there was limited evidence supporting the reverse association of depressive symptoms and subsequent screen time, and even if present, the relationship between screen time and subsequent depression tended to be stronger than the reverse. Also, see Orben (2020, p.410-411).

Overall, there is a consensus in the literature supporting the negative associations between digital use and psychological wellbeing and its heterogeneous nature. However, the current debate mainly centres on the practical significance implied by these pieces of empirical evidence (for a summary see Pearson, 2025). Several reviews and meta-analyses have concluded that these relationships are on average small or weak, with correlations generally around -0.10 to -0.15 (Orben, 2020, p.409; or see Hietajärvi et al., 2022; Tang et al., 2021).

However, some argue that effect sizes based on studies that aggregated data across types of use, gender and types of wellbeing (Twenge et al., 2020; Twenge et al., 2022) masked the heterogeneous effects. Additionally, others contended that the strength of linear correlations is an inadequate measure of practical importance. For instance, Twenge and Hamilton (2022) suggested that relative risks — which examine the number of people affected — would provide a more meaningful measure. They illustrated this with the example that while the correlation between smoking and lung cancer was about r=0.06, considered

"small" by conventional standards, the relative risk indicated that smokers were 30 times more likely to develop lung cancer than non-smokers.

These debates have prompted recent research to translate findings into more practical terms and for reviews to also investigate differential effects for specific groups of young people depending on their characteristics (e.g., Liu et al., 2022; Santos et al., 2023).

2.4 Digital use, digital literacy and wellbeing

One factor that may protect and promote youth wellbeing when using digital technologies is their digital literacy (Vissenberg et al., 2022). Despite the urging of researchers like Vissenberg et al. (2022), empirical research examining the relationship between digital use, digital literacy, and wellbeing remains relatively limited (Mayiwar et al., 2024; Vissenberg et al., 2023, p.7).

Digital literacy is defined as “the ability to access, manage, understand, integrate, communicate, evaluate, and create information safely and appropriately through digital technologies” (Law et al., 2018, p.6). In other words, digital literacy encompasses more than just technical skills, it also includes advanced critical and evaluative skills that help individuals identify ways to protect themselves from potential dangers in digital environments (see Carretero et al., 2017). According to the Cambridge International Digital Literacy curricula (Cambridge University Press and Assessment, n.d.), there are three main areas within digital literacy (p.5):

- **Using tools and creating digital content** – the ability to use technology and software with confidence to search for and create content, solve problems and innovate.
- **Sharing and interacting online** – the ability to communicate, learn and collaborate with peers, discover and share new information and generate innovative ideas with others.
- **Safety and wellbeing online** - the ability to recognise risks, stay safe online and protect wellbeing.

Vissenberg et al. (2022) argued that digital literacy can be a “promotive factor” for wellbeing, i.e., beneficial for wellbeing in general. This is because it can potentially open up opportunities for social interaction and instrumental use that enhance wellbeing, while simultaneously protecting against potential negative outcomes of online risk experiences (p.3).

Indeed, the positive association between digital literacy and wellbeing is supported by other research, such as Picton et al. (2022). The authors discovered that nearly three times as many young people with high critical digital literacy reported high mental wellbeing compared to those with low critical digital literacy. However, a systematic review by Vissenberg et al. (2022) concluded that the association between digital literacy and youth wellbeing was mixed, indicating that more research is needed to fully understand these relationships.

Findings from several empirical studies have identified potential ways in which digital literacy benefits wellbeing. Firstly, Mayiwar et al. (2024) found that adults’ subjective, i.e., self-reported, digital literacy levels were positively associated with life satisfaction, but not their

objective digital literacy levels, i.e., assessed by researchers. This suggested that one's confidence to navigate digital environments effectively could be an important determinant of their wellbeing. Secondly, a study by Pan et al. (2024) found that digital literacy was positively associated with online resilience, which was associated with higher levels of wellbeing. This finding supported the idea that digital literacy promotes wellbeing by fostering online resilience. Thirdly, digital literacy may provide individuals "the ability to evaluate online content in relation to bias and trustworthiness" (Picton et al., 2022, p.9), protecting them from misinformation and its potential negative impacts on wellbeing. For instance, in a study on politics and COVID-19 news posts, Sirlin et al. (2021) found that digital literacy predicted the ability to distinguish between true and false information when judging the accuracy of headlines. Vissenberg et al. (2023, p.8) also found that high digital skills in young people were negatively linked to misinformation risks. Lastly, highly digitally literate individuals may also be more able to search, understand, and utilise information online to promote, maintain, and restore their own wellbeing. For instance, findings from Rivadeneira et al. (2023) showed that individuals with higher digital health literacy tended to have higher subjective wellbeing during the COVID-19 pandemic. The authors posited that individuals with higher digital health literacy used social media less often and were better able to find high-quality information that protected them from infection, thereby promoting wellbeing.

Furthermore, there is also some evidence suggesting that digital literacy is related to the types of digital use, however the findings are mixed. As cited in Kunina-Habenichts and Goldhammer (2020), Senkbeil (2017) found positive associations between ICT skills and instrumental use, such as information seeking ($r = 0.12$) and learning/work ($r = 0.14$), but negative associations with social interaction use, like social exchange ($r = -0.21$) and self-representation ($r = -0.14$) (Senkbeil, 2017). On the contrary, Xiao and Sun (2022) who did a study using profile analysis of the PISA 2018 data found that US students with higher perceived ICT competence were more likely to use ICT for entertainment rather than school-related purposes. Lastly, Scherer et al. (2017) have instead found that students with higher ICT competence often use ICT frequently for *both* entertainment and academic activities.

Finally, the review by Vissenberg et al. (2022) indicated that individuals with higher digital literacy were more likely to encounter online risks — a natural consequence of spending more time online. However, experiencing more risk does not necessarily lead to more negative consequences, as digital literacy may help young people cope with these risks. However, empirical findings on this are mixed. Lee and Chae (2012) found that this association between encountering a risk and being harmed becomes weaker with increasing digital literacy, and Vandonick et al. (2013) found that digital literacy helped protect young children from online risks through coping strategies like blocking senders. In contrast, Sonck and de Haan (2013) and Staksrud et al. (2013) did not find evidence that digital competency reduces the chances of children being harmed by online risks.

3. Current study

This study aims to address two research questions:

Research Question 1: What is the association between digital use and youth wellbeing? How does the relationship vary depending on the types of use, the extent of use, the aspects of wellbeing considered, and gender?

While research generally indicated that digital use was linked to lower wellbeing, the impact varied based on the types of digital use (e.g., Santos et al.,2023, p.15) and the wellbeing outcomes considered. Therefore, we aim to contribute to the literature by exploring the relationship between wellbeing and several types of digital activities, which can be broadly categorised as instrumental, hedonic, and social uses. Furthermore, instead of focusing on a single aspect of wellbeing, we will mostly base our conceptualisation on the youth wellbeing framework of McLellan and Steward (2015) to examine how different types of digital use relate to various aspects of youth wellbeing, including life satisfaction, affect, perceived competence, interpersonal wellbeing, and physical wellbeing. This approach will help us better understand which aspects of youth wellbeing are most susceptible to the impact of each type of digital activity.

Research Question 2: What role does digital literacy play in protecting youth wellbeing in the digital world?

Given the mixed evidence, this study aims to determine whether digital literacy encourages more time spent on beneficial digital activities and whether it promotes higher wellbeing. Additionally, we will investigate if digital literacy mitigates the potential negative impacts of digital use on wellbeing.

4. Data and summary statistics

This research used PISA data from the 2022 cycle. PISA is a large-scale international assessment of 15-year-olds carried out by OECD every three years since 2000. PISA 2022, in particular, included optional wellbeing and ICT familiarity questionnaires which made it well-suited for the purpose of this research.

The information collected from the wellbeing and ICT familiarity questionnaires was pivotal to this research. Because of this, only the ten countries that had opted to administer both the wellbeing and ICT familiarity questionnaires to their students were included in our analyses. Table 1 outlines the countries analysed and the number of students in each country.

Close to half of the analysed students were from Spain and Brazil. To address this, our analyses applied survey weights to ensure that each country contributes a roughly equal weight to the results (also known in PISA as senate weights). In other words, the results in this report were not skewed by countries with large numbers of surveyed students but roughly represent a simple average of all the countries analysed. Note that, in some cases, due to missing data on certain variables, the country-aggregated results were not exactly equally weighted by country. However, the usage of weights meant that each country can

only have the equivalent of at most 5000 observations in the analyses (for a more detailed explanation, see Jerrim et al., 2017, p.6).

Table 1. PISA students unweighted count for country that administered the ICT familiarity and wellbeing questionnaires.

Country	Abbreviated country name	Number of PISA students*	% of total sample
Brazil	BRA	10798	12.3%
Costa Rica	CRI	6113	6.9%
Hong Kong (China)	HKG	5907	6.7%
Hungary	HUN	6198	7.0%
Ireland	IRL	5569	6.3%
Macao (China)	MAC	4384	5.0%
Panama	PAN	4544	5.2%
Saudi Arabia	SAU	6928	7.9%
Slovenia	SVN	6721	7.6%
Spain	ESP	30800	35.0%
Total		**87962**	**100%**

Notes: *Observations are weighted using senate weights in the analyses in this study, such that each country will only contribute the equivalent of at most 5,000 observations.

4.1 Digital use

As discussed in the literature review section, students can use digital technologies for various purposes, which can be broadly categorised into three groups: (1) hedonic, i.e., for entertainment; (2) instrumental, i.e., learning or work-related; and (3) social interactions, i.e., receiving or distributing information. The related digital use items within the PISA questionnaires were not structured based on this categorisation but can roughly be categorised in such a manner. However, we acknowledge that, in practice, usage of digital technologies may encompass more than one purpose at any given time, e.g., using social media to communicate with friends about schoolwork.

The digital use variables analysed here mainly reflect students' level of digital use in leisure activities, which presumably occurred mostly outside of school hours. The exact wording of these PISA questions didn't specifically differentiate between usage outside or inside of school. Students were asked, "[D]uring a typical weekday, how much time do you spend doing the following leisure activities[3]?"

1. "Play video-games",
2. "Browse social networks",
3. "Browse the Internet (excluding social networks) for fun", e.g., watching videos,
4. "Look for practical information online", e.g., find a place,
5. "Communicate and share digital content on social networks", and
6. "Read, listen to or view informational materials to learn how to do something", e.g., podcast.

[3] On the same PISA question, students were asked about the time spent creating or editing digital content, such as pictures, videos, music, and computer programs. However, this activity was not analysed here because it was challenging to determine which aspect of digital use it relates to. Depending on the digital content created, this activity can fall under any of the three aspects of digital use. For instance, creating a YouTube video on statistics is an instrumental activity, while editing personal pictures for Instagram would be an activity intended for social interaction.

Students were also asked the same question for their usage during a typical weekend day. Instead of providing the exact number of hours on each activity, they were asked to choose between six options:

1. No time at all
2. Less than 1 hour a day
3. Between 1 and 3 hours a day
4. More than 3 hours and up to 5 hours a day
5. More than 5 hours and up to 7 hours a day
6. More than 7 hours a day

Table 2 presents further descriptions on these variables, the aspect of digital use (i.e., instrumental, entertainment, social) we considered these variables to related to and the variable names in the PISA dataset.

Table 2. Digital use variables analysed.

Aspect of digital use	Variable name	PISA name*	Description
Instrumental	Access informational materials	IC177Q06JA IC178Q06JA	The frequency of "read[ing], listen[ing] to or view[ing] informational materials to learn how to do something (e.g. tutorial, podcast)" during a typical weekday or weekend day.
	Access practical information	IC177Q04JA IC178Q04JA	The frequency of "look[ing] for practical information online (e.g. find a place, book a train ticket, buy a product)" during a typical weekday or weekend day.
Hedonic (entertainment)	Play video games	IC177Q01JA IC178Q01JA	The frequency of "play[ing] video games (using my smartphone, a gaming console or an online platform or Apps" during a typical weekday or weekend day.
	Browse Internet for fun	IC177Q03JA IC178Q03JA	The frequency of "brows[ing] the Internet (excluding social networks) for fun (e.g. reading news, listening to podcasts and music or watching videos)" during a typical weekday or weekend day.
Social interaction	Browse social networks	IC177Q02JA IC178Q02JA	The frequency of "brows[ing] social networks (e.g. Instagram, Facebook)" during a typical weekday or weekend day.
	Share digital content	IC177Q05JA IC178Q05JA	The frequency of "communicat[ing] and shar[ing] digital content on social networks or any communication platform" during a typical weekday or weekend day.

Notes: * Variables with prefix "IC177" for a typical weekday, and "IC178" for a typical weekend day. These variables are modelled separately in this work unless mentioned otherwise.

Figure 1 shows students' daily time spent in each digital activity during a typical weekday and weekend day for the data overall. Figure 2 shows the same information for boys and girls separately. Figure 3 presents the Spearman's rank correlation between time spent on weekend and weekdays. Lastly, Figure 4 illustrates the proportion of students who spent three or more hours daily on these digital activities, broken down by country and gender. The overall weighted count of each variable can be found in Table 12 of the appendix.

Summary statistics

Figure 1 shows that students spent the most time browsing social networks, regardless of whether it is a weekend or weekday, with at least 36% reporting three or more hours daily on social networks. Conversely, they spent the least time online looking for practical information or engaging with informational materials. Time spent on the same activity tend to correlate reasonably high between weekend and weekdays, with correlation ranges between 0.65 and 0.72. However, time spent playing video games varied noticeably between weekdays and weekends. About 27% reported spending three or more hours daily on weekdays, which increased to 36% on weekends. This change of pattern most likely stems from boys than from girls as indicated by the lower correlation for boys between time spent gaming on a weekday and on a weekend as shown in Figure 3.

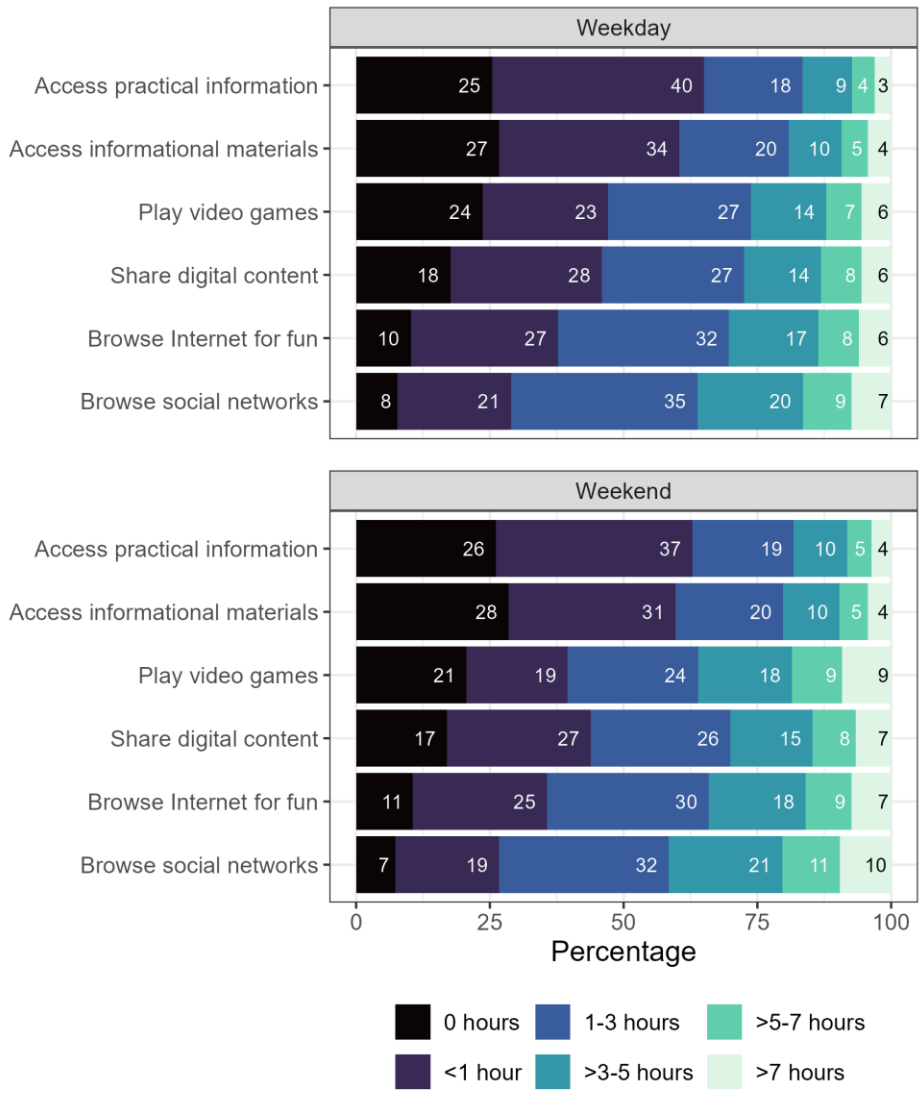

Figure 1. Daily time spent on each digital activity. Percentage of respondents (out of those with data; weighted) in each frequency category for a typical weekend and weekday.

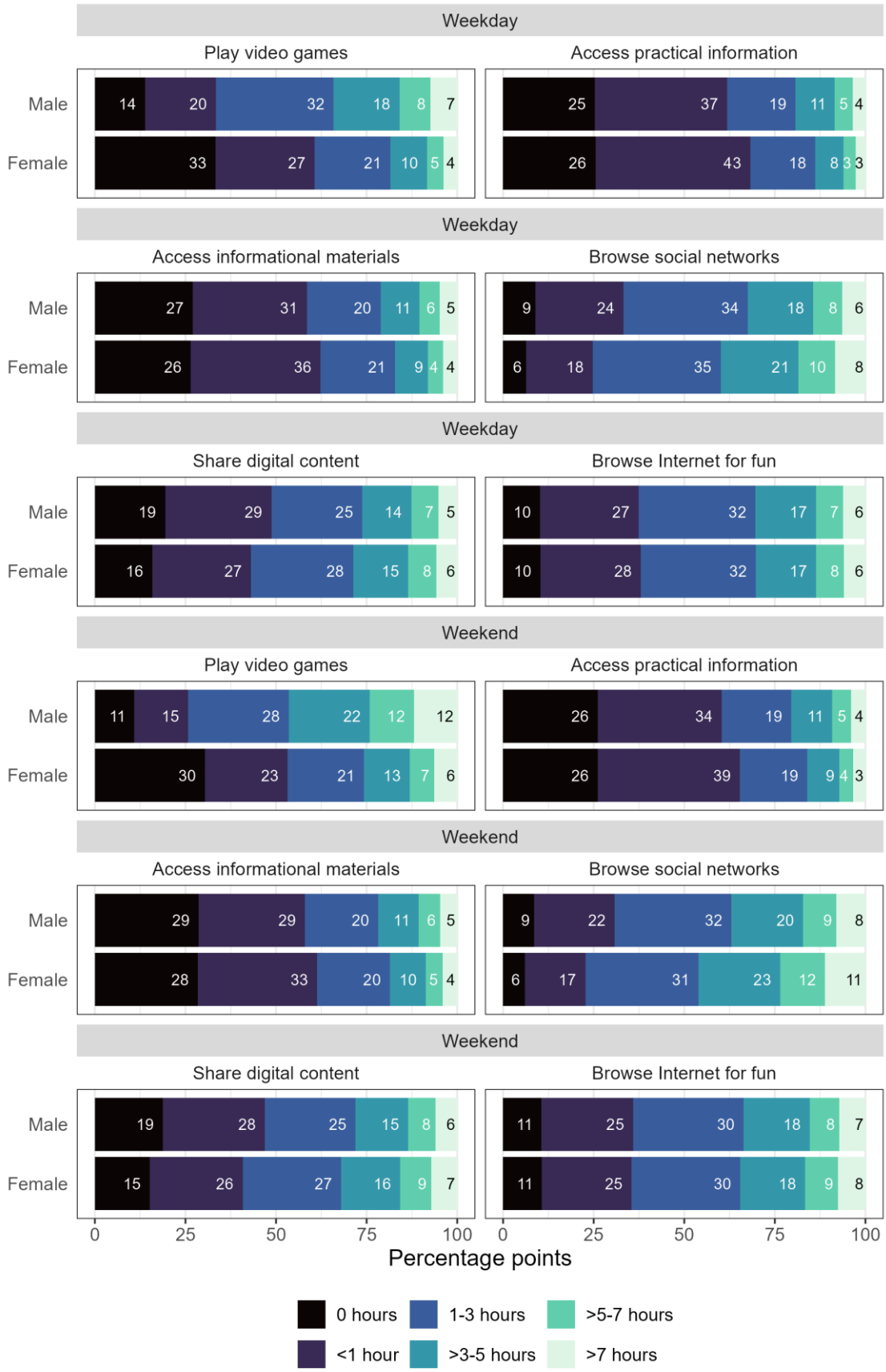

Figure 2. The percentage difference between boys and girls in each frequency category.

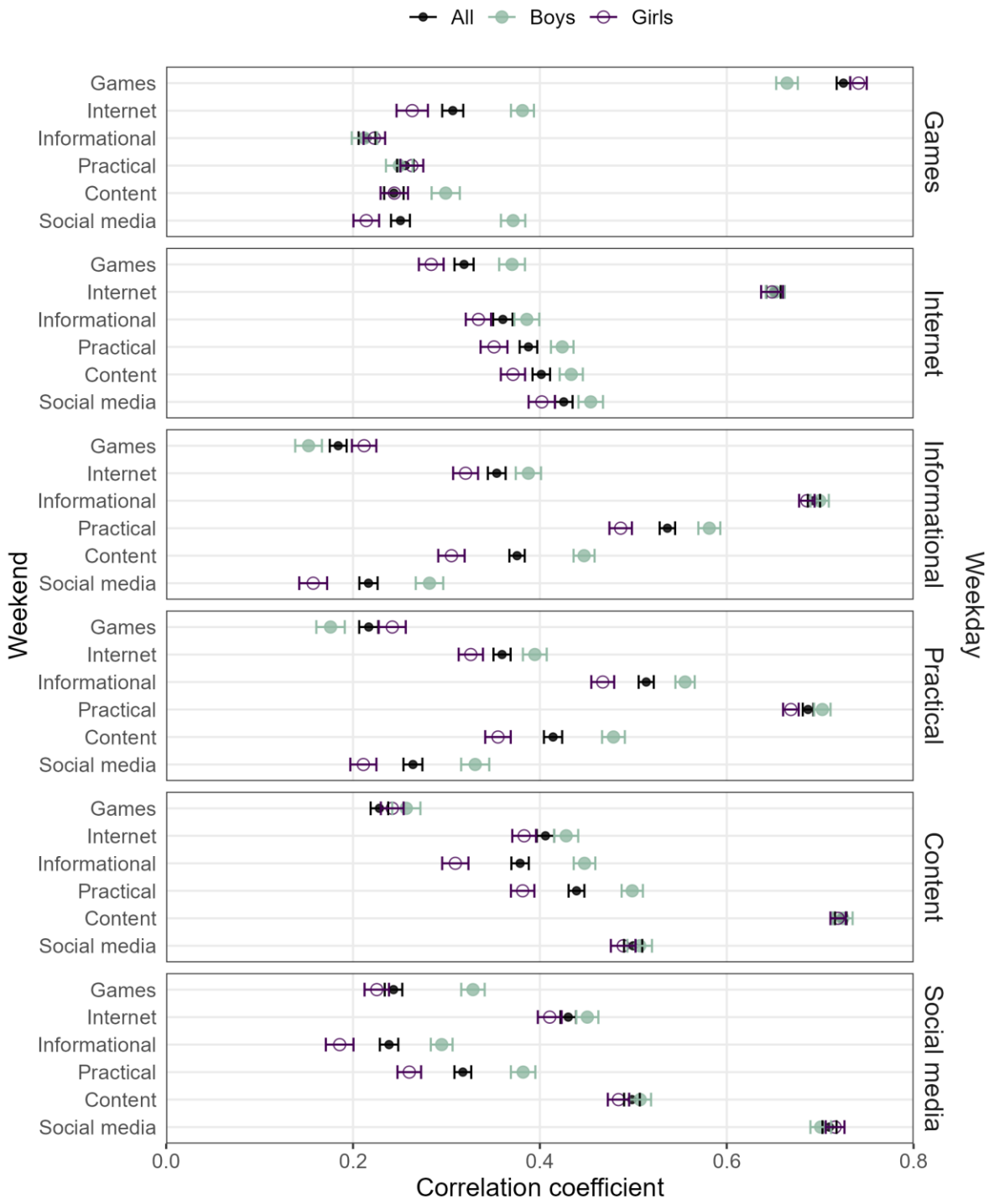

Figure 3. Spearman's rank correlations (and 95% confidence interval) between digital use on a typical weekday and weekend day.

Both Figure 2 and Figure 4 suggest that girls and boys spent similar amounts of time on most activities, especially on browsing the Internet for fun. However, noticeable gender differences emerged in two activities: playing video games and using social networks.

Across all countries, more boys spent over three hours on gaming compared to girls, while slightly more girls reported spending over three hours on social networks than boys. Particularly, in Hong Kong (HKG) and Macao (MAC), as can be seen in Figure 4, about 58% of boys reported spending over three hours on video games, followed by Hungary (HUN) at 53%. Conversely, at least half of the girls from European and South American countries, including Ireland, Spain, Brazil, and Costa Rica, reported spending over three hours daily on social media during weekends.

There were also considerable variations across countries, mostly in instrumental activities. Saudi Arabia had the highest proportion of students spending over three hours on these activities, compared to Ireland, which had the lowest proportion, with a difference of about 25 percentage points. Interestingly, a similar proportion of students across all countries reported spending three or more hours on social networks on a typical weekend day.

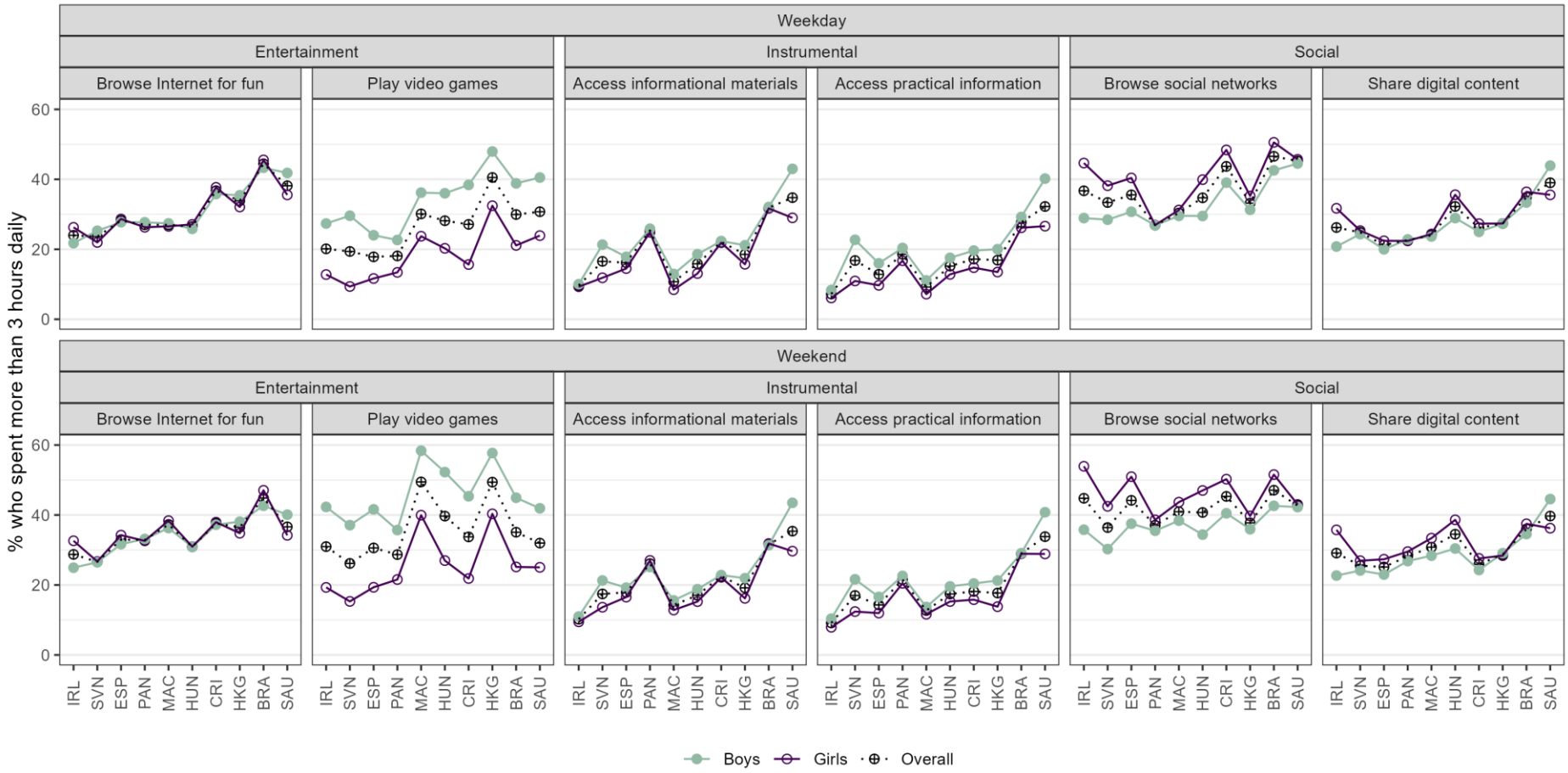

Figure 4. Percentage of respondents (out of those with data; weighted) who reported spending more than three hours daily on specific digital activities during a typical weekday and weekend, by country and gender.

4.2 Wellbeing

In PISA 2022 students were asked detailed questions about their wellbeing. This information was used (by OECD) to derive multiple measures of wellbeing such as sense of belonging at schools or general wellbeing on a typical day. We analysed seven measures relevant to the five aspects of wellbeing (though not always mutually exclusive), mostly following the conceptualisation of McLellan and Steward (2015) as discussed in the literature review section. The descriptions of these wellbeing variables are presented in Table 3, including the aspect of wellbeing they are related to. The survey items used to measure each variable are presented in Table 13 in the appendix.

Table 3. Wellbeing outcomes analysed.

Aspect of wellbeing	PISA variable name	Description
Life satisfaction	LIFESAT	Students' **satisfactions** across various life domains (health, school life, relationships, etc.). Higher values indicate higher general satisfactions in these domains.
Affect (i.e., positive emotions)	BODYIMA	Students' agreement with five statements relating to their **body image** (e.g., "I like my body"). Higher values indicate higher agreement with these statements, i.e., higher self-perceived body image.
	EXPWB	Students' wellbeing in the previous day; self-reported through six statements (e.g., "Did you smile or laugh a lot yesterday?"). Students who responded "no" to the question "Was yesterday a typical day?" were recoded as missing; hence, this variable broadly indicates students' **general wellbeing on a *typical* day** with higher values indicating a higher general wellbeing.
Interpersonal or social	BELONG	Students' **sense of belonging at schools** through six statements (e.g., I make friends easily at school.). Higher values indicate a higher sense of belonging at school.
	FEELSAFE	Students' agreement with four statements about their **perceived safety** (e.g., "I feel safe on my way to school"). Higher values indicate a higher level of self-perceived safety at school.
Perceived competence	STRESAGR	Students' agreement with 10 statements relating to **stress resistance** (e.g., "I am able to work under pressure"). Higher values indicate a higher level of self-perceived stress resistance.
Physical	PSYCHSYM	The frequency of a student experiencing **psychosomatic symptoms** (e.g., sleeping difficulty, headache, depressed etc) in the past six months. Higher values indicate a higher frequency of experiencing these symptoms.

For all but one variable, a high value indicates higher wellbeing. The exception is the variable PSYCHSYM, where a high value indicates experiencing a higher frequency of psychosomatic symptoms such as having difficulty sleeping, headache or feeling depressed. As such, a low value on this measure represents higher wellbeing instead.

These wellbeing variables were "scaled indices" derived by PISA using Item Response Theory (known as "IRT-derived variables"). Many items within the PISA questionnaire were designed to be combined to derive meaningful information about constructs we cannot observe directly (e.g., a student's sense of belonging at school). Instead of adding or arithmetically transforming a student's responses within a set of items designed to measure

the same construct, in some cases, PISA used an IRT model to produce an estimate of that latent construct for each student. The estimates were then scaled so that value 0 on the scale represents the OECD average for that construct, and +1 and -1 represent one standard deviation above and below the OECD average, respectively (for more details, see OECD, 2024, p.389-448).

Table 4 shows the extent of missingness for each wellbeing variable, their summary statistics and the internal consistency of these composite variables, as measured by Cronbach's alpha.

Table 4. Description of wellbeing outcomes analysed, count and percentage of weighted observations without missing value and summary statistics.

Variable	Short description	Weighted count		Mean		SD		Alpha
		Total	% missing	Est.	SE	Est.	SE	
BELONG	Sense of belonging at school	46634	6.73	-0.09	0.00	0.92	0.00	0.83
BODYIMA	Body image	37599	24.80	-0.12	0.01	0.91	0.00	0.85
EXPWB	Wellbeing on a typical day	32212	35.58	0.02	0.01	0.83	0.00	0.73
FEELSAFE	Perceived safety	42114	15.77	-0.09	0.01	0.91	0.00	0.88
LIFESAT	Life satisfaction	39426	21.15	-0.03	0.01	0.97	0.01	0.88
PSYCHSYM	Psychosomatic symptoms	44107	11.79	-0.05	0.01	0.98	0.00	0.89
STRESAGR	Stress resistance	36555	26.89	-0.03	0.01	0.81	0.01	0.80

Notes: Count is weighted using senate weights. "Total" is the weighed count excluding observations with missing values, with an initial total of 50000. "SD" for standard deviation; "Est" for estimate, "SE" for standard error, and "Alpha" for Cronbach's alpha.

Missingness

The general wellbeing variable (EXPWB) had the highest level of missingness. The missingness was primarily from three countries: Brazil, Panama, and Saudi Arabia. For these countries, only 50% of their effective observations (i.e., after weighting) have available data. This variable was derived from six items related to students' wellbeing on the day before the survey, such as "[W]ere you treated with respect all day yesterday?". However, students were also asked, "[W]as yesterday a typical day?". Responses were coded as missing if students answered "no" to this question, which partially explained the relatively higher level of missing data in this variable. It is unclear from the data whether the missingness was systematic —meaning only students who had an especially bad day prior to the survey were excluded here — as "atypical" could be interpreted as both an especially good and an especially bad day.

For the remaining variables with a high level of missingness, the reason was mostly because some countries did not administer a particular set of questions needed to construct the variables: Costa Rica did not collect information for the body image (BODYIMA) and life satisfaction (LIFESAT) variables, Spain not having data for self-perceived safety (FEELSAFE), and Panama and Saudi Arabia for stress resistance (STRESAGR).

Summary statistics

While Table 4 shows that the mean scores for most wellbeing variables are close to zero (OECD average), Figure 5 clearly depicts that there were noticeable variations across countries. In addition to the overall mean scores, Figure 5 also presents the mean score by gender.

Figure 5 indicates that boys generally reported higher wellbeing compared to girls across all variables and countries, with the exception of Saudi Arabia in several cases. Additionally, the gender differences in average scores varied depending on the wellbeing variable. For instance, the sense of belonging at school (BELONG) was quite similar between boys and girls within most countries. However, the gap was noticeable in the frequency of experiencing psychosomatic symptoms (PSYCHSYM) and stress resistance, where girls reported a higher frequency of psychosomatic symptoms, while boys reported having higher levels of stress resistance.

Furthermore, some variations were found across countries: students from Hong Kong and Macao tended to report noticeably lower levels of wellbeing compared to other countries in several aspects, such as sense of belonging at school and life satisfaction. In contrast, students from Saudi Arabia reported higher levels of wellbeing, particularly in life satisfaction. In summary, these findings highlight noticeable gender and country differences in student wellbeing.

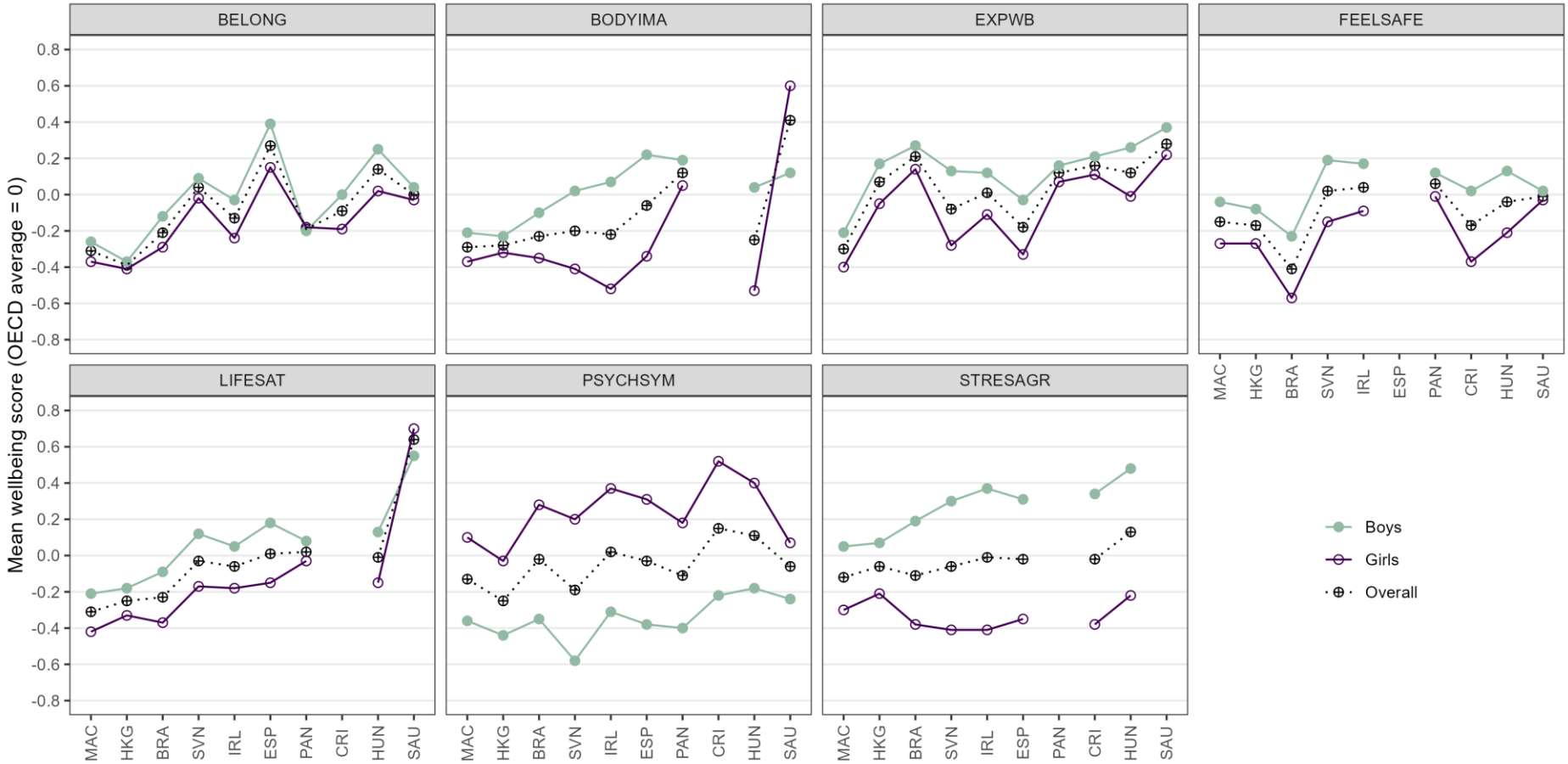

Figure 5. Average wellbeing score by country for all respondents overall and by gender.

4.3 Digital literacy

In PISA 2022, students were asked about their digital competency, and their attitudes and practices when dealing with online information. We identified three variables that could reflect students' level of digital literacy which corresponds to two main areas within the Cambridge International Digital Literacy framework (CUP&A, n.d.). These areas were 1) using tools and content creation, and 2) safety and wellbeing. Additionally, in the teacher questionnaire, teachers were asked whether they taught various ICT awareness activities to their students (e.g., "How to decide whether to trust information from the Internet"). Given the recent empirical evidence suggesting the effectiveness of school-based digital literacy programs (De La Hoz et al., 2023), we also used this variable as a crude indication of students' level of digital literacy even though it made no distinction between the various digital literacy aspects. More importantly, it also allowed us to investigate whether having digital literacy awareness in the school curriculum plays a role in mitigating any potential risks associated with digital use, both inside and outside the classroom.

Table 5 below describes the four digital literacy variables analysed and their coding where applicable.

Table 5. Digital literacy variables analysed.

Areas of digital literacy	PISA variable name	Description
Using tools and content creation	ICTEFFIC	Students' self-reported competence in using digital resources to do 14 tasks, e.g., "search for and find relevant information online", "assess the quality of information you found online". High values indicate high level of competence and efficiency in using digital resources, and a value of 0 represents the OECD average.
	IC180Q01JA	Students' response to the statement "I trust what I read online" with four possible options: strongly disagree, disagree, agree, strongly agree. Responses are recoded as a binary variable, "**TRUSTONLINE**", which takes a value of 0 if disagree (combining strongly disagree and disagree responses) and 1 if agree (combining strongly agree and agree responses).
Safety and wellbeing	ICTINFO	Students' agreement with six statements relating to their practice when dealing with online information, e.g., "I try to flag wrong information when I encounter it online." High values indicate students are taking good measures when sharing information online, and a value of 0 represents the OECD average.
School culture	ICTOTL	Teachers' response to whether they have taught any of the seven ICT awareness activities in class, e.g., "how to detect phishing or spam emails". High values indicate a high level of ICT awareness included in the teaching, and a value of 0 represents the OECD average. Since it was not possible to identify which students were in each teacher's class, we calculated a school-level average of this variable to indicate the extent to which schools had taught ICT awareness, named "**ICTOTLSCH"**.

Although we broadly categorised each variable into a distinct aspect of digital literacy, there are some overlaps. For example, while we categorised ICTEFFIC under "using tools and content creation", it included a question about whether students can "change the settings of a device or app in order to protect … [their] data and privacy", which relates more closely to

the “safety and wellbeing” aspect of digital literacy instead. It also included two questions about sharing information and collaborating with other students, which relate more closely to their competency in online interaction. However, we believe ICTEFFIC adequately represents students' competency in using digital tools and creating online content, as most questions used to derive this variable gauge students' competency in these skills.

Table 6 shows the extent of missingness for each digital literacy variable, their summary statistics and the internal consistency of these composite variables, as measured by Cronbach’s alpha.

Table 6. Description of digital literacy variables analysed, count and percentage of weighted observations without missing values and summary statistics of the variables.

Variable	Description	Weighted count		Mean		SD		Alpha
		Total	% missing	Est	SE	Est	SE	
ICTEFFIC	ICT competency	39454	21.09	-0.06	0.01	0.89	0.00	0.92
ICTINFO	ICT information practices	40612	18.78	0.10	0.01	0.91	0.01	0.83
ICTOTLSCH	Teaching ICT awareness	23066	53.87	0.02	0.01	0.28	0.01	0.83
TRUSTONLINE	Trusting of online content	40992	18.02	0.38	0.00	0.44	0.00	-

Notes: Count is weighted using senate weights. “Total” is the weighed count excluding observations with missing values, with an initial total of 50000. “SD” for standard deviation; “Est” for estimate, “SE” for standard error, and “Alpha” for Cronbach’s alpha. ICTOTLSCH is a school-average variable based ICTOTL, hence, the Cronbach’s alpha shown for this was calculated based on ICTOTL.

Missingness

Slightly more than half of the observations had a missing value for the ICTOTLSCH variable (which was based on ICTOTL). The high level of missingness was due to the fact that this variable was collected using the teacher questionnaire, which was optional and only administered by five analysed countries (out of 10). In any subsequent work involving ICT awareness in schools, the analyses were repeated twice, (1) once excluding the ICTOTLSCH variable, using the full sample and (2) another including the ICTOTLSCH variable along with all other digital literacy variables, but with a smaller dataset.

Summary statistics

Figure 6 and Figure 7 show the summary statistics of these variables by country and by gender. Firstly, boys and girls have generally reported similar levels of digital literacy. However, more boys tend to agree with the statement “I trust what I read online” than girls in almost all countries. Secondly, the extent to which ICT awareness was taught in schools (ICTOTLSCH) appeared to be almost identical between girls and boys, but this was purely driven by the fact that this was a school-level average variable. Lastly, the digital literacy levels varied across countries. Most noticeably, the difference between countries with the highest and the lowest proportion (Hong Kong vs Costa Rica) of students agreeing to the statement “I trust what I read online” was about 18 percentage points.

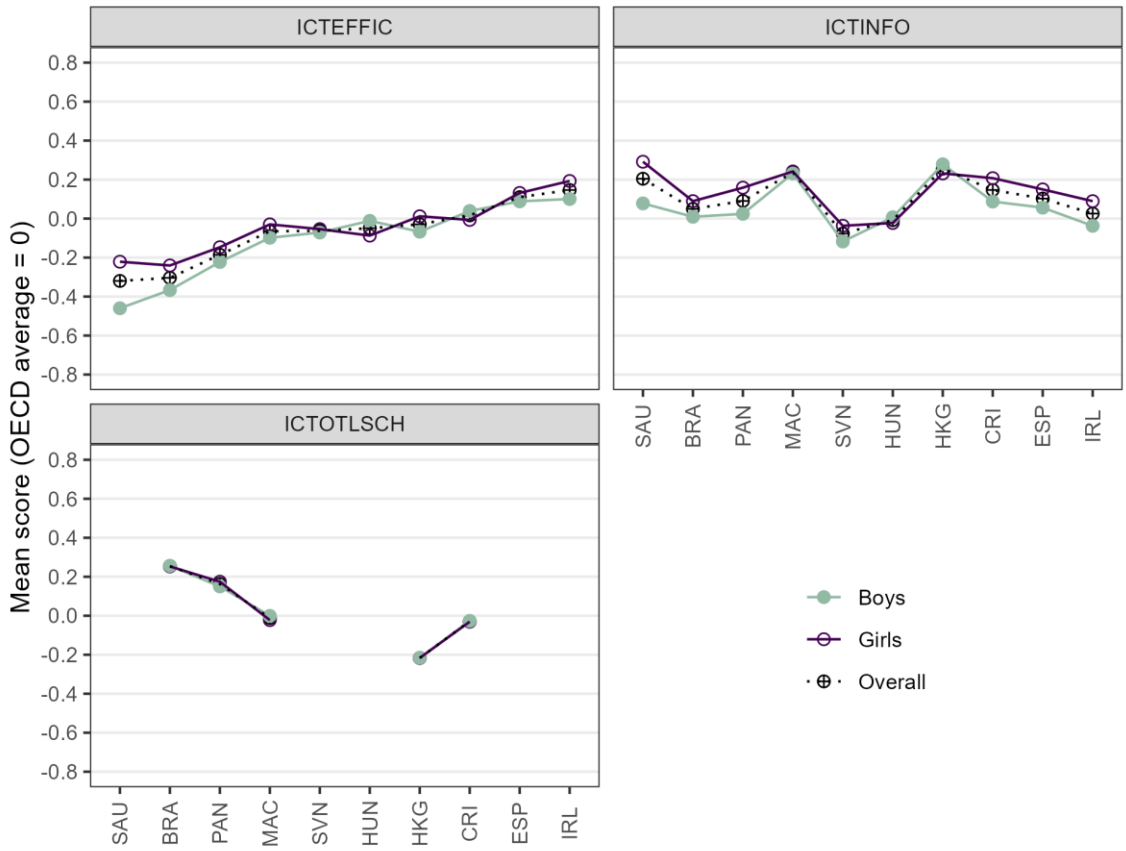

Figure 6. Average digital literacy score by country for all respondents overall and by gender.

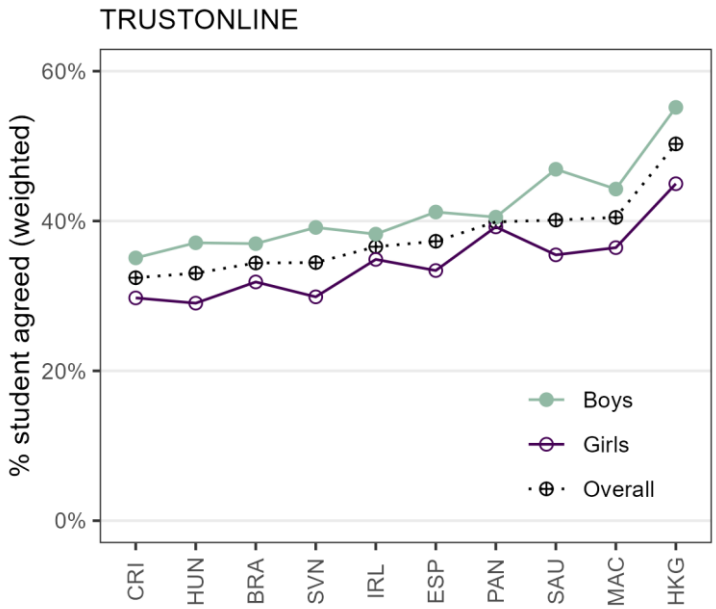

Figure 7. Percentage of students (weighted) agreeing to the statement “I trust what I read online” i.e., variable TRUSTONLINE.

5. Methodology

5.1 Digital use and wellbeing

Descriptive analyses

To explore the relationships between wellbeing outcomes and digital use, we began with descriptive statistics and correlation analyses using the "intsvy" R package (Caro & Biecek, 2017). This package calculates Pearson correlation, which would not be suitable here since the time use variable is an ordinal variable (0 hours, <1 hour, …). Consequently, we modified the relevant function to incorporate Spearman's correlation using the "wCorr" R package (Bailey et al., 2021). In both analyses, senate weights were applied to ensure equal country contributions, and replicate weights were applied to account for sampling variance in the standard error calculation.

Replicate weights

The Balanced Repeated Replication weights in the PISA dataset give larger total weights for countries with bigger populations. Since our point estimates were weighted using senate weights, we had to scale the replicate weights to ensure each country had the same total weight within each set of replicate weights. To achieve this, we applied a *constant* factor to each observation of a country, bringing its total weight to 5,000. In other words, this adjustment maintained the relative weight differences between observations within a country. These adjustments were applied to all 80 sets of replicate weights and used in all analyses.

Regression analyses

We analysed the marginal impact of digital use on youth wellbeing with a multivariate regression model estimated using Ordinary Least Squares. We fitted seven models, one for each wellbeing outcome. Each model included all digital use variables (six for weekends and six for weekdays). This approach allowed us to estimate whether — and to what extent — time spent digitally for various purposes (e.g., entertainment, instrumental, social communication) impacts youth wellbeing in distinct ways.

Specifically, the following regression equation was specified:

$$w_{isc} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{D_{isc}}) + \boldsymbol{\beta_2 X_{isc}} + \boldsymbol{\beta_3 S_{sc}} + \boldsymbol{\theta_c} + \varepsilon_{isc} \quad (1)$$

where i denotes student, s indexes school and c indexes country. The wellbeing outcome of student i from school s located in country c is represented by w_{isc}. D_{isc} is the set of digital use variables (e.g., time spent playing video games on a typical weekday; for full list, see Table 2), and β_1 is the set of corresponding coefficients. For all but one wellbeing outcome , a higher value of w_{isc} represents higher wellbeing. The only exception was the PSYCHSYM variable, where a higher value indicates a higher frequency of experiencing psychosomatic symptoms, i.e., lower wellbeing. Since senate weights were applied, β_1 represents the marginal effects of digital time spent on students' wellbeing, averaged across countries.

$\boldsymbol{X_{isc}}$ refers to a set of student background characteristics, that is, age, grade level, PISA score in mathematics[4], number of friends, frequency of exercising, frequency of being bullied, parental attention and the PISA index of socio-economic status (ESCS), which includes indicators of parental education, parental occupation, and home possession as a measure of family wealth. $\boldsymbol{S_{sc}}$ is a set of school characteristics, i.e., school type, negative school climate, student-teacher ratio and computer-student ratio as a proxy for school resources. The full list of control variables, including their descriptions and coding details, can be found in Table 14 in the appendix.

These controls are essential for accurately estimating the marginal impact of digital use on wellbeing. Students' use of digital technologies (time spent and purposes) can be closely related to their own characteristics, family background, and school characteristics, which may also affect their wellbeing. For example, students who lack parental attention may spend more time using digital technology for leisure purposes and may have lower wellbeing than students with higher parental attention.

The term θ_c indicates the country fixed effect, which helped account for unobserved country characteristics related to students' wellbeing and digital use (e.g., country's wealth). Lastly, the term ε_{isc} is the error term representing factors not captured in the model that affect w_{isc}.

Although we did not use a multilevel model, which is common in educational research, the use of Balanced Repeated Replication (BRR) weights, the inclusion of country fixed effects, and school characteristics in the model should adequately account for the hierarchical structure of the data. As noted by OECD (2009a), *"[w]hile simple linear regression models do not recognise hierarchical structure of data, it is possible to account for some hierarchical aspects of the PISA data […] in the linear regression by using BRR weights […] These models can adjust for clustering of students within schools and other aspects of survey design"* (p.229). This approach has also been used by other researchers, such as Jerrim et al. (2022).

All regression analyses were conducted using the "intsvy" R package (Caro & Biecek, 2017).

Significance level

For all regression analyses, we adopted a conservative significance level, stricter than the commonly used 5% threshold, due to the large number of hypotheses tested in each model. For instance, in the main analyses examining the effect of digital time use on wellbeing, each regression model tested 12 digital use variables, resulting in a total of 84 hypothesis tests across all seven wellbeing models. Therefore, we only considered effects as statistically significant if the p-value was less than or equal to 0.01.

[4] Given that the effects of students' mathematics performance on wellbeing are not the primary focus, only the first plausible value was used in the main analyses. We checked whether the choice of plausible value affected our conclusions and found that it had no impact on our results (based on comparing our estimates with those obtained by averaging estimates produced using each of the 10 plausible values).

Analyses by gender

As shown in Figure 4 and Figure 5 from the previous section, girls and boys spent different amounts of time gaming and browsing social media, and their reported levels of wellbeing also differ noticeably. Various studies have also found that the associations between digital use and wellbeing tend to vary by gender (e.g., Svensson et al., 2022; Twenge & Martin, 2020). Therefore, we reran the model specified in equation (1) after adding interaction terms between gender and all digital use variables to investigate whether — and to what extent — the impact of digital use on wellbeing differs between girls and boys.

Non-linear relationships

Studies have found that the links between digital use and wellbeing are likely non-linear and specifically non-monotonic. For instance, Przybylski and Weinstein (2017) analysed a sample of English adolescents and concluded that the relationship is quadratic whereby moderate usage (about 1 to 2 hours) is associated with higher wellbeing compared to less frequent or heavier usage. To account for this possibility, we reran the model specified in equation (1) after adding digital use variables in quadratic terms to investigate whether — and to what extent — the impact of digital time spent on wellbeing is quadratic.

5.2 The roles of digital literacy

The second research question aims to investigate the roles of digital literacy in protecting youth wellbeing, specifically whether digital literacy motivates usage in beneficial digital activities, promotes higher wellbeing and mitigates any potential negative impacts of digital use on wellbeing.

Motivation factor

To examine the relationship between digital literacy and digital use, we calculated descriptive statistics for each use category—for example, comparing digital literacy scores between frequent and infrequent social media users. These analyses were conducted for the overall sample and by gender. Correlation analyses were also performed to quantify the strength of these associations.

Promotive factor

To understand whether having high levels of digital literacy is generally beneficial for wellbeing, we extended the model specified in equation (1) by adding variables representing students' level of digital literacy. Specifically, the following model was estimated using Ordinary Least Squares:

$$w_{isc} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{D_{isc}}) + \gamma_1(\boldsymbol{L_{isc}}) + \beta_2\boldsymbol{X_{isc}} + \beta_3\boldsymbol{S_{sc}} + \theta_c + \varepsilon_{isc} \quad (3)$$

The new term, L_{isc}, refers to variables measuring digital literacy levels of student i. The coefficients of interest here are represented by γ_1, which indicates the relationship between the measures of digital literacy and wellbeing. If any γ_1 is statistically significant and positive, it implies that higher literacy is associated with higher wellbeing (or lower wellbeing for PSYCHSYM) for any given amount of time spent digitally, while controlling for a wide array of observable students' characteristics.

Protective factor

To investigate whether the relationships between digital use and wellbeing vary by literacy levels, we extended equation (2) by adding interaction terms between digital literacy and digital use, as follows:

$$w_{isc} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{D_{isc}}) + \gamma_1(\boldsymbol{L_{isc}}) + \gamma_2(\boldsymbol{d_{isc}} \times \boldsymbol{L_{isc}}) + \beta_2\boldsymbol{X_{isc}} + \beta_3\boldsymbol{S_{sc}} + \theta_c + \varepsilon_{isc} \quad (4)$$

Note that $\boldsymbol{d_{isc}}$ may only be a subset of digital use variables, $\boldsymbol{D_{isc}}$. This is because it is only reasonable to investigate whether literacy mitigates any negative impacts or enhances positive benefits of digital use when the time spent on the activity is found to impact wellbeing statistically significantly. As such, the regression results based on equation (1) informed the inclusion of interaction terms here.

The coefficients of interest here are represented by γ_2. Any statistically significant value in γ_2 would indicate that the marginal impact of time spent on a particular digital activity wellbeing varies by students, depending on their digital literacy level. The direction of the relationship (i.e., whether it mitigates or exacerbates the negative impacts) depends on the sign of the coefficient β_1. Specifically, if β_1 is negative[5], a positive value of γ_2 would mean that higher literacy mitigates the negative impacts of digital use on wellbeing, while a negative value indicates it exacerbates them.

5.3 Robustness checks

As shown earlier in Figure 3, the time spent on the same digital activity is reasonably highly correlated between a typical day on the weekend and a weekday (ranging from 0.65-0.72). The high correlations could make it challenging for the regression model to isolate the independent effects of digital use on weekends and weekdays (for the same activity) on wellbeing. Consequently, this can reduce the precision of the estimated coefficients (i.e., higher standard errors) and affect the robustness and reliability of the significance of the estimated coefficients. To address this concern, we re-estimated equation (1) including digital use during weekends and digital use during weekdays, separately. Then, we compared the estimated coefficients from both models to those from the main analyses to examine the robustness of our estimates.

6. Results

6.1 Digital use and wellbeing

6.1.1. Descriptives analyses

Figure 8 presents the mean wellbeing score by time spent on each digital activity on a typical weekend day. The points represent the mean and the shaded area represents the 95% confidence interval. Each panel within the figure shows results for one aspect of wellbeing. Figure 9 shows the same output by gender. Lastly, Figure 10 summarises the Spearman's rank correlation of these relationships. Within the figure, we also showed the Spearman correlation coefficients between wellbeing and being bullied to serve as a

[5] For variables other than PSYCHSYM.

comparison since one would expect youth wellbeing to be considerably correlated to whether the students were being bullied. Figures presenting results based on digital use on weekdays indicated very similar findings and are, hence, presented in the appendix (Figure 21, Figure 22 and Figure 23).

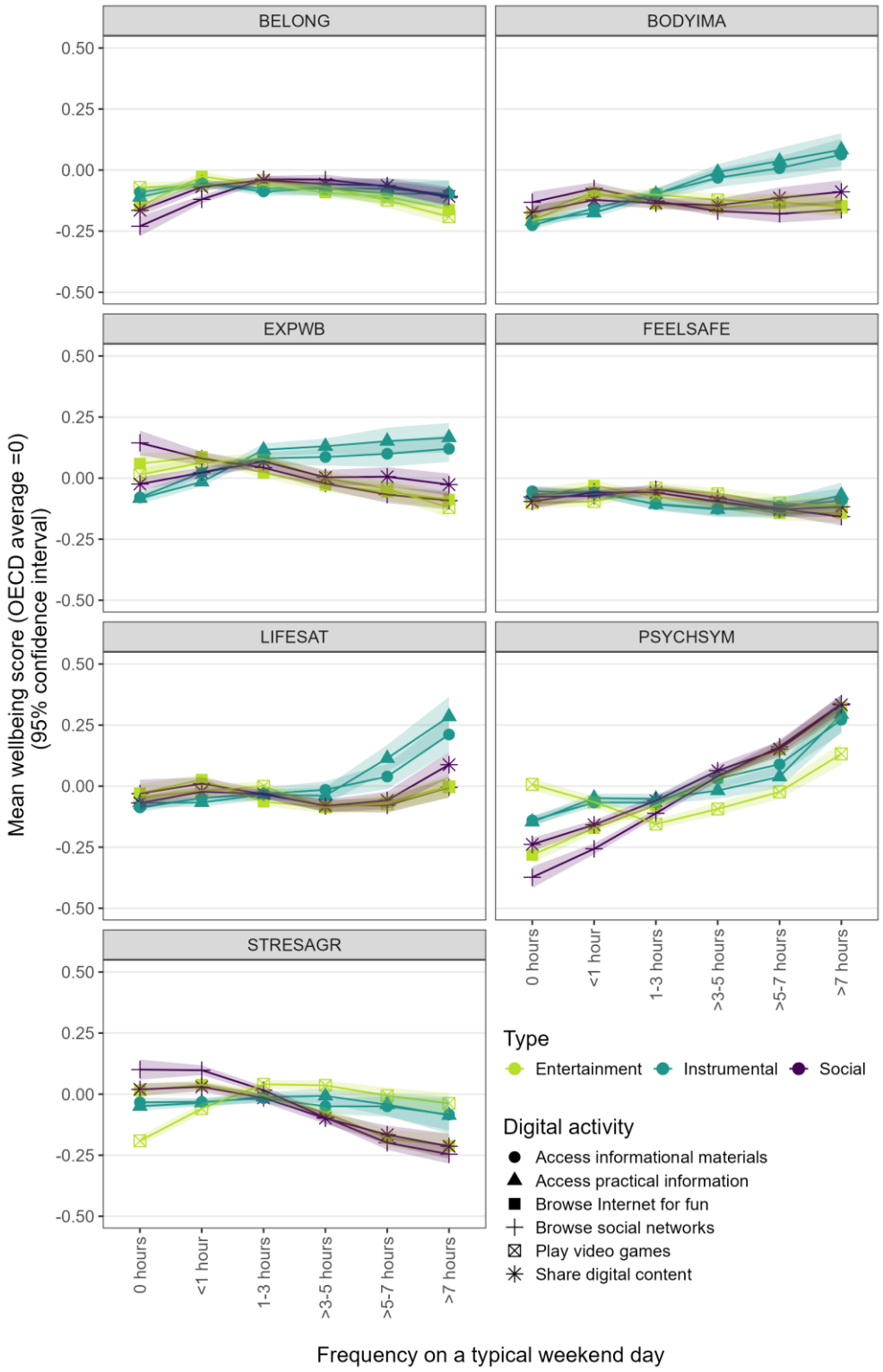

Figure 8. Mean wellbeing score (with 95% confidence interval) by time spent on each digital activity on a typical weekend day.

Figure 8 shows that the relationships between digital use and wellbeing were heterogenous, depending on the digital activities and aspects of wellbeing. These relationships can be broadly categorised into three groups: (1) no apparent relationships, (2) wellbeing was associated with digital use in the same way across all activities, and (3) wellbeing was associated with digital use in different ways depending on the activity. However, within each group, the relationships can be different for girls and boys (Figure 9), and they were in some cases non-linear.

No apparent relationships

Students' self-perceived safety (FEELSAFE) was similar across all digital activities regardless of usage frequency. For students' sense of belonging at school (BELONG), there were no associations in most digital activities, apart from mostly gaming and browsing social network. Students who reported spending more time gaming tended to report lower levels of belonging at school. Figure 9 shows that this negative relationship was observed in both girls and boys, but it was slightly stronger for girls, with a correlation of -0.09 for girls (95% confidence interval: -0.08 to -0.11) and -0.02 for boys (95% CI: -0.01 to -0.04). However, the relationship between sense of belonging and gaming was non-linear for boys. Boys who gamed between less than 1 hour and up to 5 hours reported, on average, higher levels of belonging compared to those who didn't game or gamed for more than 5 hours per day on weekends. Furthermore, the relationship between sense of belonging and browsing social media was also non-linear for both genders. Students who spent between 1-5 hours browsing social media reported a higher level of belonging on average than those who spent less or more time.

Similar relationships across all digital activities

Students who reported spending more time digitally tended to report having experienced higher frequency of psychosomatic symptoms (PSYCHSYM), regardless of the digital activities. The same negative relationship can be observed in both boys and girls, but the correlation was stronger for girls, especially for social networks usage (see Figure 10). For girls, the frequency of experiencing psychosomatic symptoms and browsing social networks correlated at 0.20 (95% CI: 0.18-0.21) – the strongest correlation observed in this study, which was close to two-thirds the correlation between being bullied and PSYCHSYM (0.32, 95% CI: 0.31-0.33). The same magnitude of correlation (0.20) was found in Twenge et al. (2022) when investigating the links between girls' social media use and poor mental health. While this magnitude of correlation was generally considered weak in the literature, the authors showed that it was stronger than the links between mental health and binge drinking, marijuana use or sexual assault (p.5).

Furthermore, higher usage across all digital activities was generally associated with higher levels of life satisfaction and body image (LIFESAT and BODYIMA). This was especially noticeable for instrumental digital activities (e.g., listening to podcasts, finding a place). However, there was a divergence in patterns between girls and boys. Increased time spent browsing social networks tended to be linked to lower levels of self-perceived body image among girls, but not boys. Specifically, compared to girls who spent less than one hour daily on social networks, girls who spent more than 3 hours daily reported an average body image score that was about 0.18 lower. This difference was comparable to the gender gap in body image scores observed in countries like Macao and Panama (see Figure 4) and was about 30% of the gender gap in body image scores in European countries such as Spain, Ireland,

and Hungary. Similarly, girls who spent more time on social networks also reported a lower level of life satisfaction, but this was not the case for boys.

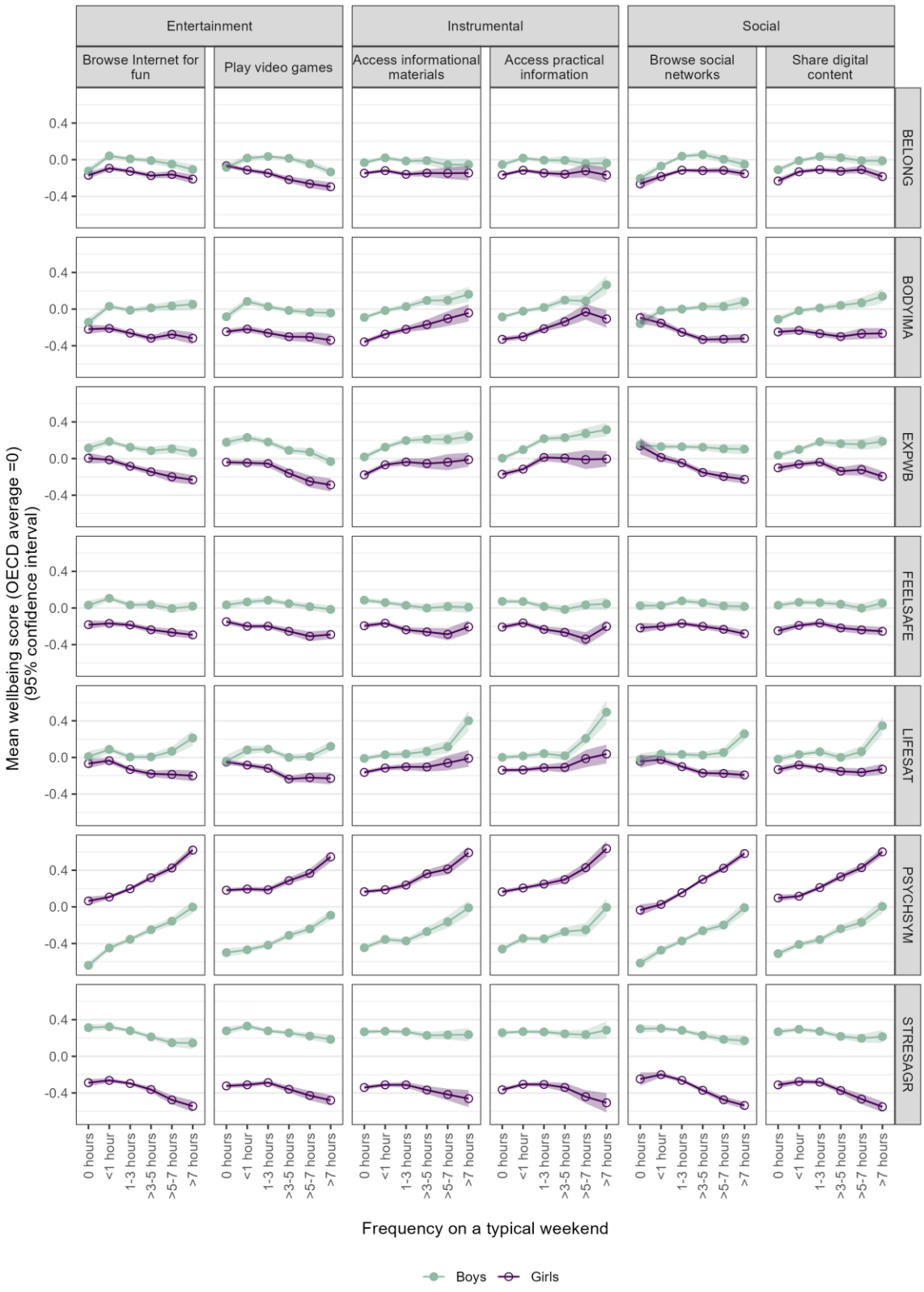

Figure 9. Mean wellbeing score (with 95% confidence interval) by time spent on each digital activity on a typical weekend day and by gender.

Relationships vary depending on digital activities

Students' self-reported stress resistance levels (STRESAGR) varied with usage frequency and digital activities. Overall, there was no relationship with instrumental use but there were negative relationships with social uses and browsing the Internet, and a quadratic relationship with gaming. These relationships existed for girls and boys, but the negative links were again more pronounced for girls. Generally, girls who reported spending more time digitally also reported lower levels of stress resistance across *all* types of activity, especially for social uses and browsing the Internet. This was less noticeable for boys. For girls, the strength of the correlation between time spent browsing social networks and stress resistance was estimated to be more than two-thirds of the strength between being bullied and stress resistance (0.13 vs 0.18).

For students' self-reported general wellbeing (EXPWB), more time spent on instrumental uses and less time spent browsing social networks tended to be linked with higher general wellbeing. While the positive relationship between instrumental use and general wellbeing was generally true for both genders, there was again a divergence in patterns for social networks and Internet usage. Girls' general wellbeing was on average substantially lower the longer the time they spent browsing social networks or the Internet. While for boys, the general wellbeing was broadly similar regardless of the time they spent on these activities.

Video gaming and wellbeing

Among the digital activities investigated, we observed a non-linear relationship between time spent gaming and wellbeing. Based on the overall data (Figure 8), those who reported spending 1-3 hours daily playing video games exhibited higher levels of stress resistance and a lower frequency of experiencing psychosomatic symptoms compared to students who didn't game or gamed very little. These non-linear patterns can be observed in both girls and boys, but the "optimal" (usage with the highest wellbeing) number of hours varied. For girls, the negative links with gaming were more noticeable, especially for those who spent more than 3 hours gaming. For boys, there were more nuances to these relationships, with the "optimal" number of hours changing depending on the aspects of wellbeing considered.

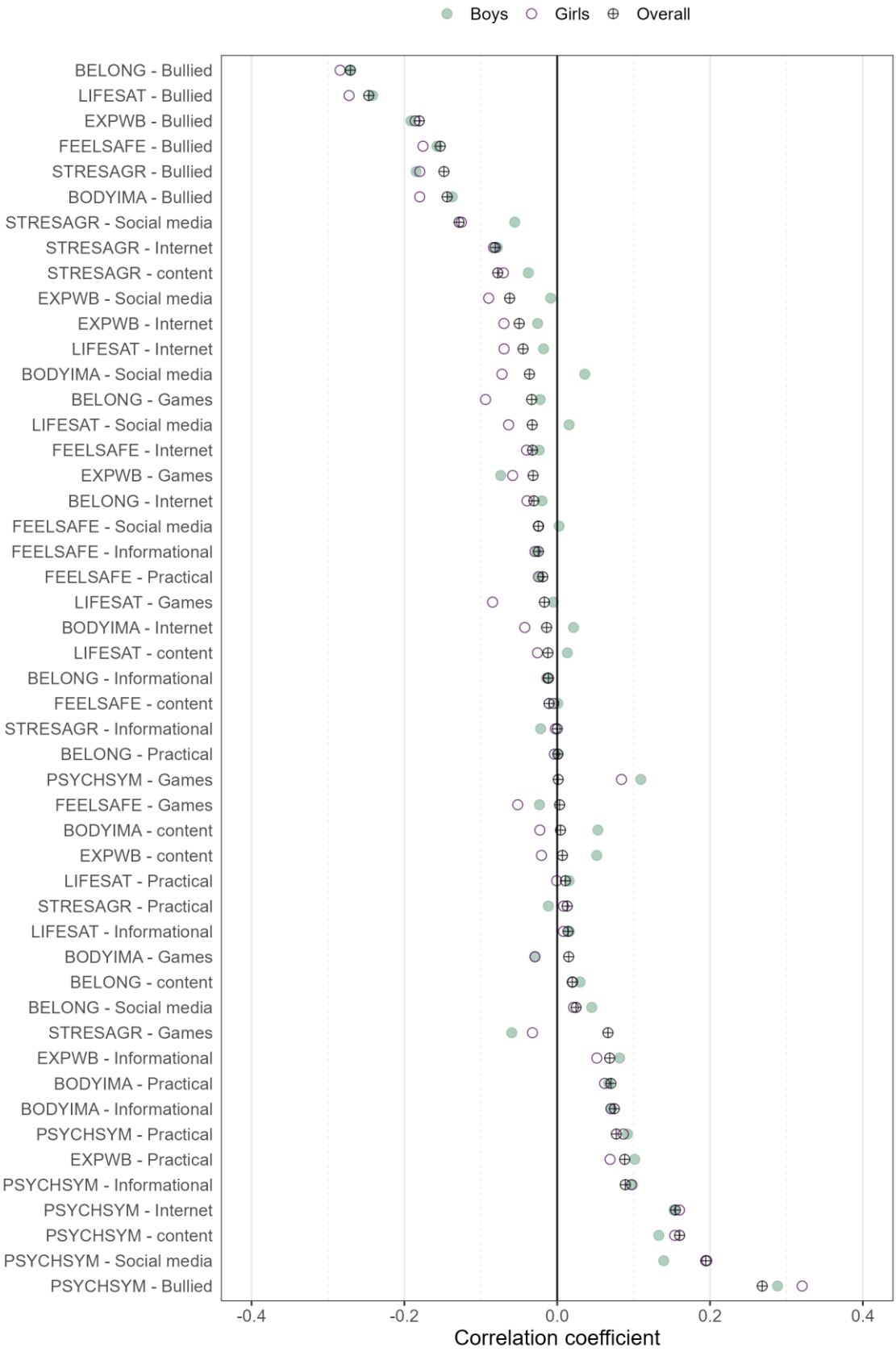

Figure 10. Spearman's rank correlation coefficient between wellbeing score and daily digital time spent on a typical weekend day, and between wellbeing score and being bullied.

6.1.2. Effects of digital use

Table 7 presents the estimated coefficients of digital use variables from each wellbeing model, along with the standard errors. Coefficients that were statistically significantly different from zero at the 1% and 0.1% levels were marked with asterisks and bolded. The full set of regression results, including estimated coefficients for control variables across all models, is available upon request.

Interpretation
As mentioned earlier, instead of asking students to provide the exact number of hours per day spent on each digital activity, the PISA survey asked them to choose from six options: 0 hours, < 1 hour, 1-3 hours, >3-5 hours, >5-7 hours, and >7 hours. These digital use variables were modelled as discrete values ranging from 1 (0 hours) to 6 (>7 hours) in our model. Given the unequal time increments between each consecutive value (e.g., the difference between values 2 and 1 is less than 1 hour, while the difference between values 5 and 6 is about 2 hours), interpreting the marginal effects of time spent digitally on wellbeing, as indicated by the coefficients, is not straightforward. Roughly speaking, five times the estimated coefficient represents the difference in wellbeing scores between a student who did not engage in the digital activity and a student who spent more than 7 hours on the same activity, holding all other controlled characteristics and time spent on all other digital activities constant.

For all outcomes *except* PSYCHSYM, a positive coefficient indicates that more time spent digitally is associated with increased wellbeing outcomes. Conversely, a negative coefficient indicates that more time spent is linked to lower wellbeing outcomes. For PSYCHSYM, the interpretation is reversed.

Table 7. Selected estimated coefficients from models with wellbeing as the outcome variable, and all digital use variables (weekend and weekday) and control variables as independent variables. Standard errors are shown in parentheses.

	(1) BELONG	(2) BODYIMA	(3) EXPWB	(4) FEELSAFE	(5) LIFESAT	(6) PSYCHSYM	(7) STRESAGR
Gender (Boys=1)	**0.106 (0.009) ****	**0.223 (0.012) ****	**0.165 (0.013) ****	**0.234 (0.012) ****	**0.129 (0.014) ****	**-0.540 (0.012) ****	**0.492 (0.011) ****
Weekday							
Access info. materials	**-0.020 (0.006) ****	0.005 (0.007)	**0.020 (0.007) ***	-0.001 (0.006)	0.002 (0.007)	**0.023 (0.007) ****	-0.002 (0.006)
Access practical info.	0.003 (0.006)	**0.025 (0.008) ****	**0.028 (0.007) ****	-0.004 (0.007)	0.002 (0.008)	-0.006 (0.006)	0.003 (0.007)
Browse Internet for fun	-0.012 (0.005)	0.001 (0.006)	-0.013 (0.007)	0.000 (0.007)	0.001 (0.006)	**0.015 (0.006) ***	-0.002 (0.005)
Browse social networks	**0.028 (0.006) ****	-0.005 (0.008)	-0.013 (0.008)	0.011 (0.006)	-0.008 (0.007)	**0.039 (0.007) ****	**-0.029 (0.006) ****
Play video games	**-0.015 (0.005) ***	0.014 (0.006)	-0.000 (0.006)	-0.010 (0.006)	0.010 (0.006)	-0.011 (0.005)	0.012 (0.006)
Share digital content	0.007 (0.005)	0.006 (0.007)	0.003 (0.007)	0.002 (0.006)	0.002 (0.007)	0.011 (0.006)	0.001 (0.007)
Weekend							
Access info. materials	-0.000 (0.006)	0.011 (0.006)	-0.009 (0.006)	-0.008 (0.006)	-0.002 (0.006)	**0.015 (0.006) ***	0.000 (0.005)
Access practical info.	-0.003 (0.006)	0.016 (0.007)	**0.046 (0.006) ****	-0.001 (0.006)	0.012 (0.007)	**-0.019 (0.006) ****	**0.029 (0.007) ****
Browse Internet for fun	-0.012 (0.005)	-0.008 (0.006)	**-0.028 (0.006) ****	-0.010 (0.006)	-0.014 (0.005)	**0.028 (0.006) ****	**-0.025 (0.005) ****
Browse social networks	**0.019 (0.006) ****	-0.019 (0.007)	**-0.030 (0.007) ****	-0.003 (0.007)	0.003 (0.007)	**0.036 (0.006) ****	**-0.024 (0.006) ****
Play video games	-0.007 (0.005)	-0.002 (0.005)	**-0.023 (0.005) ****	-0.002 (0.005)	0.008 (0.005)	**0.018 (0.005) ****	0.002 (0.005)
Share digital content	**0.017 (0.005) ****	-0.004 (0.006)	0.000 (0.007)	**0.018 (0.006) ***	0.003 (0.005)	**0.017 (0.006) ***	-0.013 (0.006)
R-squared	0.203 (0.004)	0.152 (0.004)	0.186 (0.004)	0.125 (0.004)	0.228 (0.004)	0.221 (0.004)	0.160 (0.004)
Weighted count	37282	31575	28115	33505	33431	37192	31181

*Notes: The digital use variable were modelled as numeric values ranging from 1 (0 hours), 2 (<1 hours), … , to 6 (>7 hours). Coefficients significantly different from 0 at p value ≤ 0.001 were indicated by **, and * for those significant at p ≤ 0.01. The linear model included country fixed effects and a set of student, family, and school characteristics. Standard errors were estimated using Balanced Repeated Replication weights, which were adjusted to ensure equal country representation. These weights accounted for the clustering of students within schools and other aspects of the survey design.*

Findings

The results showed that, even after accounting for all other student characteristics, more time spent in gaming, browsing social networks and the Internet were statistically significantly associated with a lower level of general wellbeing, increased frequency of psychosomatic symptoms, and lower levels of stress resistance (see Table 7, columns 3, 6, and 7). Among them, the effect size of browsing social networks was particularly noticeable. For instance, between students with the same observable characteristics, the frequency of experiencing psychosomatic symptoms was estimated to be about 0.20 higher for those who spent at least seven hours per day browsing social networks at the weekday than those who did not spend any time on it. We didn't find time spent *sharing* digital content on social networks to have the same negative impacts on wellbeing.

Positive associations between digital use and wellbeing were mostly consistently found for one activity – accessing practical information (e.g., find a place, book a train ticket). More time spent accessing practical information positively predicted greater wellbeing in several aspects, including higher levels of self-perceived body image, general wellbeing and stress resistance, and lower frequency of experiencing psychosomatic symptoms. However, the link between wellbeing and time spent in the *other* instrumental use of digital technologies– accessing informational materials (e.g., tutorials, podcasts) – was mixed. More time spent accessing informational materials was associated with higher general wellbeing, but a lower sense of belonging at school and a higher frequency of experiencing psychosomatic symptoms. In other words, we did find some evidence suggesting potential positive benefits of instrumental use of digital devices but not across all aspects of wellbeing.

Digital use did not statistically significantly (at 1% level) predict students' level of sense of safety and life satisfaction, as can be seen in columns 4 and 5 of Table 7. The one exception was engagement in sharing digital content on social networks. More time spent on this activity was significantly linked to a higher sense of safety. But the effect size was practically small – an increase of about 0.09 from not engaging in this activity to spending 7 hours on it. Therefore, broadly and practically speaking, the findings for sense of safety aligned with what we observed earlier, i.e., no apparent relationships for the most parts. The positive relationship between life satisfaction and digital use seen earlier, specifically for instrumental use, was no longer apparent here. This suggests that the positive link between life satisfaction and higher instrumental use of digital devices was possibly driven by students' background characteristics.

Lastly, we observed that the relationship between digital use and students' sense of belonging differed from other wellbeing outcomes. More time spent on social networks, whether browsing or sharing content, was linked to a greater sense of belonging at school. Conversely, more time spent on gaming and accessing information materials (e.g., podcasts) was associated with a lower sense of belonging. One interpretation is that engaging in digital activities that provide ample opportunities for social interaction can help foster students' friendships outside of school time. On the other hand, engaging in digital activities with limited social interaction and with the possibility to displace time spent on other offline socialising activities, might alienate students' sense of connectedness with their friends from school.

An alternative interpretation is that our regression models suffer from reverse causality – where students' sense of belonging influenced their time spent in various digital activities. In this case, students with, e.g., more friends at school (leading to the higher sense of belonging) may spend more time on social networks, and those with smaller friendship circle may choose to spend more time doing activities requiring less socialising with friends from school, such as gaming and listening to podcasts. If this is true, we would be overestimating the positive impact of social network usage and the negative impact of gaming and accessing informational materials on sense of belonging. While we have controlled for the number of close friends each student has within our set of control variables, there might be other factors driving the reverse causality.

6.1.3. Effects by gender

The estimated regression coefficients of the gender interaction terms, together with the main effects of gender, are shown in Table 8. For the interaction terms, a positive coefficient implies digital use having either a smaller negative impact or a greater positive impact on wellbeing for boys than for girls, and a negative coefficient implies a smaller positive impact or a larger negative impact for boys.

As can be seen in Table 8, the effect of digital use on wellbeing was statistically significantly different for girls and boys for three activities: accessing information materials (e.g., podcasts), gaming, and browsing social networks. The magnitude of difference implied by these coefficients is presented in Figure 11. In this figure, we showed the predicted mean wellbeing score for girls and boys separately, assuming they have the same observable characteristics, apart from their gender.

Table 8. Estimated coefficients of the gender interaction terms, from models with wellbeing as the outcome variable, and all digital use variables (weekend and weekday), their interaction terms with gender, and control variables as independent variables.

	(1) BELONG	(2) BODYIMA	(3) EXPWB	(4) FEELSAFE	(5) LIFESAT	(6) PSYCHSYM	(7) STRESAGR
Gender (1=boys)	0.055 (0.027)	0.077 (0.035)	0.042 (0.031)	0.198 (0.033) **	-0.078 (0.038)	-0.523 (0.033) **	0.389 (0.034) **
Gender interaction term							
Weekday							
Access info. materials	0.007 (0.012)	-0.014 (0.014)	**-0.034 (0.012) ***	0.014 (0.012)	-0.011 (0.013)	0.015 (0.012)	0.001 (0.015)
Access practical info.	0.001 (0.012)	0.009 (0.015)	0.020 (0.014)	-0.004 (0.014)	0.002 (0.014)	-0.014 (0.012)	-0.011 (0.014)
Browse Internet for fun	0.004 (0.011)	-0.001 (0.013)	-0.004 (0.017)	0.010 (0.013)	0.011 (0.013)	0.005 (0.012)	0.008 (0.013)
Browse social networks	0.024 (0.012)	0.008 (0.014)	0.025 (0.016)	0.003 (0.014)	-0.010 (0.014)	-0.013 (0.013)	0.031 (0.012)
Play video games	0.008 (0.010)	-0.004 (0.012)	0.024 (0.012)	0.001 (0.012)	**0.040 (0.012) ****	0.005 (0.011)	-0.018 (0.012)
Share digital content	-0.009 (0.012)	-0.000 (0.014)	-0.021 (0.015)	-0.002 (0.013)	-0.004 (0.013)	0.014 (0.012)	-0.017 (0.014)
Weekend							
Access info. materials	**-0.027 (0.010) ***	-0.022 (0.012)	0.015 (0.012)	-0.021 (0.012)	0.014 (0.011)	-0.015 (0.011)	-0.007 (0.014)
Access practical info.	-0.014 (0.011)	-0.035 (0.015)	-0.013 (0.014)	-0.006 (0.012)	-0.016 (0.014)	-0.009 (0.011)	0.007 (0.013)
Browse Internet for fun	-0.006 (0.010)	0.009 (0.011)	0.003 (0.014)	0.003 (0.012)	-0.002 (0.010)	0.015 (0.014)	-0.023 (0.014)
Browse social networks	0.002 (0.012)	**0.047 (0.012) ****	0.014 (0.016)	0.010 (0.013)	**0.034 (0.013) ***	-0.020 (0.012)	0.024 (0.013)
Play video games	0.002 (0.009)	0.010 (0.012)	-0.020 (0.013)	-0.005 (0.011)	0.007 (0.011)	0.012 (0.010)	0.008 (0.011)
Share digital content	0.018 (0.010)	0.025 (0.013)	0.029 (0.013)	0.005 (0.012)	0.002 (0.012)	-0.002 (0.012)	0.022 (0.012)
R-squared	0.204 (0.004)	0.154 (0.004)	0.187 (0.004)	0.125 (0.004)	0.229 (0.004)	0.221 (0.004)	0.161 (0.004)
Weighted count	37281.943	31574.750	28114.990	33505.247	33430.737	37192.426	31181.104

*Notes: The digital use variable were modelled as discrete values ranging from 1 (0 hours), 2 (<1 hours), … , to 6 (>7 hours). Coefficients significantly different from 0 at p value ≤ 0.001 were indicated by **, and * for those significant at p ≤ 0.01. The linear model included country fixed effects and a set of student, family, and school characteristics. Standard errors were estimated using Balanced Repeated Replication weights, which were adjusted to ensure equal country representation. These weights accounted for the clustering of students within schools and other aspects of the survey design.*

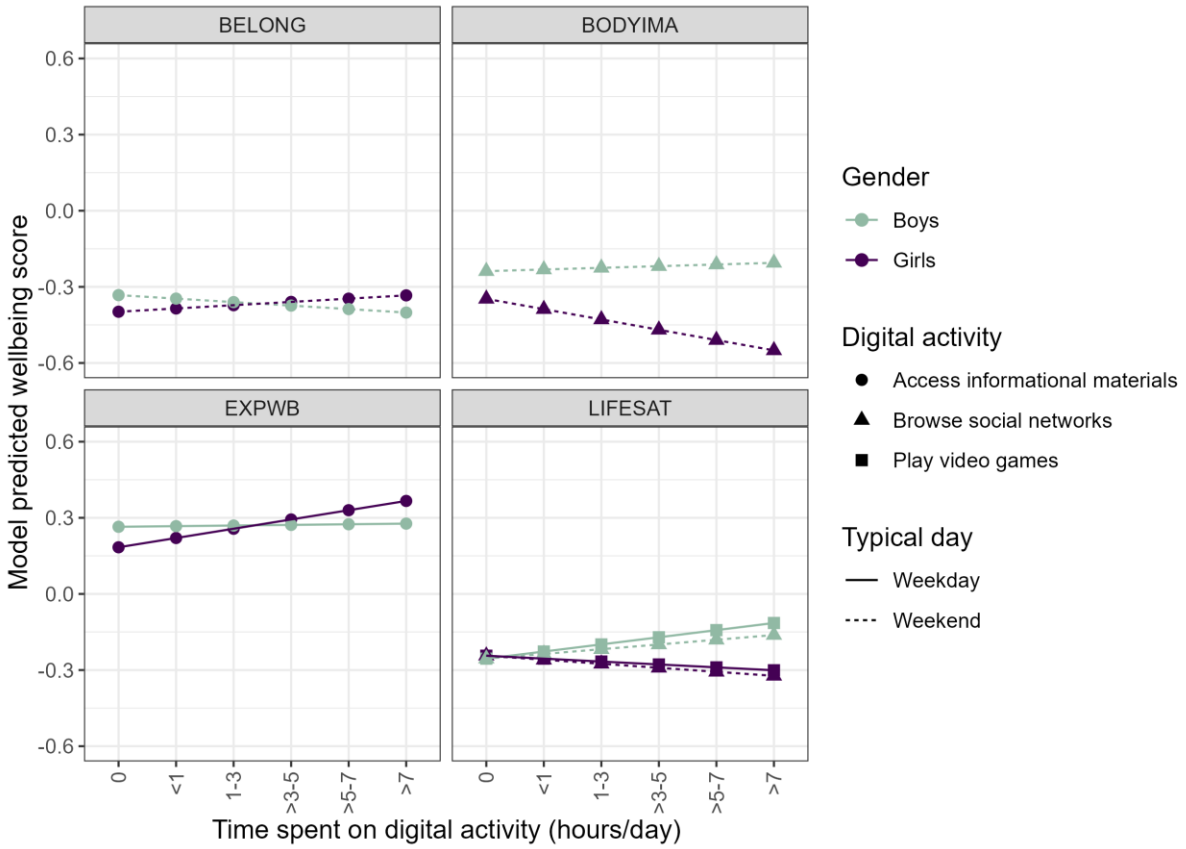

Figure 11. Predicted wellbeing scores by gender for digital activities with statistically significantly different effects on the wellbeing of girls and boys. Predictions were for 15-year-old students from group 5 of Economics, Social and Cultural Status, with medium levels of family support, number of close friends, quality of relationship with teachers, frequency of bullying, and body mass index. Students were in grade 10, not skipping classes two weeks prior to the PISA test, not working outside of school, spending 2 days per week with friends after school, not exercising, from Ireland, studying in a public school with medium student-teacher ratio, computer-student ratio, negative school climate, and a plausible math score of 450. Time spent in all other digital activities were assumed to be zero hours.

From the figure, we can see that more time spent engaging with informational materials was associated with a higher sense of belonging and general wellbeing in girls. For boys, more hours spent on this activity tended to lead to a marginally lower level of sense of belonging and no change in general wellbeing. However, the magnitude of the difference between gender appeared small especially when compared with those observed for body image perception and life satisfaction.

The more noticeable gender differences were in gaming and browsing social networks. While both girls and boys who didn't spend any time on social networks were estimated to have the same level of life satisfaction, the difference in life satisfaction grew bigger the longer the time spent on social networks. In particular, more hours on social networks predicted lower levels of life satisfaction for girls but higher levels for boys. The same pattern was also found between gaming and life satisfaction.

An even more striking divergence was seen in the relationship between self-perceived body image and time spent on social networks. While a small gap in body image score existed between girls and boys who did not spend any time on social networks, this gap became larger the longer the time spent on social networks. For girls and boys who spent about 1 to 3 hours daily on social networks on a typical weekend day, the estimated difference in body image score was about 0.20, and this gap increased to 0.35 for those who spent more than 7 hours on social networks. Note that in all body image models, we included body mass index among the control variables.

Lastly, it is worth noting that the coefficient for the gender variable itself (first row of Table 8) was no longer statistically significant for several wellbeing outcomes compared to Table 7 (when the effect of digital use on wellbeing was not allowed to vary by gender). This suggests that the differences in wellbeing score that exist even after controlling for observable characteristics may be explained by the differing impact of digital use on girls and boys. The drop in the gender coefficient for the body image model was particularly noticeable (comparing column 2 of Table 7 and Table 8). This change and the effect of social network usage on body image suggest that the gender gap in self-perceived body image could largely be driven by the differential impact of social networks on girls and boys.

6.1.4. Effects by time

To examine the potential non-linear effects between digital use and wellbeing, we extended our model to include quadratic terms. The estimated coefficients of these quadratic terms are presented in Table 9, with statistically significant terms indicating quadratic relationships. To aid the interpretation of effect sizes, Figure 12 visualises the predicted wellbeing scores by time spent on activities found to have statistically significant quadratic relationships with wellbeing.

Table 9. Estimated coefficients of the quadratic terms for digital activities, from models with wellbeing as the outcome variable. These models include all digital use variables (weekend and weekday), their quadratic terms, and control variables as independent variables.

	(1) BELONG	(2) BODYIMA	(3) EXPWB	(4) FEELSAFE	(5) LIFESAT	(6) PSYCHSYM	(7) STRESAGR
Gender (1=boys)	**0.104 (0.009) ****	**0.217 (0.012) ****	**0.162 (0.013) ****	**0.233 (0.012) ****	**0.125 (0.014) ****	**-0.536 (0.012) ****	**0.491 (0.012) ****
Quadratic terms							
Weekday							
Access info. materials	-0.001 (0.003)	0.001 (0.004)	-0.009 (0.004)	0.003 (0.004)	0.006 (0.004)	0.004 (0.003)	0.002 (0.003)
Access practical info.	0.003 (0.004)	0.005 (0.004)	0.006 (0.004)	0.007 (0.004)	**0.012 (0.004) ***	**-0.010 (0.004) ***	0.004 (0.003)
Browse Internet for fun	0.005 (0.003)	-0.000 (0.004)	0.001 (0.004)	-0.002 (0.004)	0.006 (0.003)	-0.005 (0.003)	0.002 (0.003)
Browse social networks	-0.002 (0.004)	0.010 (0.004)	-0.000 (0.005)	-0.007 (0.004)	-0.006 (0.004)	0.001 (0.003)	0.005 (0.004)
Play video games	0.002 (0.003)	**-0.009 (0.003) ***	0.005 (0.003)	**0.010 (0.003) ****	-0.001 (0.003)	-0.006 (0.003)	0.001 (0.003)
Share digital content	-0.002 (0.003)	-0.004 (0.004)	-0.004 (0.004)	-0.003 (0.004)	0.001 (0.004)	-0.001 (0.003)	0.003 (0.004)
Weekend							
Access info. materials	**0.009 (0.003) ***	0.002 (0.004)	0.002 (0.003)	**0.010 (0.003) ***	0.003 (0.003)	-0.002 (0.003)	0.004 (0.003)
Access practical info.	-0.001 (0.003)	0.006 (0.003)	0.003 (0.004)	0.004 (0.004)	**0.014 (0.004) ****	-0.002 (0.004)	0.001 (0.003)
Browse Internet for fun	-0.002 (0.003)	-0.004 (0.003)	0.005 (0.003)	0.003 (0.003)	-0.001 (0.003)	0.000 (0.003)	-0.002 (0.004)
Browse social networks	-0.004 (0.003)	-0.005 (0.004)	0.005 (0.005)	0.000 (0.003)	-0.002 (0.004)	-0.001 (0.004)	-0.001 (0.003)
Play video games	**-0.007 (0.002) ***	-0.003 (0.003)	**-0.014 (0.003) ****	-0.007 (0.003)	-0.001 (0.003)	**0.011 (0.002) ****	-0.001 (0.003)
Share digital content	-0.005 (0.003)	0.003 (0.004)	-0.002 (0.004)	-0.001 (0.004)	-0.001 (0.004)	-0.001 (0.003)	-0.007 (0.004)
R-squared	0.204 (0.004)	0.153 (0.004)	0.187 (0.004)	0.126 (0.004)	0.231 (0.004)	0.222 (0.004)	0.161 (0.004)
Weighted count	37282	31575	28115	33505	33431	37192	31181

*Notes: The digital use variable were modelled as discrete values ranging from 1 (0 hours), 2 (<1 hours), … , to 6 (>7 hours). Coefficients significantly different from 0 at p value ≤ 0.001 were indicated by **, and * for those significant at p ≤ 0.01. The linear model included country fixed effects and a set of student, family, and school characteristics. Standard errors were estimated using Balanced Repeated Replication weights, which were adjusted to ensure equal country representation. These weights accounted for the clustering of students within schools and other aspects of the survey design.*

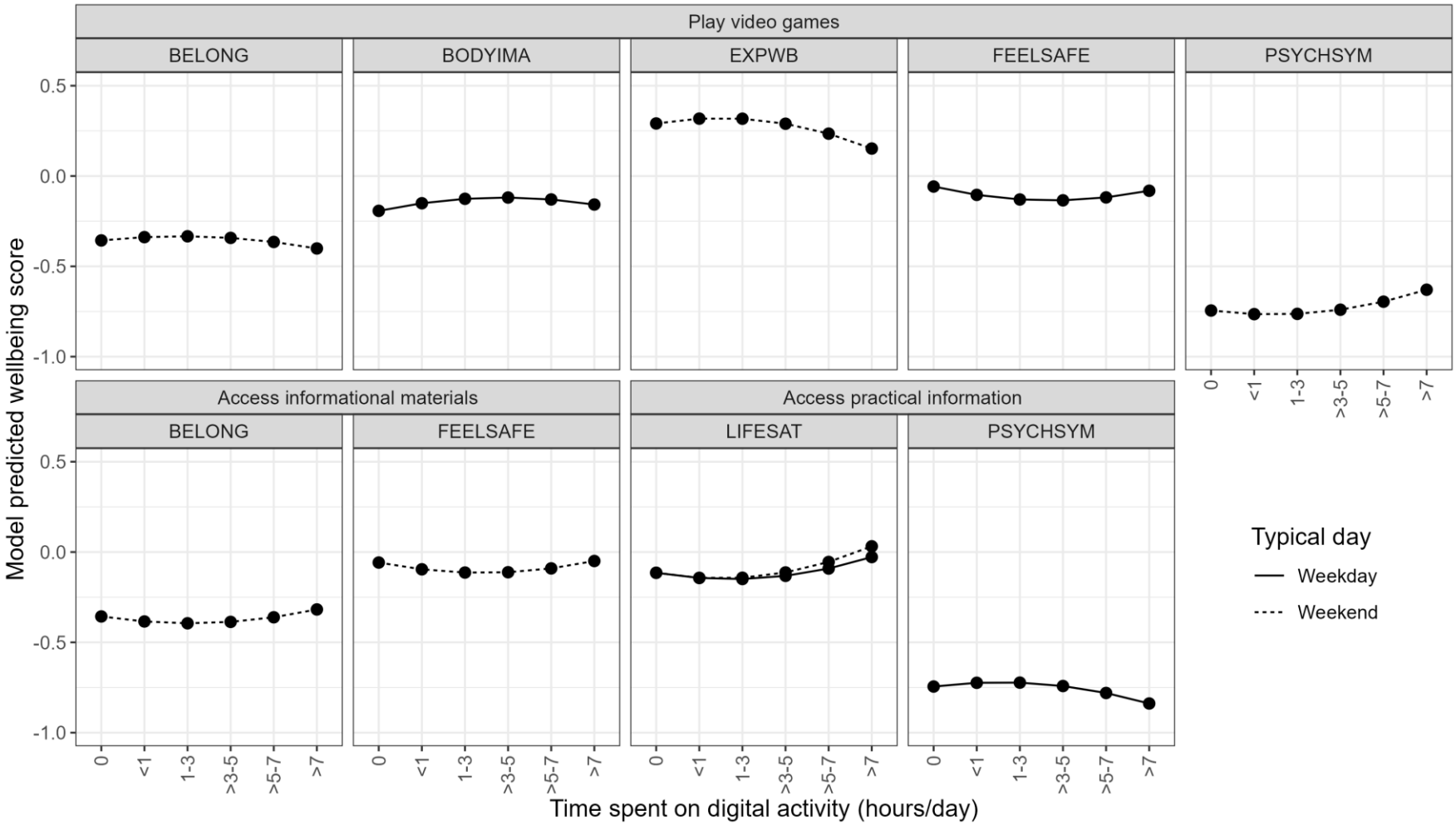

Figure 12. Predicted wellbeing scores by time spent on digital activities, for variables with statistically significant quadratic relationship with wellbeing. Predictions were for 15-year-old boys from group 5 of Economics, Social and Cultural Status, with medium levels of family support, number of close friends, quality of relationship with teachers, frequency of bullying, and body mass index. Students were in grade 10, not skipping classes two weeks prior to the PISA test, not working outside of school, spending 2 days per week with friends after school, not exercising, from Ireland, studying in a public school with medium student-teacher ratio, computer-student ratio, negative school climate, and a plausible math score of 450. Time spent on all other digital activities were assumed to be zero hours.

The findings indicated that non-linear relationships with wellbeing were primarily observed for gaming, which was consistent with the descriptive results. The most noticeable quadratic relationships were found between time spent gaming and students' general level of wellbeing as well as the frequency of experiencing psychosomatic symptoms. General wellbeing was predicted to be lower, and frequency of experiencing psychosomatic symptoms was predicted to be higher only for those who gamed more than 3 hours daily. For instance, the general wellbeing of those who gamed for more than 7 hours a day was predicted to be half of those who gamed for less than 3 hours (0.15 vs 0.30). It is possible that the quadratic relationships only hold for girls or for boys, but this was not investigated in this study.

Additionally, the positive effects of time spent accessing practical information only seemed to apply to those who spent more than 5 hours a day on it. These students were estimated to have a higher life satisfaction and a lower frequency of experiencing psychosomatic symptoms compared to those who spent less time digitally for this purpose. While it is unclear what specific information these students are accessing, one possible explanation is that they were less likely to engage in other potentially harmful digital activities not captured in our model. Alternatively, the time spent accessing practical information may facilitate the execution of real-life activities that led to higher wellbeing.

Lastly, non-linear relationships were also found for time spent accessing informational materials (e.g., podcasts) but they were not practically significant.

6.2 The roles of digital literacy

6.2.1. Motivation factor

One way digital literacies can protect students in the digital world is by encouraging beneficial digital activities and reducing time spent on harmful ones. Our earlier findings indicated that digital activities that are potentially beneficial for wellbeing were primarily those for instrumental use, while time spent browsing social networks, browsing the Internet and gaming tended to have negative links with several aspects of wellbeing.

Figure 13 shows the mean literacy scores (ICTEFFIC and ICTINFO) by time spent on each digital activity, while Figure 14 breaks down these results by gender.

As illustrated in Figure 13, non-users (those spending zero hours) reported being significantly less digitally competent (ICTEFFIC) and less critical in handling online information (ICTINFO) compared to users, regardless of the digital activities involved. Buchan et al. (2024) suggested that low digital literacy among young people was prevalent in areas with limited digital access and connectivity (p.3), which can hinder their engagement and development of digital literacy skills. In our data, the availability of digital devices and connectivity may only be a partial barrier. Although proportionally fewer non-users possessed digital devices or had Internet access compared to users, the majority of non-users still owned a computer (~70%), a cellphone with Internet access, and had home Internet connection (~85%). Supporting data for these statistics are presented in Figure 24 to Figure 27 in the appendix.

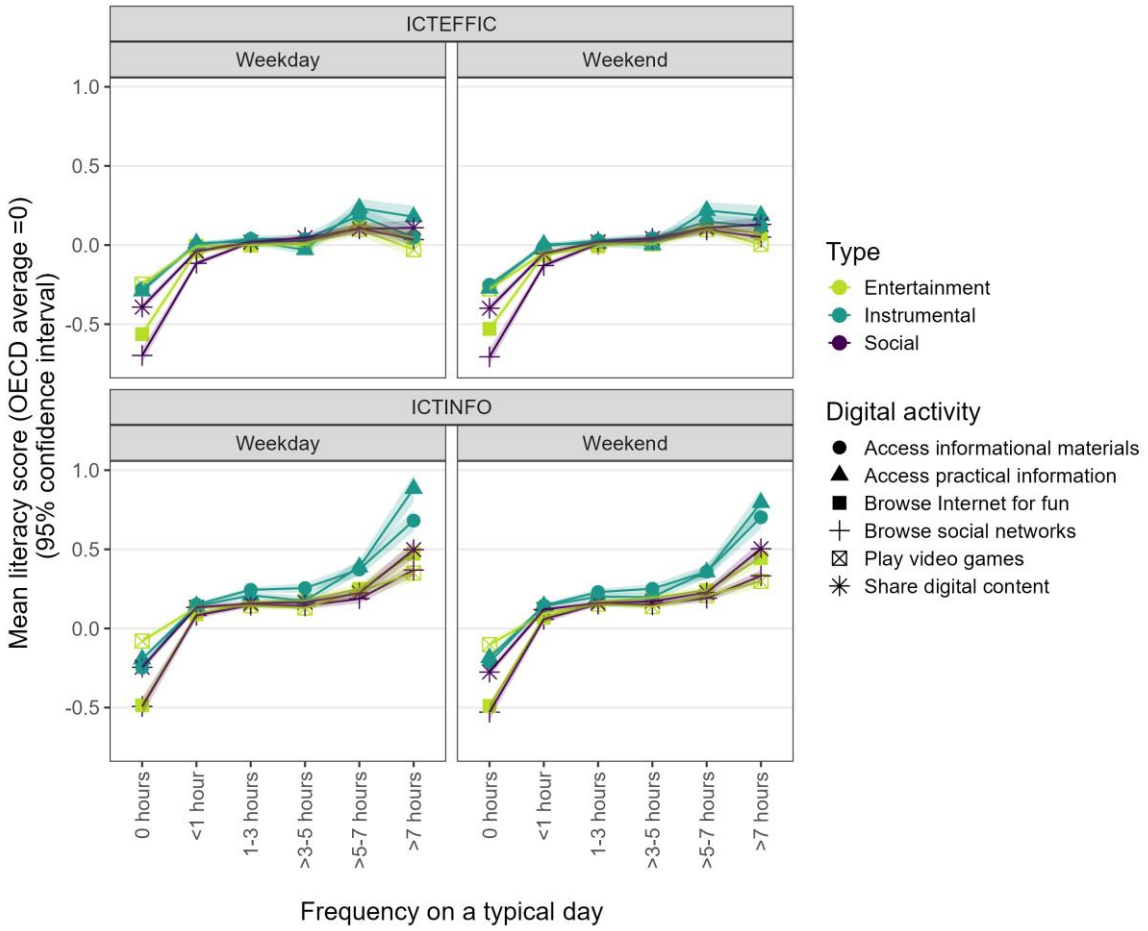

Figure 13. Mean ICTEFFIC and ICTINFO scores by time spent on each digital activity.

Among users, digital competency levels (ICTEFFIC) were broadly similar across all usage frequencies greater than zero. However, more frequent users reported following better practices in handling digital information (ICTINFO) compared to less frequent users. Specifically, those who spent 5 or more hours on instrumental use reported significantly higher ICTINFO scores on average than those who spent less time digitally for the same purpose. Furthermore, those who reported spending more than seven hours daily on social and entertainment purposes also reported higher level of ICTINFO compared to those who spent fewer hours. As shown by Figure 14, this trend was observed for both girls and boys, with a more pronounced increase in ICTINFO scores for boys as time spent increased.

Another observation from Figure 13 is that among users who spend more than 5 hours daily, those using it for instrumental purposes tend to report higher ICTINFO, compared to those using it for non-instrumental purposes. It is challenging to determine the direction of causality from observational data. It is unclear whether spending more time accessing informational materials and practical information online provides an opportunity for users to practice better handling of digital information, or whether being more competent in handling digital information encourages users to spend more time online for instrumental rather than social or entertainment purposes. Nonetheless, it is at least reassuring that instrumental use appears to be more strongly associated with better practices in handling digital information.

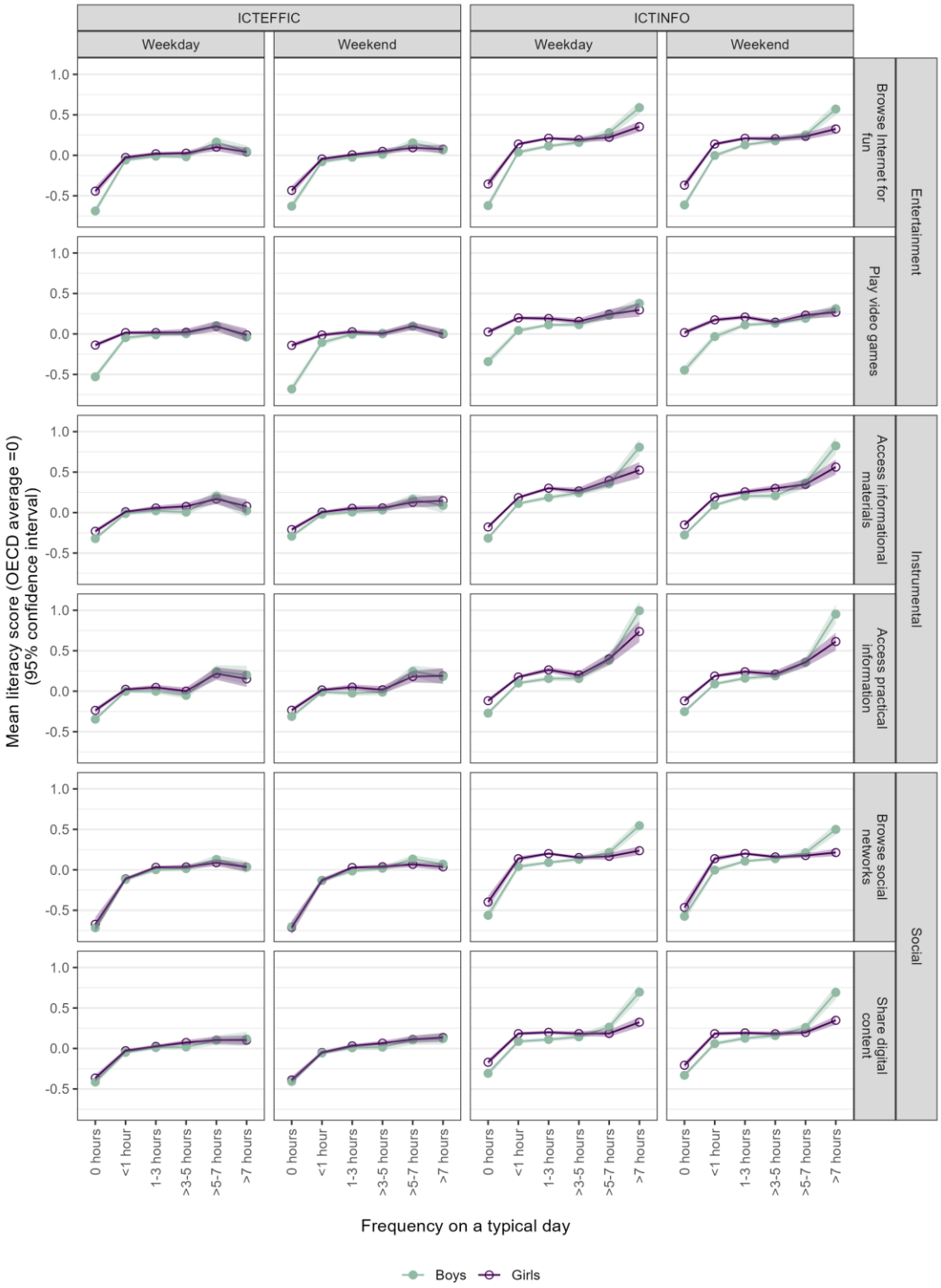

Figure 14. Mean ICTEFFIC and ICTINFO scores by time spent on each digital activity, by gender.

Figure 15 presents the Spearman's rank correlation of the relationships between digital literacy and digital use. The left column shows the correlations for all students (users and non-users), while the right column shows correlations based only on students who reported spending non-zero hours on the activities (users only). As expected, the correlations were lower when only users were considered. Among users, the strongest correlation was 0.09

between ICTINFO and time spent accessing informational materials on weekends, followed by 0.08 for the same activity on weekdays. Senkbeil (2018) found a correlation of 0.16 between digital literacy and instrumental use of digital devices (p.172) using a sample of students from Germany, which was comparable to our findings when all students were included, but much higher than our correlation for users only. However, it was unclear whether the data used in Senkbeil (2018) included non-users. Additionally, these correlation coefficients did not suggest that higher digital literacy (both ICTINFO and ICTEFFIC) was negatively associated with time spent digitally for social and entertainment purposes unlike those in the paper by Senkbeil (2018, p.172).

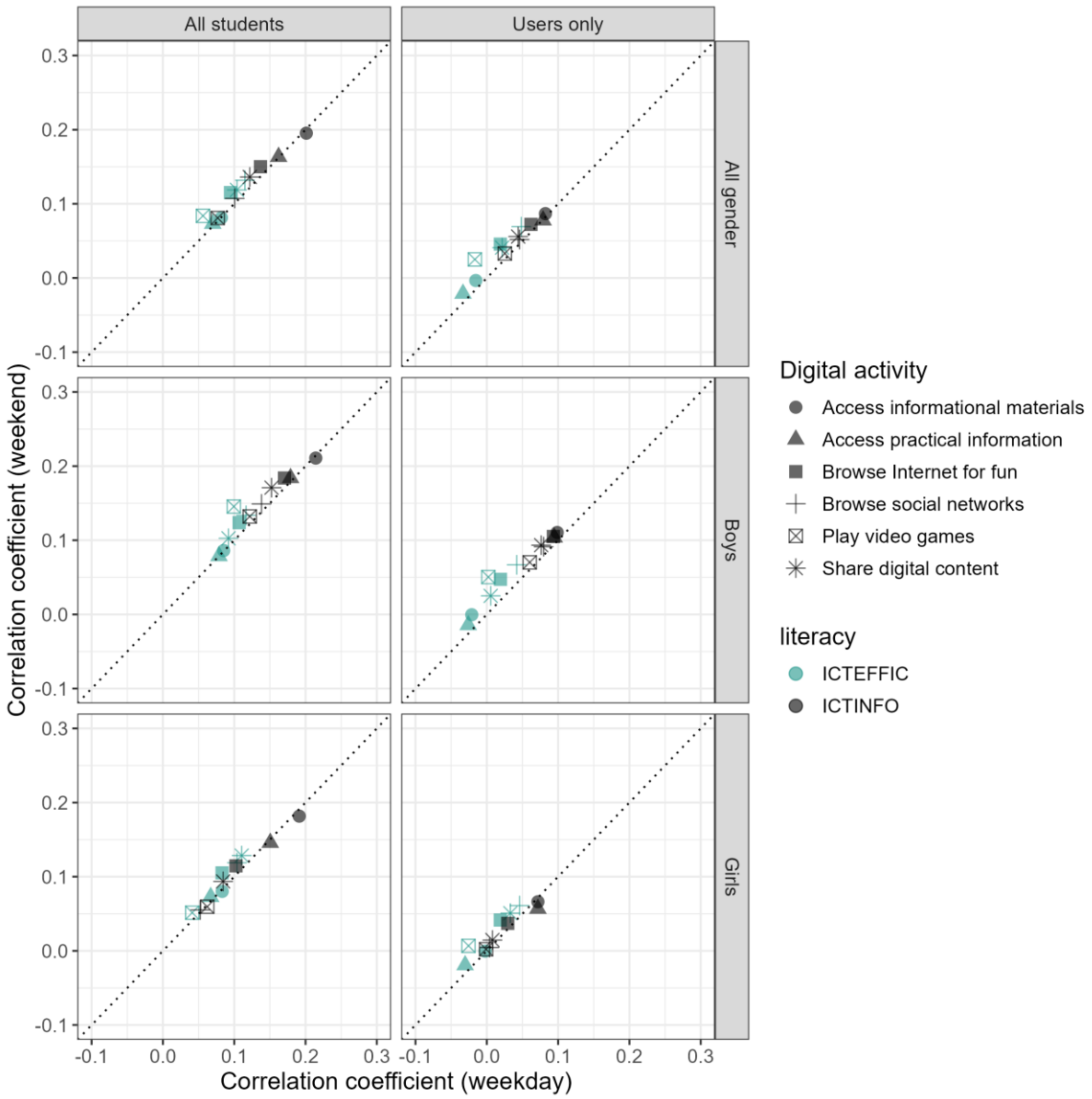

Figure 15. Spearman's rank correlation between literacy score and daily digital time spent on weekday (x axis) and on a typical weekend day (y axis), for all students (users and non-users) and users only.

Next, we examined the relationship between students' responses to the statement "I trust what I read online" and their time spent online on various activities. These responses can indicate students' attitudes towards the information they encountered online. Figure 16 depicts the percentage of students (after weighting) who agreed with the statement, categorised by the time spent on each digital activity. Figure 17 presents the same results, broken down by gender.

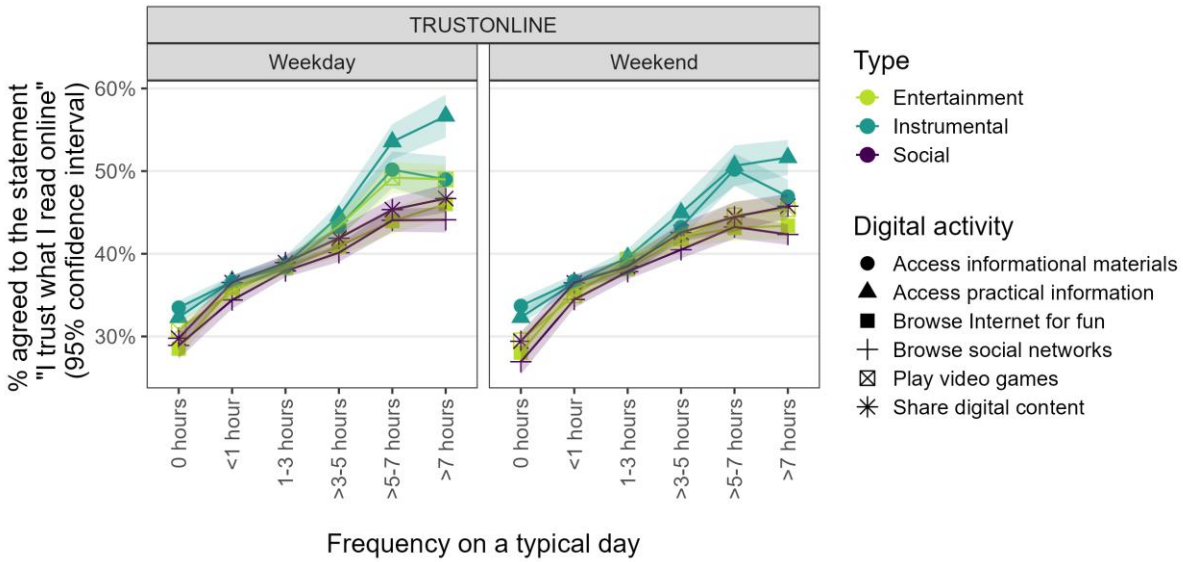

Figure 16. Percentage of students (after weighting) who agreed to the statement “I trust what I read online”, by time spent on each digital activity.

Interestingly, students who spent more time digitally were more likely to report trusting what they read online than those who spent relatively less time. This trend was observed for both boys and girls, with proportionally more boys agreeing to this statement across all usage frequencies. This finding is unexpected, as we would expect students to be exposed to more inappropriate and harmful content the longer the time they spent online, thus growing less trusting of online information. Our data supported this, showing that the longer the time students spent online, the higher the percentage reporting having encountered inappropriate and disturbing content (see Figure 18). Figure 18 also reveals that students who *disagreed* with the statement "I trust what I read online" were *less likely* to encounter harmful content and to have their personal details disclosed without consent compared to those who agreed, despite spending roughly the same amount of time online. This underscores the importance of a cautious approach and attitude when dealing with online information.

A reassuring finding from Figure 16 was that proportionally more users who spent over 5 hours on instrumental activities were more likely to agree with the statement than those who spent the same amount of time browsing social media or the Internet. This is encouraging since harmful contents for young people are often concentrated on social media (5Rights Foundation, 2025) rather than other non-interactive platforms. Lastly, it is interesting to note that non-users were proportionally less likely to agree with the statement, suggesting another potential factor (besides device availability and connectivity) hindering their digital use.

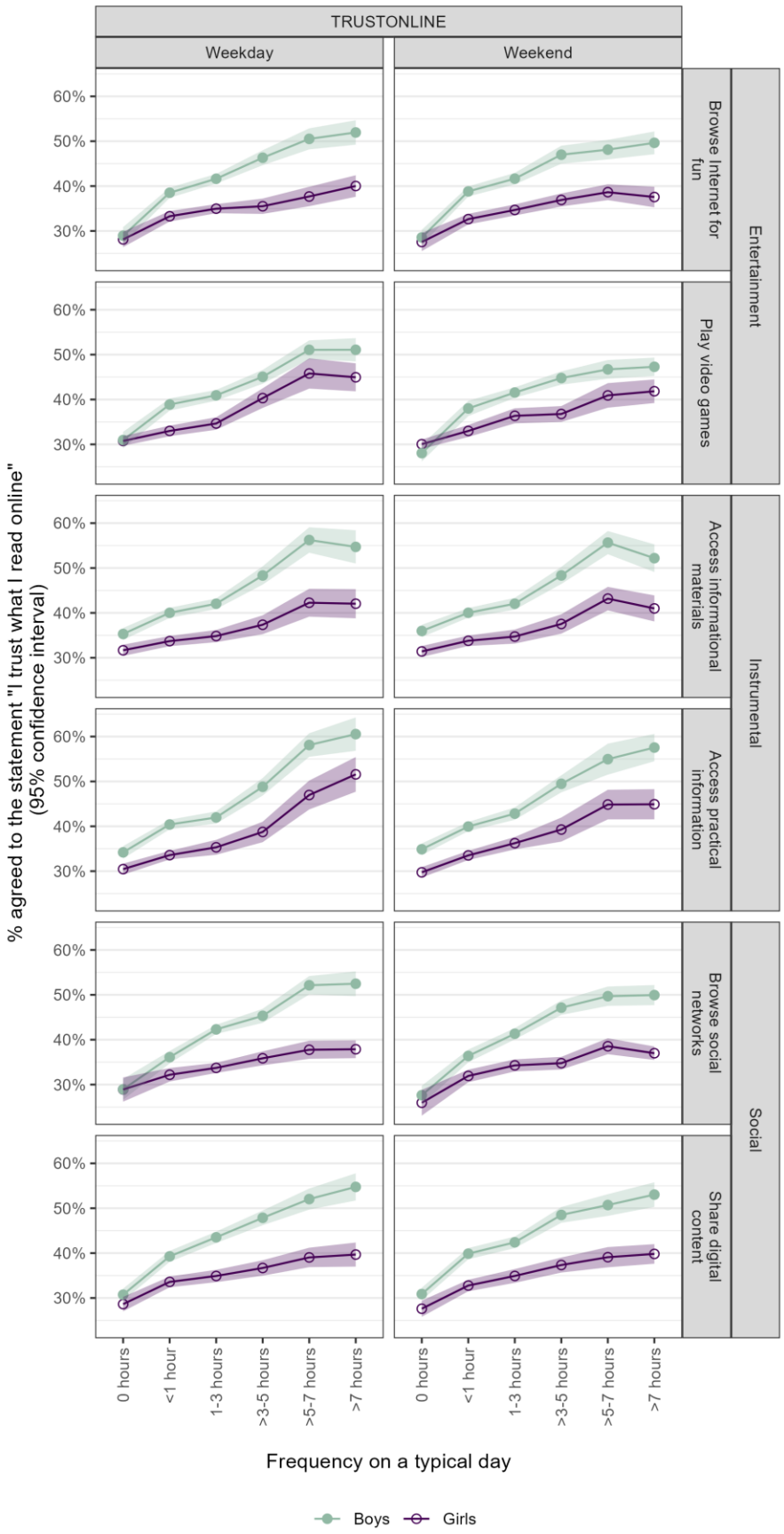

Figure 17. Percentage of boys and girls (after weighting) who agreed to the statement “I trust what I read online”, by time spent on each digital activity.

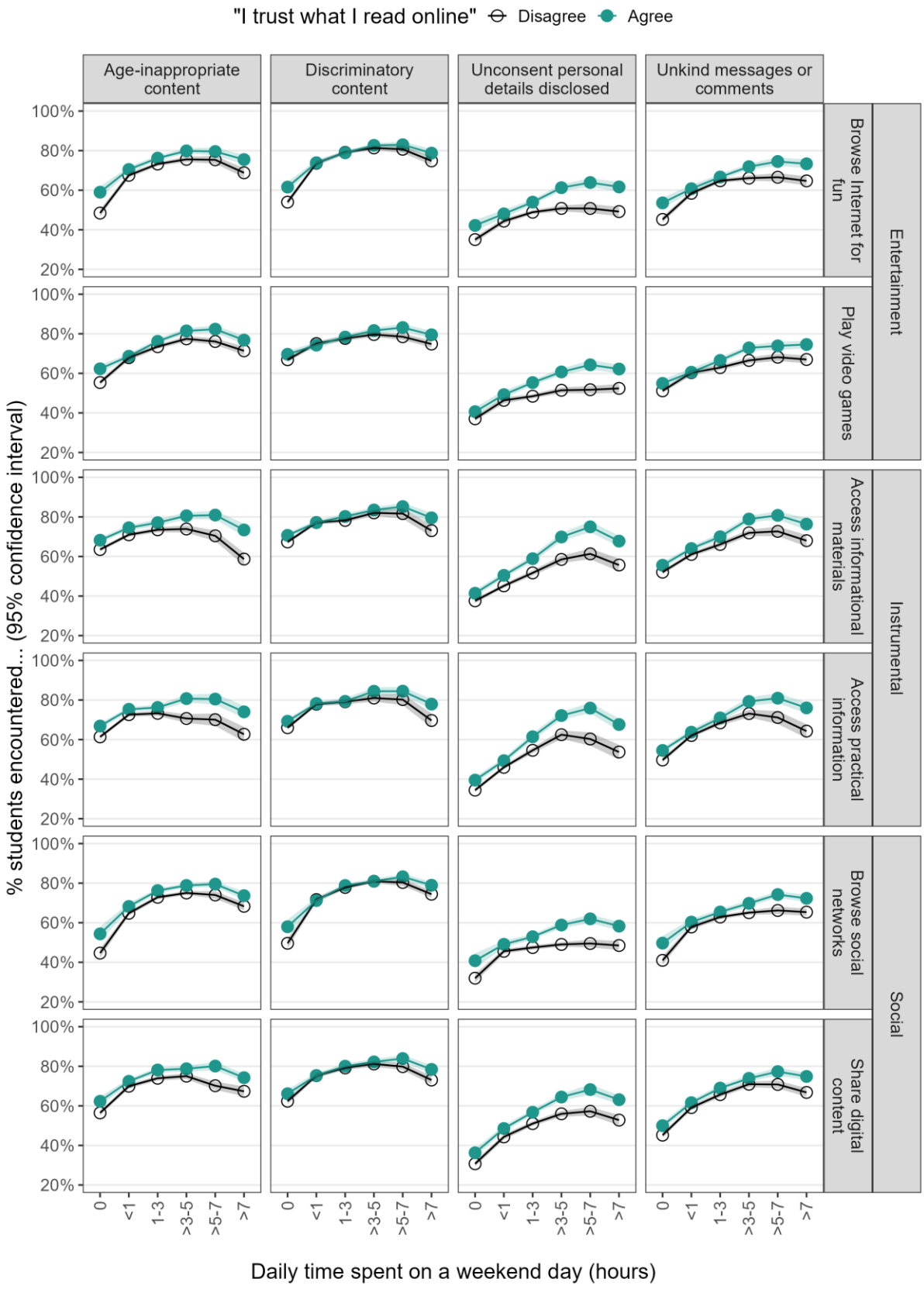

Figure 18. Percentage of students (after weighting) who reported having encountered various disturbing content and experiences online, by time spent on each digital activity and by whether they agreed or disagreed with the statement “I trust what I read online”.

In summary, the findings suggest that while digital competency levels (ICTEFFIC) are broadly consistent among users regardless of usage frequency, more frequent use—particularly for instrumental purposes—is associated with better practices in handling digital information (ICTINFO). We also did not find evidence to suggest higher digital competency or practicing better handling of online information is associated with less frequent digital use in social and entertainment purpose. Interestingly, students who spend more time online also tend to trust online information more, despite being more likely to encounter harmful content.

6.2.2. Promotive factor

To understand the relationships between digital use, digital literacy, and wellbeing, we added the digital literacy variables — ICTEFFIC, ICTINFO, and TRUSTONLINE — to the original regression model (equation 1) used to estimate the impact of digital use on wellbeing. The estimated coefficients of these variables are presented in Table 10, with one column for each wellbeing outcome.

Interpretation

For all but one aspect of wellbeing, a positive estimated coefficient for ICTEFFIC and ICTINFO would suggest that higher levels of self-reported competence in using digital resources and adherence to good practices when dealing with online information were associated with higher levels of wellbeing, for any given digital use and holding all other characteristics constant. Conversely, for PSYCHSYM, a positive coefficient indicates that higher levels of literacy are linked to a higher frequency of experiencing psychosomatic symptoms (i.e., lower levels of wellbeing). Furthermore, the estimated coefficient for TRUSTONLINE indicates the difference in average wellbeing scores between students who agreed and disagreed with the statement "I trust what I read online," while controlling for their characteristics and digital use. Therefore, a positive coefficient (negative for PSYCHSYM) would imply that students who trust online information tend to have higher wellbeing scores on average than those who did not.

Findings

The results indicated that among students with similar digital use, those with higher ICTINFO or ICTEFFIC scores tended to have higher levels of wellbeing compared to those who reported lower ICTINFO and ICTEFFIC scores, holding all controlled characteristics constant. This link can be seen across almost all aspects of wellbeing. However, the effect sizes were generally small. For all but one relationship, a one standard deviation increase in ICTEFFIC or ICTINFO was associated with at most 0.07 standard deviations increase in the wellbeing score (see Table 10). The one exception was in students' life satisfaction scores, where a one standard deviation increase in ICTINFO was associated with about a 0.1 standard deviation increase in the wellbeing score.

For TRUSTONLINE, the results were perhaps unexpected. For almost all statistically significant coefficients, the results suggested that those who agreed they trust what they read online tend to have higher levels of wellbeing. This is despite the fact those who agreed were more likely to report having encountered more online risks such as age-inappropriate content (see, e.g., Figure 18).

Table 10. Estimated coefficients from models including digital literacy variables. These models include all digital use variables (weekend and weekday), digital literacy variables, and control variables as independent variables. The dependent variables are the respective wellbeing outcomes. Coefficients of digital literacy that are statistically significant are **bolded.**

	(1) BELONG	(2) BODYIMA	(3) EXPWB	(4) FEELSAFE	(5) LIFESAT	(6) PSYCHSYM	(7) STRESAGR
Gender (Boys=1)	0.120 (0.009) **	0.235 (0.012) **	0.169 (0.011) **	0.241 (0.012) **	0.144 (0.013) **	-0.541 (0.012) **	0.495 (0.012) **
Time use weekday							
Access info. materials	-0.025 (0.006) **	-0.002 (0.007)	0.016 (0.008)	-0.006 (0.007)	-0.007 (0.008)	0.016 (0.007)	-0.003 (0.006)
Access practical info.	-0.003 (0.007)	0.020 (0.008)	0.026 (0.007) **	-0.005 (0.007)	-0.010 (0.008)	-0.009 (0.006)	-0.001 (0.007)
Browse Internet for fun	-0.013 (0.005)	-0.000 (0.007)	-0.015 (0.008)	-0.003 (0.007)	0.001 (0.006)	0.017 (0.006) *	-0.003 (0.005)
Browse social networks	0.029 (0.006) **	-0.011 (0.008)	-0.012 (0.008)	0.011 (0.006)	-0.014 (0.008)	0.039 (0.008) **	-0.033 (0.007) **
Play video games	-0.017 (0.005) **	0.013 (0.006)	-0.001 (0.006)	-0.011 (0.006)	0.007 (0.006)	-0.012 (0.005)	0.013 (0.006)
Share digital content	0.008 (0.006)	0.010 (0.007)	0.001 (0.007)	0.002 (0.007)	0.003 (0.007)	0.013 (0.006)	-0.002 (0.007)
Time use weekend							
Access info. materials	-0.003 (0.006)	0.005 (0.006)	-0.012 (0.006)	-0.008 (0.007)	-0.013 (0.007)	0.014 (0.006)	-0.002 (0.005)
Access practical info.	-0.005 (0.006)	0.016 (0.007)	0.045 (0.006) **	-0.006 (0.007)	0.011 (0.008)	-0.020 (0.006) **	0.029 (0.007) **
Browse Internet for fun	-0.016 (0.005) *	-0.010 (0.006)	-0.028 (0.006) **	-0.010 (0.006)	-0.018 (0.006) **	0.026 (0.006) **	-0.028 (0.005) **
Browse social networks	0.018 (0.006) **	-0.019 (0.008)	-0.035 (0.007) **	-0.002 (0.007)	0.004 (0.007)	0.032 (0.006) **	-0.021 (0.006) **
Play video games	-0.008 (0.005)	-0.002 (0.005)	-0.025 (0.005) **	-0.002 (0.005)	0.004 (0.005)	0.017 (0.005) **	0.001 (0.006)
Share digital content	0.014 (0.006)	-0.011 (0.006)	-0.003 (0.007)	0.016 (0.007)	-0.002 (0.005)	0.017 (0.006) *	-0.015 (0.006)
Digital literacy variable							
ICTEFFIC	**0.051 (0.005) ** **	**0.068 (0.006) ** **	**0.065 (0.006) ** **	**0.026 (0.006) ** **	**0.072 (0.006) ** **	**-0.031 (0.007) ** **	**0.073 (0.005) ** **
ICTINFO	**0.046 (0.006) ** **	**0.065 (0.007) ** **	**0.031 (0.007) ** **	**0.033 (0.006) ** **	**0.101 (0.007) ** **	**0.039 (0.006) ** **	0.008 (0.007)
TRUSTONLINE	0.016 (0.009)	**0.054 (0.011) ** **	**0.086 (0.013) ** **	**0.045 (0.012) ** **	0.024 (0.009)	**-0.039 (0.009) ** **	**-0.038 (0.010) ** **
R-squared	0.211 (0.004)	0.165 (0.004)	0.193 (0.004)	0.128 (0.004)	0.244 (0.004)	0.225 (0.004)	0.166 (0.004)
Weighted count	34970	29732	26682	31378	31409	34993	29784

*Notes: The digital use variable was modelled as discrete values ranging from 1 (0 hours), 2 (<1 hours), … , to 6 (>7 hours). TRUSTONLINE was a binary variable that equals to 1 if students agreed to the statement "I trust what I read online", 0 otherwise. Coefficients significantly different from 0 at p value ≤ 0.001 were indicated by **, and * for those significant at p ≤ 0.01. The linear model included country fixed effects and a set of student, family, and school characteristics. Standard errors were estimated using Balanced Repeated Replication weights, which were adjusted to ensure equal country representation. These weights accounted for the clustering of students within schools and other aspects of the survey design.*

Table 11. Estimated coefficients from models including the full set of digital literacy variables, using a smaller sample. These models include all digital use variables (weekend and weekday), digital literacy variables, and control variables as independent variables. The dependent variables are the respective wellbeing outcomes. Coefficients of digital literacy variables that are statistically significant are **bolded.**

	(1) BELONG	(2) BODYIMA	(3) EXPWB	(4) FEELSAFE	(5) LIFESAT	(6) PSYCHSYM	(7) STRESAGR
Gender (Boys=1)	0.094 (0.015) **	0.133 (0.018) **	0.125 (0.017) **	0.223 (0.016) **	0.151 (0.019) **	-0.511 (0.018) **	0.382 (0.017) **
Time use weekday							
Access info. materials	-0.032 (0.010) *	-0.004 (0.010)	0.026 (0.013)	-0.013 (0.010)	0.005 (0.013)	0.025 (0.009) *	-0.010 (0.008)
Access practical info.	-0.011 (0.010)	0.017 (0.013)	0.025 (0.011)	-0.000 (0.011)	-0.015 (0.011)	-0.005 (0.011)	-0.006 (0.009)
Browse Internet for fun	-0.012 (0.009)	-0.015 (0.012)	-0.017 (0.011)	-0.012 (0.010)	-0.003 (0.009)	0.027 (0.009) *	-0.001 (0.008)
Browse social networks	0.020 (0.010)	-0.011 (0.014)	-0.021 (0.014)	0.004 (0.009)	-0.027 (0.013)	0.037 (0.011) **	-0.027 (0.011)
Play video games	-0.011 (0.008)	0.010 (0.009)	0.009 (0.010)	-0.000 (0.009)	0.018 (0.010)	-0.028 (0.009) **	0.015 (0.009)
Share digital content	0.012 (0.010)	0.029 (0.011)	-0.000 (0.010)	0.015 (0.009)	0.004 (0.012)	0.004 (0.010)	-0.024 (0.010)
Time use weekend							
Access info. materials	0.005 (0.008)	0.011 (0.010)	-0.017 (0.010)	-0.016 (0.009)	-0.017 (0.011)	0.014 (0.008)	-0.011 (0.008)
Access practical info.	-0.010 (0.009)	0.013 (0.011)	0.040 (0.009) **	-0.009 (0.010)	0.008 (0.010)	-0.023 (0.009) *	0.030 (0.009) **
Browse Internet for fun	-0.006 (0.007)	0.001 (0.010)	-0.026 (0.010) *	-0.002 (0.009)	-0.013 (0.008)	0.019 (0.009)	-0.015 (0.007)
Browse social networks	0.020 (0.010)	-0.023 (0.013)	-0.025 (0.011)	-0.003 (0.010)	0.018 (0.012)	0.035 (0.010) **	-0.019 (0.009)
Play video games	-0.008 (0.008)	-0.008 (0.008)	-0.039 (0.008) **	-0.002 (0.008)	-0.006 (0.008)	0.023 (0.008) *	-0.001 (0.009)
Share digital content	0.014 (0.009)	-0.009 (0.011)	0.010 (0.010)	0.010 (0.009)	-0.003 (0.010)	0.010 (0.010)	0.004 (0.009)
Digital literacy variable							
ICTEFFIC	**0.064 (0.008) ** **	**0.065 (0.010) ** **	**0.069 (0.010) ** **	**0.027 (0.009) * **	**0.062 (0.010) ** **	**-0.039 (0.009) ** **	**0.090 (0.008) ** **
ICTINFO	**0.067 (0.009) ** **	**0.066 (0.013) ** **	**0.036 (0.009) ** **	**0.042 (0.009) ** **	**0.111 (0.012) ** **	**0.044 (0.010) ** **	0.019 (0.010)
TRUSTONLINE	-0.004 (0.015)	0.059 (0.019) *	**0.093 (0.021) ** **	**0.063 (0.017) ** **	0.003 (0.015)	-0.038 (0.016)	-0.025 (0.015)
ICTOTLSCH	0.035 (0.017)	0.034 (0.019)	0.048 (0.028)	**0.104 (0.025) ** **	0.053 (0.025)	**-0.071 (0.025) * **	**0.065 (0.020) ** **
R-squared	0.175 (0.008)	0.140 (0.008)	0.186 (0.007)	0.112 (0.007)	0.196 (0.008)	0.211 (0.007)	0.136 (0.006)
Weighted count	15895	11621	12624	15976	12428	15957	13994

*Notes: The digital use variable was modelled as discrete values ranging from 1 (0 hours), 2 (<1 hours), … , to 6 (>7 hours). TRUSTONLINE was a binary variable that equals to 1 if students agreed to the statement "I trust what I read online", 0 otherwise. Coefficients significantly different from 0 at p value ≤ 0.001 were indicated by **, and * for those significant at p ≤ 0.01. The linear model included country fixed effects and a set of student, family, and school characteristics. Standard errors were estimated using Balanced Repeated Replication weights, which were adjusted to ensure equal country representation. These weights accounted for the clustering of students within schools and other aspects of the survey design. The sample sizes of these models were smaller than Table 10 as only a subset of countries had data for the ICTOTLSCH variable.*

Findings for ICT awareness teaching

To understand how the teaching of various ICT awareness activities at schools (e.g., how to decide whether to trust information from the Internet) might be associated with wellbeing, we included the ICTOTLSCH variable in the model. This variable was calculated using the "ICTOTL" PISA variable averaged across teachers within each school. A higher value for this variable (ICTOTLSCH) indicates a greater extent to which ICT awareness was taught at schools. The estimated coefficients of this variable are presented in Table 11, and the effect sizes of statistically significant ICTOTLSCH variables are visualised in Figure 19.

As shown in Table 11, the effective sample sizes of these models were about half of those without the ICTOTLSCH variable included (Table 10 & Table 11). This was because only five countries (out of ten) had administered the teacher questionnaires and had responses for this variable. Despite this, the coefficients of the main digital literacy variables (ICTEFFIC, ICTINFO, TRUSTONLINE) remained similar to the models with the full sample included which was reassuring.

The findings indicated that students from schools where ICT awareness was taught to a greater extent tended to have a higher wellbeing compared to similar students from schools where ICT awareness was taught to a lesser extent, controlling for some school characteristics, such as school resources. However, compared to ICTINFO and ICTEFFIC, the ICTOTLSCH variable was statistically significant in fewer aspects of wellbeing, likely due to the large standard errors of the estimators resulting from low variation in the variable (since all students in a school have the same value). However, the effect size of this variable was comparable to those of ICTINFO and ICTEFFIC, with a one standard deviation increase associated with at most about a 0.1 standard deviation increase in wellbeing outcomes.

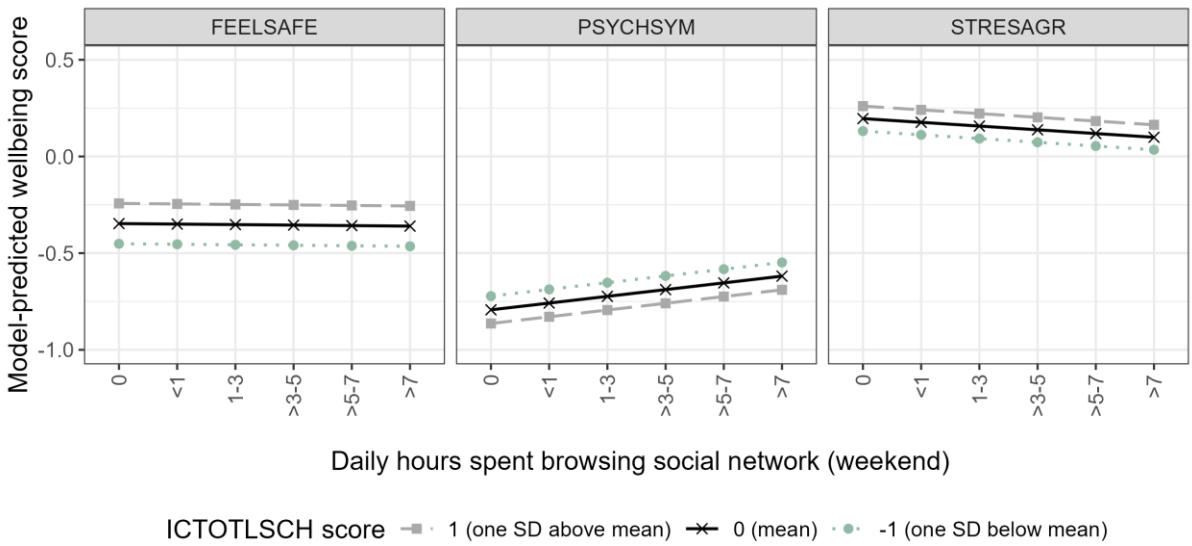

Figure 19. Predicted wellbeing scores by time spent on digital activities and ICTOTLSCH levels, for those with statistically significant relationship with wellbeing. Predictions were for 15-year-old boys from Brazil, group 5 of Economics, Social and Cultural Status, with medium levels of family support, number of close friends, quality of relationship with teachers, frequency of bullying, and body mass index. Students were in grade 10, not skipping classes two weeks prior to the PISA test, not working outside of school, spending 2 days per week with friends after school, not exercising, studying in a public school with medium student-teacher ratio, computer-student ratio, negative school climate, and a plausible math score of 450. Furthermore, the predictions were based on

spending 0 hours on all other digital activities, a value of 0 for TRUSTONLINE (i.e., disagree), ICTEFFIC and ICTINFO variables (i.e., OECD average).

In summary, we did find evidence suggesting that (1) being more digitally competent, (2) being more critical in handling online information, and (3) including more ICT awareness teaching at schools, were associated with marginally higher wellbeing across many aspects of wellbeing, even after controlling for digital use and students' background characteristics.

6.2.3. Protective factor

The analyses above assumed that changes in wellbeing as a result of an increase in time spent digitally are the same across all levels of digital literacy. We also examined whether students with higher digital literacy were more likely to experience a smaller negative impact or a bigger positive impact of digital use than students with lower levels of literacy. We did this by including interaction terms between digital literacy and digital use variables in the model. We didn't find much evidence suggesting that the relationship between wellbeing and digital literacy varied by digital use. Only three estimated coefficients —across all six models, totalling 76 coefficients of interest— were statistically significant at the 1% level. For brevity, these results are not shown and further discussed here and is available upon request.

6.3 Robustness checks

Figure 20 presents the estimated coefficients of the digital use variables from the main analyses, where daily usage during weekends and weekdays were modelled together in a single model ("weekend+weekday"), and from the sensitivity analyses, where daily usage during weekends and weekdays were modelled separately for each aspect of wellbeing ("weekend/weekday").The figure shows that all the digital use variables that were statistically significant in the main analyses remained significant in the sensitivity analyses. This indicates that our results were robust to the inclusion of usage on weekends and weekdays in a single model. However, the sensitivity analyses also suggest that we may have underestimated the magnitude of both the positive and negative relationships found in our main analyses. To put this another way, the original models show the effect of each variable when holding usage during the alternative time period (e.g., weekends rather than weekdays) constant. In reality, heavy digital users in the week are likely to also be heavy users at the weekend and this will exacerbate the effects. Additionally, there were likely more significant relationships than those suggested in the main analyses.

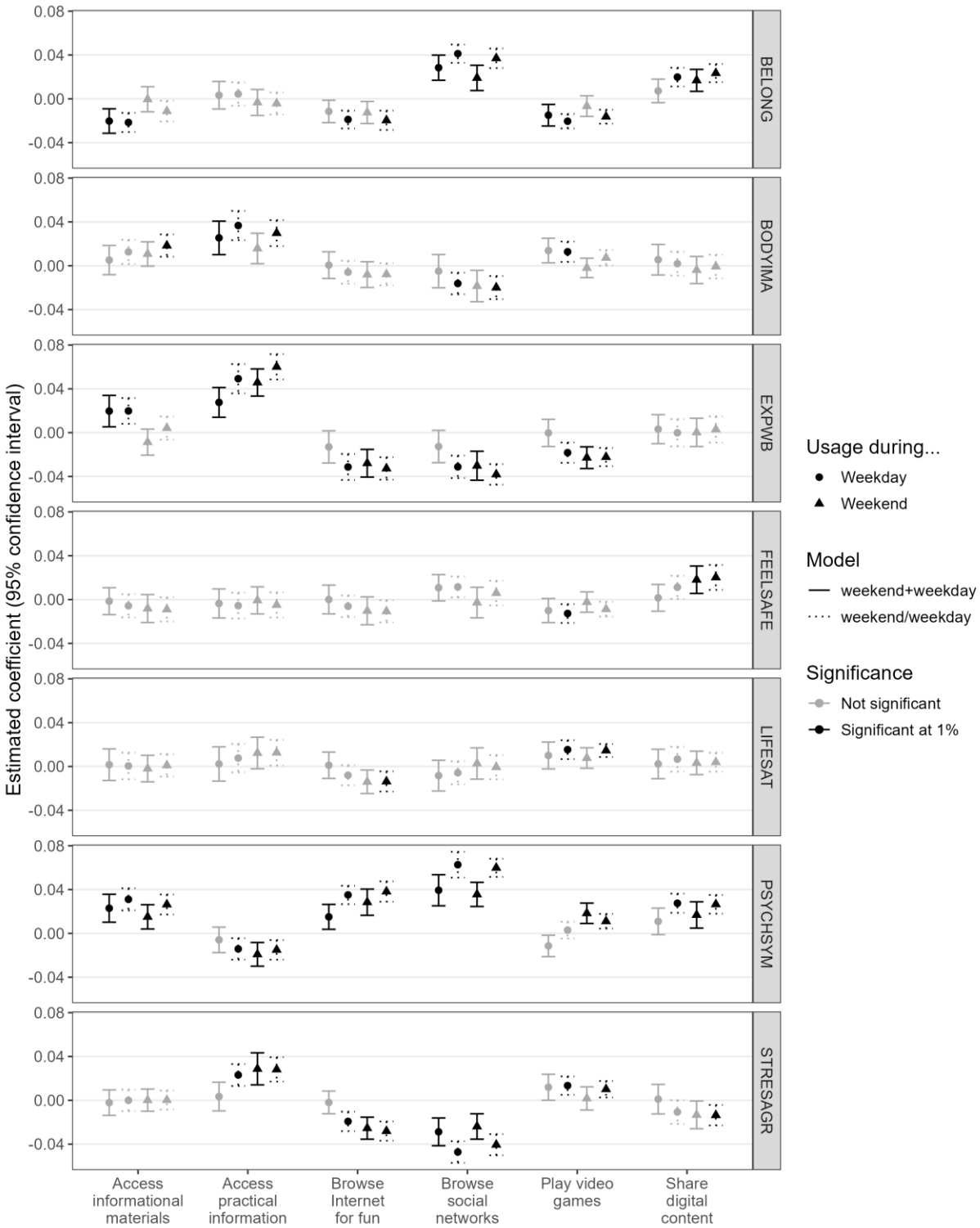

Figure 20. Estimated coefficients (and their 95% confidence interval) from regression models with (1) all weekend and weekday digital use variables included in one model (solid line) and (2) either all weekend or all weekday digital use variables included in one model (dotted line).

7. Discussions

7.1. Digital use and wellbeing

Our study revealed that the relationships between digital use and youth wellbeing were highly heterogeneous, varying depending on students' characteristics, types of digital use, and the specific aspects of wellbeing considered. Among the 84 pairs of relationships investigated, we found evidence supporting all types of associations—positive, negative, and no association. This underscores the complexity of these relationships and echoes the recommendations of other researchers: future studies should clearly define the specific uses of digital technologies (e.g., Santos et al., 2023), characteristics of the population being studied (e.g., Orben, 2020), and the aspects of wellbeing being examined (e.g., Fumagalli et al., 2024). Any blanket conclusions are likely to obscure the nuances in these relationships.

Positive links with instrumental use

Higher instrumental usage of digital devices was linked to better body image perceptions, higher general wellbeing, and higher stress resistance, especially when used to seek practical information (e.g., finding a place). This implies that digital use that facilitates real-life needs can be beneficial. Additionally, girls' general wellbeing and sense of belonging were slightly more positively associated with increased hours spent accessing informational materials (e.g., podcasts) compared to boys', but, from a practical perspective, the difference was small.

Negative links with Internet use

Time spent browsing the Internet was linked to lower general wellbeing, lower stress resistance, and a higher frequency of experiencing psychosomatic symptoms for both genders. We did not find evidence suggesting robust relationships with life satisfaction, sense of belonging and safety at school, and body image.

Differential impact of gaming for girls and boys

Time spent on gaming was associated with lower general wellbeing and a higher frequency of experiencing psychosomatic symptoms for both genders. However, for girls, gaming was negatively linked with life satisfaction, while for boys, it was positively linked, even after controlling for their background characteristics, such as the number of close friends. Among others, this gender difference may be attributed to the fact that gaming offers boys more opportunities for agency-building activities, such as competing, exploring, and playing war, which are more aligned with their developmental needs (Haidt, 2024, p. 176). Additionally, studies also indicated that gaming experiences differ between genders. For example, survey data from the Pew Research Center (Gottfried & Sidoti, 2024) showed that girls were less likely than boys to report making friends or developing problem-solving and social skills through video gaming.

Lastly, the relationships between gaming and wellbeing were likely non-monotonic, particularly, for general wellbeing and the frequency of experiencing psychosomatic symptoms. A small amount of gaming was associated with higher wellbeing compared to non-use. The negative associations only became evident when daily usage exceeded three hours on weekends. This aligns with Przybylski and Weinstein's (2017, p. 207) finding that mental wellbeing was on average highest with three hours of weekend gaming, and a body

of research that found several benefits to adolescents who play video games (see Haidt, 2024, p.190 for the list of studies). Recent research (e.g., Li et al., 2025) suggested these non-monotonic relationships may differ by gender, though this was not investigated here.

Differential impact of social media use for girls and boys

Time spent browsing social media was associated with lower levels of general wellbeing, reduced stress resistance, and a higher frequency of experiencing psychosomatic symptoms for both genders. However, social media use was particularly linked to lower body image perception and life satisfaction among girls, but not boys. Our findings suggest that the gender gap in self-perceived body image may largely be driven by the differential impact of social media on girls and boys.

This difference could be explained by the types of social media platforms that girls and boys tend to use. Girls gravitate to visually-oriented platforms such as Snapchat and Instagram (Lenhart, 2015), while boys tend to prefer text-based platforms like the former Twitter (now X) or Reddit (Haidt, 2024, p.150). Content on visually-oriented platforms is mostly digital media of oneself and one's life, which can lead to social comparisons and raise one's ideal self-image, thereby increasing the actual-ideal body image gap and causing body image concerns. This is exacerbated by the finding that girls are more affected by visual social comparisons. Among others, this aligned with a randomised controlled trial study by Kleemans et al. (2018) who found that exposure to visually-manipulated Instagram photos lowers girls' body image. This further supports the notion that reducing time spent on social media, especially visually-oriented platforms, can have positive effects on mental health and self-perception.

Sharing digital content did not have the same negative impact on girls, and generally had a minimal link to wellbeing for both genders, implying that how users utilised social media platform matters, as well as the time spent on it. This aligns with experimental and longitudinal evidence from Verduyn et al. (2015) who found that passive use of Facebook led to a decline in affective wellbeing by increasing feelings of envy.

Mixed links with school belonging

Time spent on social media outside of schools, whether browsing or sharing content, was associated with a higher sense of belonging at school. These findings aligned with existing literature indicating that social media could foster social connectedness (e.g., Sampasa-Kanyinga et al., 2019; Žanić et al., 2023), but as discussed earlier, it did not come without costs. We did however find time spent gaming to be negatively linked to sense of belonging at schools, especially if the daily usage was more than 3 hours. This implies that engaging in digital activities that offer ample social interaction outside of school hours may foster students' friendships, while those with limited social interaction and those that could potentially displace in-person socialising may alienate students from their school friends.

Most impacted aspects of wellbeing

The frequency of experiencing psychosomatic symptoms (e.g., anxiety, depression, headache, back pain) was the aspect of wellbeing most strongly associated with digital time use. Students who reported spending more time digitally tended to experience higher frequencies of psychosomatic symptoms, regardless of the types of digital activities and their gender. This relationship remained even after controlling for background characteristics,

including exercise frequency. For girls, the correlation between the frequency of experiencing psychosomatic symptoms and browsing social networks was the strongest and was close to two-thirds the correlation between being bullied and experiencing psychosomatic symptoms. For boys, it was browsing the Internet—slightly more than half the strength of the correlation between being bullied and experiencing psychosomatic symptoms.

7.2. The roles of digital literacy

Motivational factor

Results from our analyses indicate that digital use is not linked to digital competency among users, and students who spent more time online were more likely to report trusting what they read online than those who spent relatively less time. However, students who reported spending more time online, especially for instrumental purposes, reported better practices in handling online information. It was challenging to determine the direction of causality based on observational data. Our findings also did not suggest that digital competency and good practices in handling online information are associated with less frequent digital use for social and entertainment purposes. This finding suggests that these aspects of digital literacy may not be sufficient to motivate a more beneficial allocation of screen time across various digital activities.

Promotive factor

We did find evidence indicating that digital competency and prudent use of online information are associated with marginally higher wellbeing in almost all aspects, even after controlling for students' characteristics such as ability and family socio-economic status. The links between students' levels of trust in online information and their wellbeing were more sparse, limited only to their perceived safety and general wellbeing. However, our result shows that the practical significance of these relationships is likely small—one unit increase in digital literacy score is associated with at most one-tenth of an increase in wellbeing score. That said, this may reflect the fact that many factors contribute to youth wellbeing, and does not negate the importance of digital literacy in enhancing wellbeing.

Protective factor

Lastly, our findings did not suggest that students with higher digital literacy experience smaller negative impacts or larger positive impacts of digital use.

In summary, our findings suggest that digital literacy alone is not sufficient in encouraging more time spent on beneficial activities rather than harmful ones but it might play a promotive role in enhancing wellbeing. One potential explanation, as suggested by Mayiwar et al. (2024), is that young people who self-reported higher digital literacy levels are more likely to feel safe and in control of their online activities. This sense of security and control boosts their confidence in navigating the increasingly digitalised world, which subsequently enhances their wellbeing.

Our finding that digital literacy does not play a protective role aligns with Vissenberg et al. (2022), who indicated that digital literacy is more often seen as a promotive factor of wellbeing—a resource that has beneficial effects in general—rather than a protective factor, which has greater effects under risky circumstances. The authors suggested that online resilience tends to be seen as a protective factor. While the effectiveness of online resilience

is not covered in this study, our results concur with the idea that online resilience may be required to mitigate any negative impacts of digital use, as digital literacy alone does not seem to have such an effect or is insufficient to mitigate the impacts. In other words, knowing how to utilise digital resources and handle online information may not be sufficient to shield students from the negative impacts of digital use. The skills and ability to rebound from adversity are essential, as encountering risks is inherently a consequence of greater online exposure.

7.3. Strengths and limitations

This study has several strengths. Firstly, it utilised a large-scale representative sample of students from countries worldwide, extending beyond the typical Anglosphere nations (e.g., UK and US) commonly analysed in similar research. Secondly, to our knowledge, this is the first study to analyse such a diverse range of digital activities alongside numerous aspects of youth wellbeing. This comprehensive approach allowed us to better understand how specific digital uses can impact various facets of youth wellbeing.

However, the study also has several limitations. Firstly, it relies on self-reported data for wellbeing, digital use and digital literacy, which can be prone to inaccuracies. Students may misremember their digital time use and misjudge their digital literacy levels, and their interpretation of wellbeing questions may vary depending on the cultural context. For instance, Walsh et al. (2021) found that most participants inaccurately estimated their smartphone usage when comparing self-reported data to actual usage recorded by Apple's screen time function (r=0.55). Similarly, our time usage variable is a crude measure, categorised into groups of hours rather than exact hours. This limitation may hinder the detection of any non-linear effects that might exist.

Secondly, we might be underestimating the total effect of digital use on wellbeing according to time displacement theory (Moy et al., 1999; Putnam, 2000). Time replacement theory suggests that time spent on digital activities can displace beneficial offline activities like exercising. With the intention to estimate a direct effect closer to causal (i.e., how wellbeing changes with one hour increase in digital use), we included factors related to both wellbeing and digital use in our model, such as exercise frequency and days spent with friends. Thus, if time displacement theory holds true, our results may have underestimated the impact of digital use on wellbeing due to the unaccounted indirect effects.

Thirdly, the composite measure of psychosomatic symptoms encompasses both physical and mental health aspects. It is possible that digital use may affect mental aspects (e.g., anxiety) more significantly than physical aspects (e.g., headaches), or vice versa. However, by using this composite measure, we were unable to determine whether and if digital use impacted these aspects differently.

Next, there are several methodological limitations. There is a possibility of simultaneous causality, e.g., where wellbeing might also influence digital use, which could limit the validity of our regression estimates. For instance, if students with lower wellbeing are likely to use digital devices more often, our results might have overestimated the negative impacts and underestimated any positive effects of digital use. We attempted to address this issue using instrumental variable estimation, considering the availability of mobile phones, computers/laptops/desktops, and Internet access as potential instruments. However, this

approach was unfruitful due to low variation in these variables across the time spent among students in the countries analysed. Furthermore, our findings are based on relationships being statistically significant at a strict 1% threshold, which may have missed other potential relationships between wellbeing and digital use. Readers should interpret insignificant results with equal amount of caution, as they may be significant at a level very close to 1%.

Last but not least, the PISA wellbeing measures we used were in standard deviation units, making it difficult to distil any practical significance from the estimated relationships. Future research using the same or similar data could consider determining a threshold within the wellbeing score that is deemed concerning and investigate how likely students are to fall into that category based on their time spent in each digital activity. A similar approach was taken in The Good Childhood Report (The Children's Society, 2024) where, in addition to the mean score, the report also considered those scoring below the midpoint on the 0 to 10 life satisfaction scale (PISA item ST016; different from the one used here) to have low life satisfaction.

7.4. Conclusions

In conclusion, our study, which utilised a large-scale representative sample of 15-year-olds from multiple continents who participated in the PISA 2022 tests, reveals the multifaceted relationships between digital use and youth wellbeing. These associations are highly variable depending on user characteristics, types of digital use, and specific aspects of wellbeing considered.

Positive outcomes were primarily linked to instrumental digital use, while negative associations were noted with social media browsing, gaming, and Internet use, though the extent varied. The link between sharing content on social media and wellbeing was less evident. Gender differences were particularly pronounced in gaming and social media use. Specifically, social media browsing was negatively associated with girls' body image perceptions and life satisfaction, but not boys'. Among the various aspects of wellbeing examined, the frequency of psychosomatic symptoms was most impacted and was observed across almost all digital use, regardless of purpose or user’s gender. For girls, the link between psychosomatic symptoms and social media browsing was close to two-thirds as strong as the correlation between being bullied and psychosomatic symptoms; for boys, it was slightly more than half. This highlights the need for policies and parental guidance to address the physical impacts of sedentary digital device use and the mental effects of prolonged digital immersion on young people, particularly for social media browsing.

Our research also suggests that digital literacy alone may not be sufficient to mitigate the potential negative impacts of digital use or to promote more beneficial screen time use, even though it can generally enhance wellbeing. This implies that young people need to be equipped with additional skills, such as digital resilience, to better protect themselves in the digital world.

8. References

5Rights Foundation. (2025). Child accounts shown harmful content within hours, new study finds. Retrieved from https://5rightsfoundation.com/child-accounts-shown-harmful-content-within-hours-new-study-finds/

Azem, L., Al Alwani, R., Lucas, A., Alsaadi, B., Njihia, G., Bibi, B., Alzubaidi, M. & Househ, M. (2023). Social media use and depression in adolescents: A scoping review. Behavioral Sciences, 13(6), 475.

Bailey, P., Sikali, E., Emad, A., & Buehler, E. (2021). wCorr: Weighted correlations (Version 1.9) [R package]. Retrieved from https://CRAN.R-project.org/package=wCorr[1](https://ropensci.org/blog/2021/11/16/how-to-cite-r-and-r-packages/).

Buchan, M. C., Bhawra, J., & Katapally, T. R. (2024). Navigating the digital world: development of an evidence-based digital literacy program and assessment tool for youth. Smart Learning Environments, 11(1), 8.

Cambridge University Press and Assessment. (n.d.). The Cambridge Life Competencies Framework: Digital Literacy. Retrieved March 11, 2025, from https://issuu.com/cambridgeupelt/docs/clc_digital_literacy_issuu

Caro, D. H., & Biecek, P. (2017). intsvy: An R package for analyzing international large-scale assessment data. Journal of Statistical Software, 81(7), 1–44. https://doi.org/10.18637/jss.v081.i07[1](https://ropensci.org/blog/2021/11/16/how-to-cite-r-and-r-packages/).

Carretero, S., Vuorikari, R., & Punie, Y. (2017). The digital competence framework for citizens. Publications Office of the European Union, 21(5), 222-235.

De La Hoz, A. B. B., Fuentes, A. R., Cara, M. J. C., & Montes, C. D. P. G. (2023). Effectiveness of a digital literacy program in High School Basic education students. Espiral. Cuadernos del Profesorado, 16(34), 2.

Department for Education (2019). State of the Nation 2019: Children and Young People's Wellbeing. https://assets.publishing.service.gov.uk/media/5f29457e8fa8f57acc8d8223/State_of_the_Nation_2019_young_people_children_wellbeing.pdf

Department of Health and Social Care & Department for Education (2018). Government Response to the Consultation on Transforming Children and Young People's Mental Health Provision: a Green Paper and Next Steps. https://assets.publishing.service.gov.uk/media/5b583d30ed915d0b6985cc21/government-response-to-consultation-on-transforming-children-and-young-peoples-mental-health.pdf

Fumagalli, E., Shrum, L. J., & Lowrey, T. M. (2024). The effects of social media consumption on adolescent psychological wellbeing. Journal of the Association for Consumer Research, 9(2), 119-130.

Gottfried, J., & Sidoti, O. (2024, May 9). *Teens and video games today.* Pew Research Center. https://www.pewresearch.org/internet/2024/05/09/teens-and-video-games-today/

Haidt, J. (2024). The anxious generation: How the great rewiring of childhood is causing an epidemic of mental illness. Penguin Press.

Hancock, J. T., Liu, S. X., Luo, M., & Mieczkowski, H. (2022). Social media and psychological wellbeing.

Hietajärvi, L., Maksniemi, E., & Salmela-Aro, K. (2022). Digital Engagement and Academic Functioning: A Developmental-Contextual Approach. European Psychologist, 27(2), 102–115. https://doi.org/10.1027/1016-9040/a000480

Hilty, D. M., Stubbe, D., McKean, A. J., Hoffman, P. E., Zalpuri, I., Myint, M. T., ... & Li, S. T. T. (2023). A scoping review of social media in child, adolescents and young adults:

research findings in depression, anxiety and other clinical challenges. BJPsych open, 9(5), e152.
Jerrim, J., Lopez-Agudo, L. A., & Marcenaro-Gutierrez, O. D. (2022). The impact of test language on PISA scores. New evidence from Wales. British Educational Research Journal, 48(3), 420-445.
Jerrim, J., Lopez-Agudo, L. A., Marcenaro-Gutierrez, O. D., & Shure, N. (2017). What happens when econometrics and psychometrics collide? An example using the PISA data. Economics of Education Review, 61, 51-58.
Kleemans, M., Daalmans, S., Carbaat, I., & Anschütz, D. (2018). Picture perfect: The direct effect of manipulated Instagram photos on body image in adolescent girls. Media Psychology, 21(1), 93-110.
Kunina-Habenicht, O., & Goldhammer, F. (2020). ICT engagement: A new construct and its assessment in PISA 2015. Large-Scale Assessments in Education, 8(1), 6.
Law, N. W. Y., Woo, D. J., De la Torre, J., & Wong, K. W. G. (2018). A global framework of reference on digital literacy skills for indicator 4.4.2.
Lee, S. J., & Chae, Y. G. (2012). Balancing participation and risks in children's internet use: The role of internet literacy and parental mediation. Cyberpsychology, Behavior, and Social Networking, 15(5), 257-262.
Lenhart, A. (2015, April 9). Teens, social media & technology 2015. Pew Research Center: Internet, Science & Tech. https://www.pewresearch.org/internet/2015/04/09/teens-social-media-technology-2015/
Li, Q., Chan, K. K. Y., Ramos, M. R., Wang, X., Wong, S. Y. S., & Yang, X. (2025). Non-linear relationships and interaction effects between different types of screen time and mental health issues among Hong Kong adolescents. Psychiatry Research Communications, 5(1), 100205.
Liebherr, M., Heyder, A., Brailovskaia, J., Burkardt, T. M., Latrouite, C., Montag, C., & Antons, S. (2025). The Digital Media-use Effects (d-MUsE) Model: A comprehensive framework for exploring/studying functional and dysfunctional effects on adolescent wellbeing. Journal of Behavioral Addictions.
Liu, M., Kamper-DeMarco, K. E., Zhang, J., Xiao, J., Dong, D., & Xue, P. (2022). Time spent on social media and risk of depression in adolescents: a dose–response meta-analysis. International journal of environmental research and public health, 19(9), 5164.
Marquez, J., Taylor, L., Boyle, L., Zhou, W., & De Neve, J.-E. (2024). Child and adolescent wellbeing: Global trends, challenges and opportunities. World Happiness Report. Wellbeing Research Centre, University of Oxford. http://doi.org/10.18724/whr-91b0-ek06
Mayiwar, L., Asutay, E., Tinghög, G., Västfjäll, D., & Barrafrem, K. (2024). Determinants of digital wellbeing. AI & SOCIETY, 1-11.
McLellan, R., & Steward, S. (2015). Measuring children and young people's wellbeing in the school context. Cambridge Journal of Education, 45(3), 307–332. https://doi.org/10.1080/0305764X.2014.889659
McLellan, R. (2019). Enhancing Wellbeing: The Necessity and Implications of a Culturally Grounded Interdisciplinary Conceptualisation. The Psychology of Education Review, 43 (2) 37-47.
Meier, A., & Krause, H. V. (2022). Does passive social media use harm wellbeing? Journal of Media Psychology.
Moose, A., & Bhargawa, R. (2024, April). Youth and young people's happiness. World Economic Forum. https://www.weforum.org/stories/2024/04/youth-young-people-happiness/
Moy, P., Scheufele, D. A., & Holbert, R. L. (1999). Television use and social capital: Testing Putnam's time displacement hypothesis. *Mass Communication and Society*, 2(1-2), 27-45.

Nett, K. (2025). Screen time and educational outcomes of children and adolescents: A complex, multifaceted relationship. NESET ad hoc report. Luxembourg: Publications Office of the European Union.
Odgers, C. L., & Jensen, M. R. (2020). Annual research review: Adolescent mental health in the digital age: Facts, fears, and future directions. Journal of Child Psychology and Psychiatry, 61(3), 336-348.
OECD. (2009a). Multilevel Analyses. In PISA Data Analysis Manual: SAS, Second Edition, OECD Publishing, Paris.
OECD. (2009b). Plausible Values. In PISA Data Analysis Manual: SAS, Second Edition, OECD Publishing, Paris.
OECD. (2018a). Children & Young People's Mental Health in the Digital Age. Shaping the Future. https://www.oecd.org/els/health-systems/Children-and-Young-People-Mental-Health-in-the-
OECD (2023). PISA 2022 Assessment and Analytical Framework, PISA, OECD Publishing, Paris, https://doi.org/10.1787/dfe0bf9c-en.
OECD. (2024). PISA 2022 Technical Report. Retrieved from https://www.oecd.org/publications/pisa-2022-technical-report-01820d6d-en.htm
Ofcom (2020). Children and parents: Media use and attitudes report 2019. Retrieved from https://www.ofcom.org.uk/media-use-and-attitudes/media-habits-children/children-and-parents-media-use-and-attitudes-report-2019/
Ofcom. (2024a). Children and Parents: Media Use and Attitudes Report 2024. Retrieved from https://www.ofcom.org.uk/media-use-and-attitudes/media-habits-children/children-and-parents-media-use-and-attitudes-report-2024/
Ofcom. (2024b). Children and parents: Media use and attitudes report 2024 [Interactive data]. Retrieved from https://www.ofcom.org.uk/media-use-and-attitudes/media-habits-children/children-and-parents-media-use-and-attitudes-report-2024-interactive-data/
Orben, A. (2020). Teenagers, screens and social media: a narrative review of reviews and key studies. Social psychiatry and psychiatric epidemiology, 55(4), 407-414.
Orben, A., Meier, A., Dalgleish, T., & Blakemore, S. J. (2024). Mechanisms linking social media use to adolescent mental health vulnerability. Nature Reviews Psychology, 3(6), 407-423.
Orben, A., Przybylski, A. K., Blakemore, S. J., & Kievit, R. A. (2022). Windows of developmental sensitivity to social media. Nature Communications, 13(1), 1649.
Pan, Q., Lan, M., Tan, C. Y., Tao, S., Liang, Q., & Law, N. (2024). Protective factors contributing to adolescents' multifaceted digital resilience for their wellbeing: A socio-ecological perspective. Computers in Human Behavior, 155, 108164.
Pearson, H. (2025). Do smartphones and social media really harm teens' mental health? Nature. https://doi.org/10.1038/d41586-025-00933-3
Picton, I., Clark, C., Riad, L., & Cole, A. (2022). Insights into Young People's Literacy, Critical Digital Literacy, Online Communication and Wellbeing. A National Literacy Trust Research Report. National Literacy Trust.
Prensky, M. (2009). H. Sapiens Digital: From Digital Immigrants and Digital Natives to Digital Wisdom. Innovate: Journal of Online Education, 5, 3. https://nsuworks.nova.edu/innovate/vol5/iss3/1
Przybylski, A. K., & Weinstein, N. (2017). A large-scale test of the goldilocks hypothesis: quantifying the relations between digital-screen use and the mental wellbeing of adolescents. Psychological science, 28(2), 204-215.
Putnam, R. (2000). Bowling alone: The collapse and revival of American community. New York: Simon & Schuster.
Rivadeneira, M. F., Salvador, C., Araujo, L., Caicedo-Gallardo, J. D., Cóndor, J., Torres-Castillo, A. L., Miranda-Velasco, M. J., Dadaczynski. K. & Okan, O. (2023). Digital health literacy and subjective wellbeing in the context of COVID-19: A cross-sectional study among university students in Ecuador. Frontiers in public health, 10, 1052423.

Salmela-Aro, K., & Motti-Stefanidi, F. (2022). Digital Revolution and Youth: Consequences for Their Development and Education. European Psychologist, 27(2), 73–75. https://doi.org/10.1027/1016-9040/a000483
Sampasa-Kanyinga, H., Chaput, J. P., & Hamilton, H. A. (2019). Social media use, school connectedness, and academic performance among adolescents. The journal of primary prevention, 40, 189-211.
Sanders, T., Parker, P. D., del Pozo-Cruz, B., Noetel, M., & Lonsdale, C. (2019). Type of screen time moderates effects on outcomes in 4013 children: evidence from the Longitudinal Study of Australian Children. International Journal of Behavioral Nutrition and Physical Activity, 16, 1-10.
Santos, R. M. S., Mendes, C. G., Sen Bressani, G. Y., de Alcantara Ventura, S., de Almeida Nogueira, Y. J., de Miranda, D. M., & Romano-Silva, M. A. (2023). The associations between screen time and mental health in adolescents: a systematic review. BMC psychology, 11(1), 1-21.
Scherer, R., Rohatgi, A., & Hatlevik, O. E. (2017). Students' profiles of ICT use: Identification, determinants, and relations to achievement in a computer and information literacy test. Computers in Human Behavior, 70, 486–499. https://doi.org/10.1016/j.chb.2017.01.034
Seligman, M. E. P., & Csikszentmihalyi, M. (2000). Positive psychology: An introduction. American Psychologist, 55(1), 5–14. https://doi.org/10.1037/0003-066X.55.1.5
Senkbeil, M. (2017). Profile computerbezogener Anreizfaktoren: Zusammenhänge mit ICT Literacy und sozialen Herkunftsmerkmalen. Ergebnisse aus der internationalen Schulleistungsstudie ICILS 2013. Psychologie in Erziehung und Unterricht, 64, 138–155.
Senkbeil, M. (2018). Development and validation of the ICT motivation scale for young adolescents. Results of the international school assessment study ICILS 2013 in Germany. Learning and Individual Differences, 67, 167-176.
Senkbeil, M., & Ihme, J. M. (2017). Motivational factors predicting ICT literacy: First evidence on the structure of an ICT motivation inventory. Computers & Education, 108, 145–158. https://doi.org/10.1016/j.compedu.2017.02.003
Senkbeil, M., Ihme, J. M., & Gerick, J. (2016). Motivationale Typen der Computernutzung [Motivational types of computer usage]. In B. Eickelmann, J. Gerick, K. Drossel, & W. Bos (Eds.), ICILS 2013. Vertiefende Analysen zu computer- und informationsbezogenen Kompetenzen von Jugendlichen (pp. 194–219). Waxmann: Münster.
Shaw, D. J., Kaye, L. K., Ngombe, N., Kessler, K., & Pennington, C. R. (2022). It's not what you do, it's the way that you do it: An experimental task delineates among passive, reactive and interactive styles of behaviour on social networking sites. Plos one, 17(12), e0276765.
Sirlin, N., Epstein, Z., Arechar, A. A., & Rand, D. G. (2021). Digital literacy is associated with more discerning accuracy judgments but not sharing intentions. *Harvard Kennedy School (HKS) Misinformation Review*. https://doi.org/10.37016/mr-2020-83.
Sonck, N., & de Haan, J. (2013). How the internet skills of European 11-to 16-year-olds mediate between online risk and harm. Journal of Children and Media, 7(1), 79-95.
Su, W., Han, X., Yu, H., Wu, Y., & Potenza, M. N. (2020). Do men become addicted to internet gaming and women to social media? A meta-analysis examining gender-related differences in specific internet addiction. Computers in Human Behavior, 113, 106480.
Staksrud, E., Ólafsson, K., & Livingstone, S. (2013). Does the use of social networking sites increase children's risk of harm?. Computers in human behavior, 29(1), 40-50.
Stavropoulos, V., Motti-Stefanidi, F., & Griffiths, M. D. (2022). Risks and Opportunities for Youth in the Digital Era: A Cyber-Developmental Approach to Mental Health. European Psychologist, 27(2), 86–101. https://doi.org/10.1027/1016-9040/a000451

Stiglic, N., & Viner, R. M. (2019). Effects of screentime on the health and wellbeing of children and adolescents: A systematic review of reviews. BMJ Open, 9(1), e023191. https://doi.org/10.1136/bmjopen-2018-023191
Svensson, R., Johnson, B., & Olsson, A. (2022). Does gender matter? The association between different digital media activities and adolescent wellbeing. BMC public health, 22(1), 273.
Tang, S., Werner-Seidler, A., Torok, M., Mackinnon, A. J., & Christensen, H. (2021). The relationship between screen time and mental health in young people: A systematic review of longitudinal studies. Clinical psychology review, 86, 102021.
The Children's Society. (2024). The Good Childhood Report 2024. https://www.childrenssociety.org.uk/information/professionals/resources/good-childhood-report-2024
Twenge, J. M., & Farley, E. (2021). Not all screen time is created equal: associations with mental health vary by activity and gender. *Social psychiatry and psychiatric epidemiology*, *56*, 207-217.
Twenge, J. M., Haidt, J., Joiner, T. E., & Campbell, W. K. (2020). Underestimating digital media harm. Nature Human Behaviour, 4(4), 346-348.
Twenge, J. M., Haidt, J., Lozano, J., & Cummins, K. M. (2022). Specification curve analysis shows that social media use is linked to poor mental health, especially among girls. Acta psychologica, 224, 103512.
Twenge, J. M., & Hamilton, J. L. (2022). Linear correlation is insufficient as the sole measure of associations: the case of technology use and mental health. Acta Psychologica, 229, 103696.
Twenge, J. M., & Martin, G. N. (2020). Gender differences in associations between digital media use and psychological wellbeing: Evidence from three large datasets. Journal of adolescence, 79, 91-102.
UNESCO Institute for Statistics (n.d.). Information and communication technologies (ICT). https://uis.unesco.org/en/glossary-term/information-and-communication-technologies-ict
Valkenburg, P. M., Beyens, I., Pouwels, J. L., van Driel, I. I., & Keijsers, L. (2022). Social media browsing and adolescent wellbeing: Challenging the “Passive Social Media Use Hypothesis”. Journal of Computer-Mediated Communication, 27(1), zmab015.
Vandoninck, S., d'Haenens, L., & Roe, K. (2013). Online risks: Coping strategies of less resilient children and teenagers across Europe. Journal of children and media, 7(1), 60-78.
Verduyn, P., Gugushvili, N., & Kross, E. (2022). Do social networking sites influence wellbeing? The extended active-passive model. Current Directions in Psychological Science, 31(1), 62-68.
Verduyn, P., Lee, D. S., Park, J., Shablack, H., Orvell, A., Bayer, J., Ybarra, O., Jonides, J., & Kross, E. (2015). Passive Facebook usage undermines affective wellbeing: Experimental and longitudinal evidence. Journal of Experimental Psychology: General, 144(2), 480–488. https://doi.org/10.1037/xge0000057
Vissenberg, J., De Coninck, D., Mascheroni, G., Joris, W., & d’Haenens, L. (2023). Digital skills and digital knowledge as buffers against online mis/disinformation? Findings from a survey study among young people in Europe. Social Media+ Society, 9(4), 20563051231207859.
Vissenberg, J., d’Haenens, L., & Livingstone, S. (2022). Digital Literacy and Online Resilience as Facilitators of Young People’s Wellbeing?: A Systematic Review. European Psychologist, 27(2), 76–85. https://doi.org/10.1027/1016-9040/a000478
Xiao, F., & Sun, L. (2022). Profiles of student ICT use and their relations to background, motivational factors, and academic achievement. Journal of Research on Technology in Education, 54(3), 456-472.
Žanić, M., Miletić, G. M., & Milak, M. (2023). The impact of digital technology use on youth sense of community: a case study from Croatia. Journal of Community Positive Practices, (1), 67-83.

9. Appendices

Table 12. Weighted observation counts for each digital activity.

Digital activity	Weighted count (no missing)	% missing (out of 50000)
Weekday		
Play video games	41996	16
Browse social networks	41671	17
Browse Internet for fun	41753	16
Access practical information	41569	17
Share digital content	41691	17
Access informational materials	41763	16
Weekend		
Play video games	40629	19
Browse social networks	40330	19
Browse Internet for fun	40356	19
Access practical information	40269	19
Share digital content	40415	19
Access informational materials	40307	19

Table 13. PISA survey items included in the wellbeing outcomes analysed.

PISA IRT-derived variable	PISA item ID	Item wording	Reverse coded?
BELONG	ST034Q01TA	Agree/disagree: I feel like an outsider (or left out of things) at school.	
	ST034Q02TA	I make friends easily at school.	Yes
	ST034Q03TA	I feel like I belong at school.	Yes
	ST034Q04TA	I feel awkward and out of place in my school.	
	ST034Q05TA	Other students seem to like me.	Yes
	ST034Q06TA	I feel lonely at school.	
FEELSAFE	ST265Q01JA	Agree/disagree: I feel safe on my way to school.	Yes
	ST265Q02JA	I feel safe on my way home from school.	Yes
	ST265Q03JA	I feel safe in my classrooms at school.	Yes
	ST265Q04JA	I feel safe at other places at school (e.g. hallway, cafeteria, restroom).	Yes
LIFESAT	WB155Q01HA	How satisfied are you with each of the following: Your health	
	WB155Q02HA	The way that you look	
	WB155Q03HA	What you learn at school	
	WB155Q04HA	The friends you have	
	WB155Q05HA	The neighbourhood you live in	
	WB155Q06HA	All the things you have	
	WB155Q07HA	How you use your time	
	WB155Q08HA	Your relationship with your parents/guardians	
	WB155Q09HA	Your relationship with your teachers	
	WB155Q10HA	Your life at school	
EXPWB	WB178Q01HA1	Yes/no: Overall, did you feel that you accomplished something yesterday?	Yes
	WB178Q02HA1	Were you treated with respect all day yesterday?	Yes
	WB178Q03HA1	Did you smile or laugh a lot yesterday?	Yes
	WB178Q04HA1	Did you learn or do something interesting yesterday?	Yes
	WB178Q05HA1	Did you have enough energy to get things done yesterday?	Yes
	WB178Q06HA1	Overall, are you satisfied with how you spent your time yesterday?	Yes
STRESAGR	ST345Q01JA	Agree/disagree: I get nervous easily.	Yes
	ST345Q02JA	I am more relaxed than most people I know.	
	ST345Q03JA	I worry about many things.	Yes

PISA IRT-derived variable	PISA item ID	Item wording	Reverse coded?
	ST345Q04JA	I panic easily.	Yes
	ST345Q05JA	I am able to work under pressure.	
	ST345Q06JA	I remain calm under stress.	
	ST345Q07JA	I feel nervous about approaching exams.	Yes
	ST345Q08JA	I can recover quickly after something bad has happened.	
	ST345Q09JA	I handle stress well.	
	ST345Q10JA	I am afraid of many things.	Yes
PSYCHSYM	WB154Q01HA	In the past six months, how often have you had the following: Headache	
	WB154Q02HA	Stomach pain	
	WB154Q03HA	Back pain	
	WB154Q04HA	Feeling depressed	
	WB154Q05HA	Irritability or bad temper	
	WB154Q06HA	Feeling nervous	
	WB154Q07HA	Difficulties in getting to sleep	
	WB154Q08HA	Feeling dizzy	
	WB154Q09HA	Feeling anxious	
BODYIMA	WB153Q01HA	Thinking about yourself, how much do you agree: I like my look just the way it is.	
	WB153Q02HA	I consider myself to be attractive.	
	WB153Q03HA	I am not concerned about my weight.	
	WB153Q04HA	I like my body.	
	WB153Q05HA	I like the way my clothes fit me.	

Table 14. List of control variables included in the regression analyses.

Variable name	PISA variable name	Description	Value type
AGE	AGE	Students' age.	Continuous
Grade	ST001D01T	Students' international grade as derived by PISA with categories from grades 7 to 12 and ungraded.	Categorical
Ability	PV1MATH-PV10MATH	Students' ability as approximated by their math performance provided by PISA as plausible values. PV1MATH was used in the main analyses, and all other ability measures were used in the sensitivity analyses.	Continuous
ESCSG	ESCS	PISA's index of economic, social and cultural status derived based on highest parental occupation status, highest parental education, and home possessions. These values were used to categorise students into ten roughly equally sized groups (unweighted), representing students from family with the lowest levels of status (a value of 1) to the highest (a value of 10). A "missing" category was created for students with missing data which included all the students from Costa Rica.	Categorical
FAMSUPG	FAMSUP	Students' rating of the frequency someone in their family engaged in activities indicative of family support. High values indicate students have high levels of family support outside of schools. These values were used to categorise students into three roughly equally sized groups (unweighted), representing students from family with "High", "Medium" or "Low" levels of support. A "missing" category was created for students with missing data, which included all the students from Costs Rica.	Categorical
SKIP	SKIPPING	An indication on whether students had skipped classes two weeks prior to their PISA test. Values recoded to three categories: "skipped", "no skip", "missing".	Categorical
Gender	ST004D01T	Students' gender with two categories: male and female students.	Categorical
WORKP	WORKPAY	The frequency students worked for pay before/after schools during a typical school week. Values range from 0 to 10 with 0 indicating no work, 1 indicating once per week, …, and 10 indicating at least 10 times per school week. A "missing" category was also created for students with missing data.	Categorical
WORKH	WORKHOME	The frequency students worked in the household or caring for a family member before/after schools during a typical school week. Values range from 0 to 10 with 0 indicating no work, 1 indicating once per week, ..., and 10 indicating at least 10 times per school week. A "missing" category was also created for students with missing data.	Categorical
DFREN	WB158Q01HA	The number of days students spent with their friends right after school. Values recoded to 0 to 6, with 0 representing 0 days, 6 representing 6 days. A "missing" category was created for students with missing data.	Categorical
NFREN	WB156Q01HA	Students' answer to the number of close friends they have at time of survey. These values were used to categorise students into three broadly equally sized groups (unweighted), representing	Categorical

		students with “High”, “Medium” or “Low” number of close friends. A “missing” category was also created for students with missing data.	
RELATSTG	RELATST	Students’ agreement with six statements relating to their relationships with their teachers, e.g., “The teachers at my school are interested in students' wellbeing”. High values indicate students feel that they have a good relationship with their teachers. These values were used to categorise students into three roughly equally sized groups (unweighted), representing students with “High”, “Medium” or “Low” quality of relationship with their teachers. A “missing” category was also created for students with missing data.	Categorical
BULLIEDG	BULLIED	The frequency of a student being bullied at school in the past 12 months as indicated in statements, e.g., “I was in a physical fight on school property”. High values indicate high frequency of being bullied at school. These values were used to categorise students into three roughly equally sized groups (unweighted), representing students with “High”, “Medium” or “Low” frequency of being bullied at schools. A “missing” category was also created for students with missing data.	Categorical
EXER	EXERPRAC	Students’ answers on how many days during a typical school week they exercised or practised a sport before going to school and/or after leaving school. Values range from 0 to 10, with 0 representing no exercise or sports. 1 representing exercising once per week, …, 10 representing 10 or more times exercise or sports per school week. A “missing” category was also created for students with missing data.	Categorical
BMIG	STUBMI	A student’s Body Mass Index. These values were used to categorise students into three equally sized groups, representing students with “High”, “Medium” or “Low” BMI. A “Missing” category was also created for students with missing data. This variable was only used in regression models with body image as the outcome variable.	Categorical
STRATIOG	STRATIO	Student-teacher ratio in the school the student was studying at time of survey, as a proxy for school resources. These values were used to categorise students into three roughly equally sized groups (unweighted), representing students from schools with “High”, “Medium” or “Low” student-teacher ratio. A “missing” category was also created for students with missing data.	Categorical
SCHTYPEG	SCHLTYPE	School type as classified by PISA based on school type and sources of fundings reported by school principal; three categories: private independent, private government-dependent and public. A “missing” category was also created for students with missing data.	Categorical
NEGSCH	NEGSCLIM	The extent of behavioural issues contributing to negative climate in the school the student was studying at time of survey. Using values provided by PISA, schools were categorised into three roughly equally sized categories (unweighted) representing groups of schools where problematic behaviours has negatively influenced school climate to a “Severe”, “Medium” or a “Low” extent. A missing category was also created which mainly consisted of Spanish schools since the survey items used to construct this scale was not administered in Spain.	Categorical

CSRATIOG	RATCMP1	Computer-student ratio in the school the student was attending at time of survey, as a proxy for school resources. The ratio was calculated by PISA by dividing the number of desktop or laptop available for educational purpose by the total number of 15-year-old students in the school. These values were used to categorise students into three equally sized groups, representing students from schools with “High”, “Medium” or “Low” computer-student ratio. A “missing” category was also created for students with missing data.	Categorical

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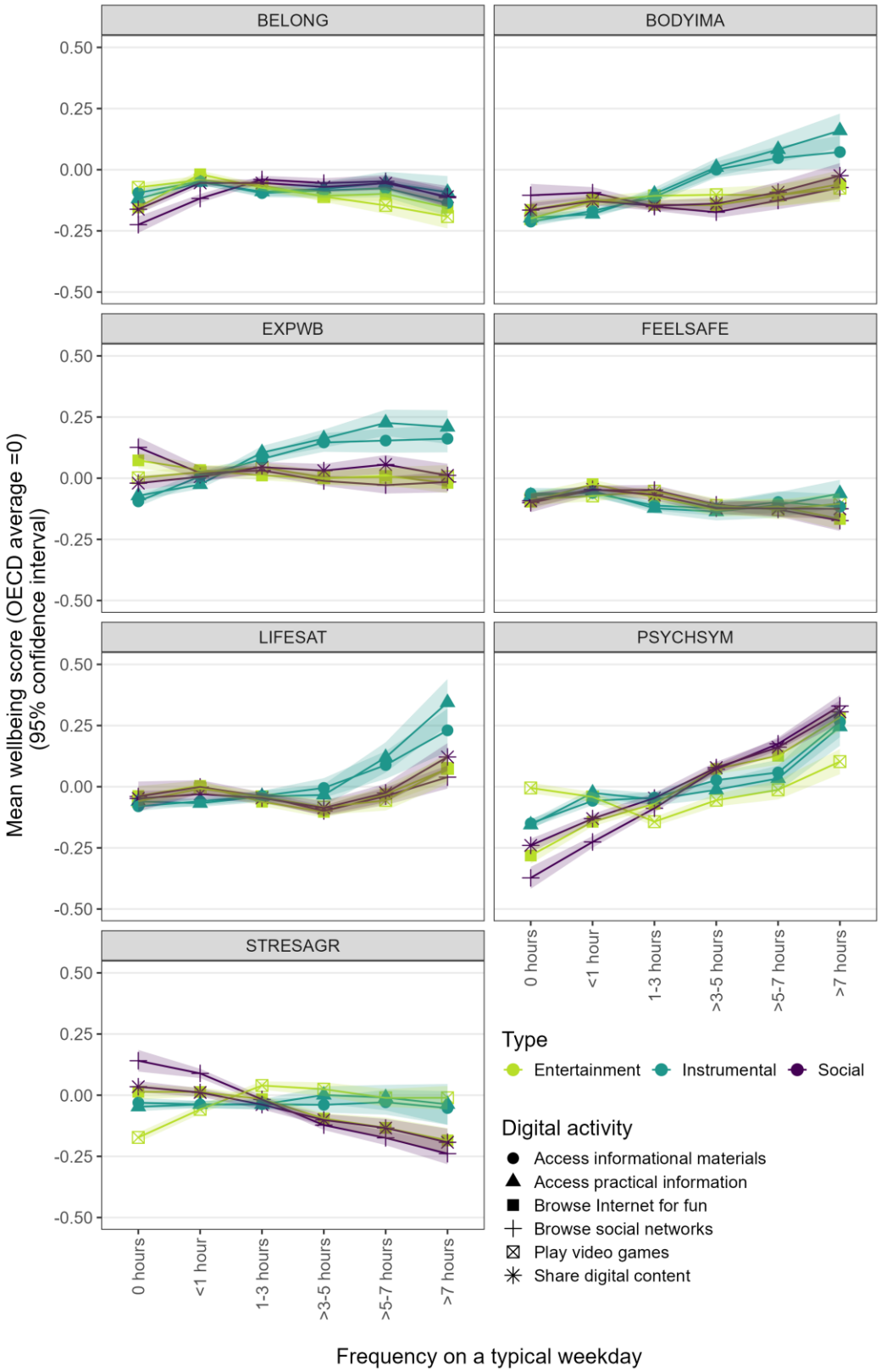

Figure 21. Mean wellbeing score (with 95% confidence interval) by time spent on each digital activity on a typical weekday.

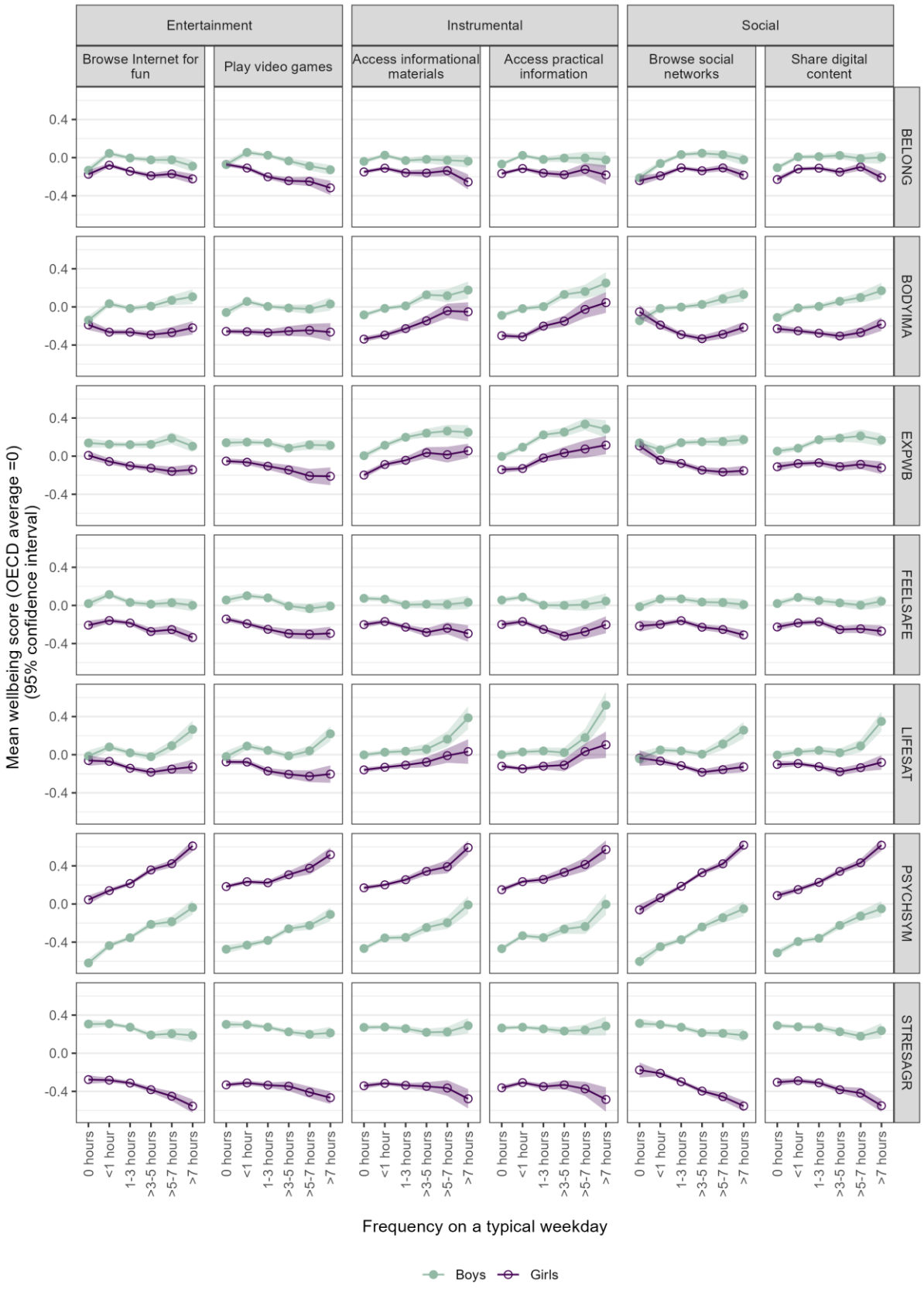

Figure 22. Mean wellbeing score (with 95% confidence interval) by time spent on each digital activity on a typical weekday and by gender.

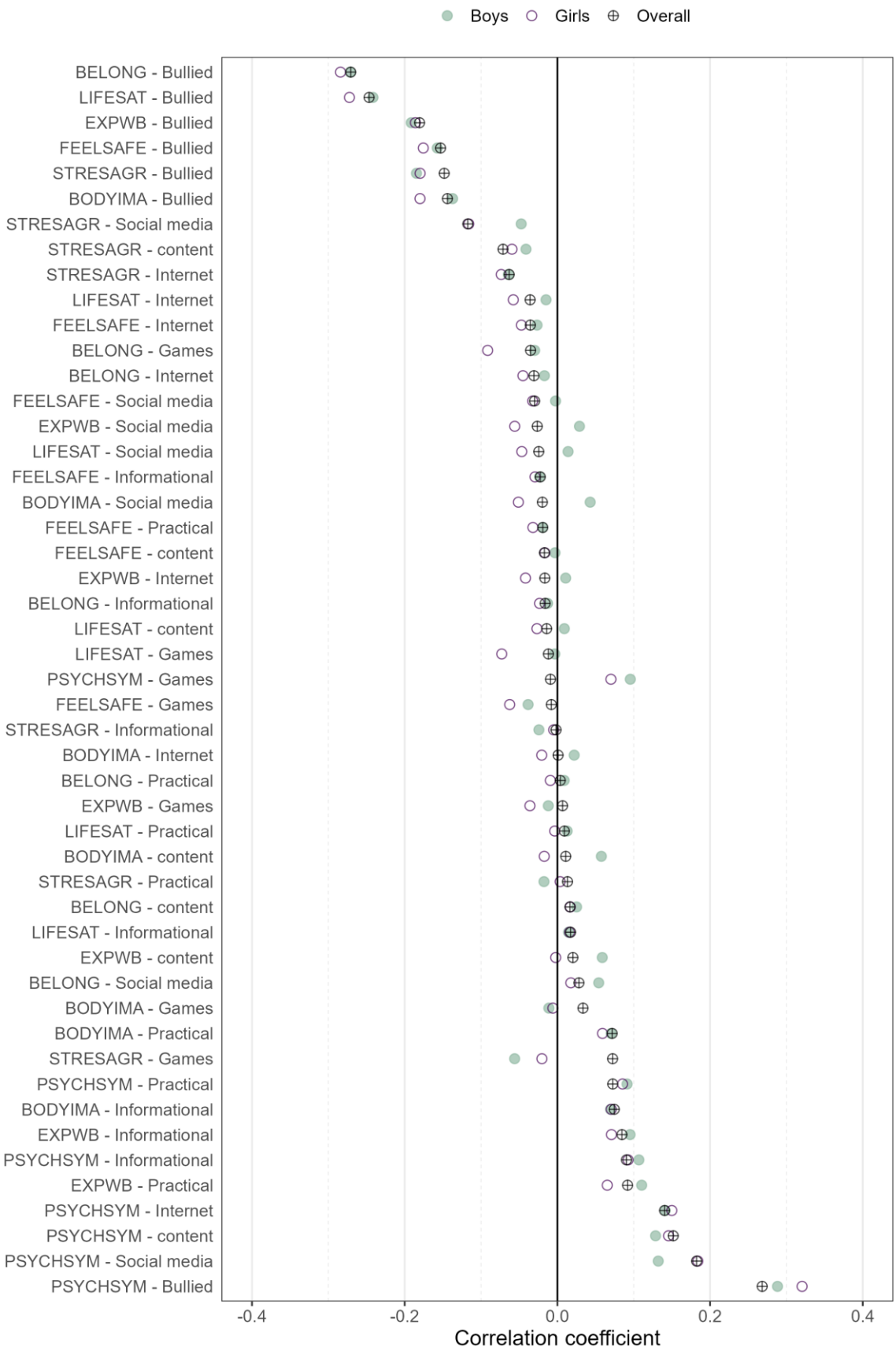

Figure 23. Spearman's rank correlation coefficient between wellbeing score and daily digital time spent on a typical weekday, and between wellbeing score and being bullied.

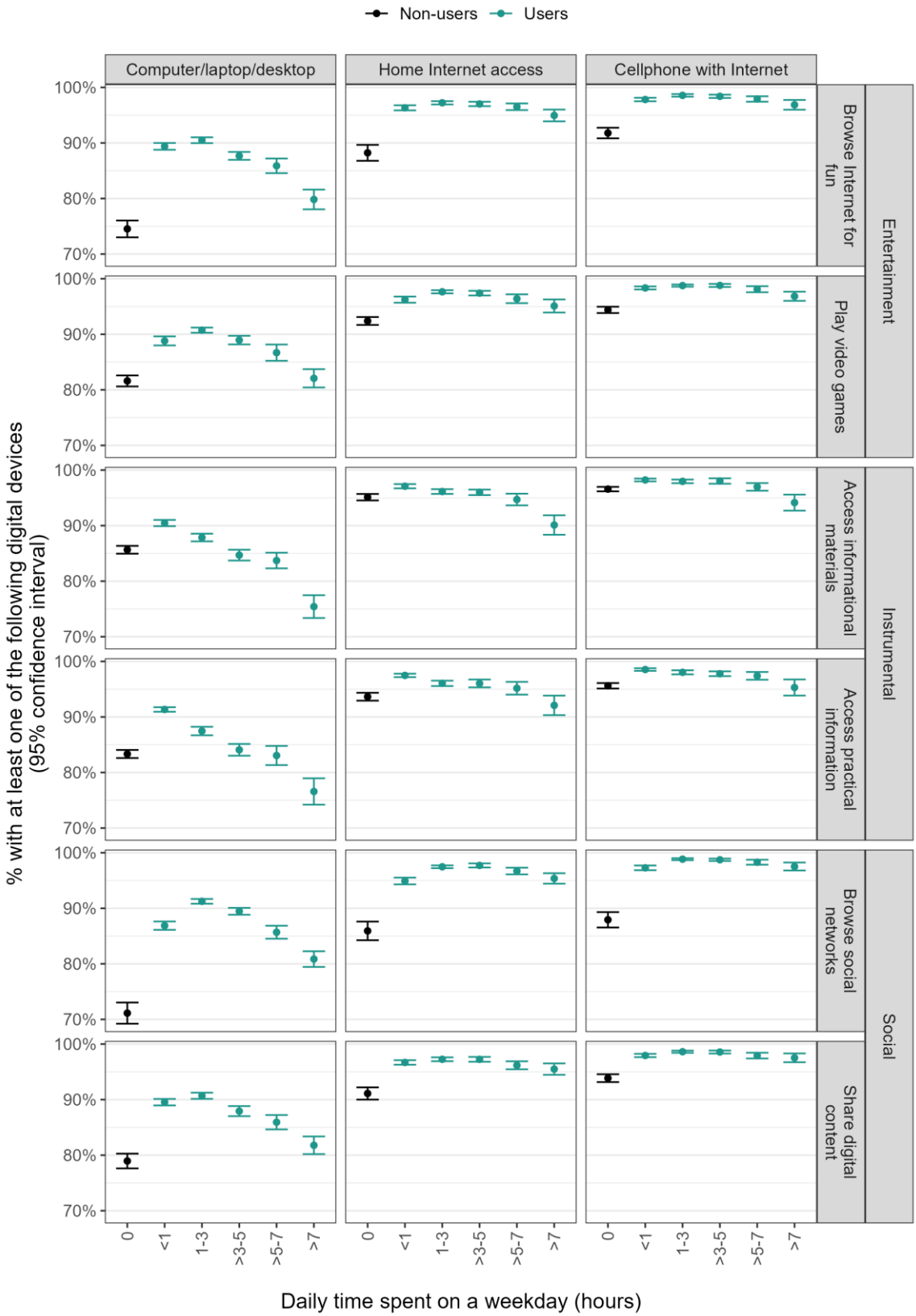

Figure 24. Percentage of students (after weighting) within each time spent category who reported having at least a computer (or similar devices), home Internet access (excluding through mobile phone) and a cellphone with Internet connectivity, by time spent on a typical **weekday** on each digital activity.

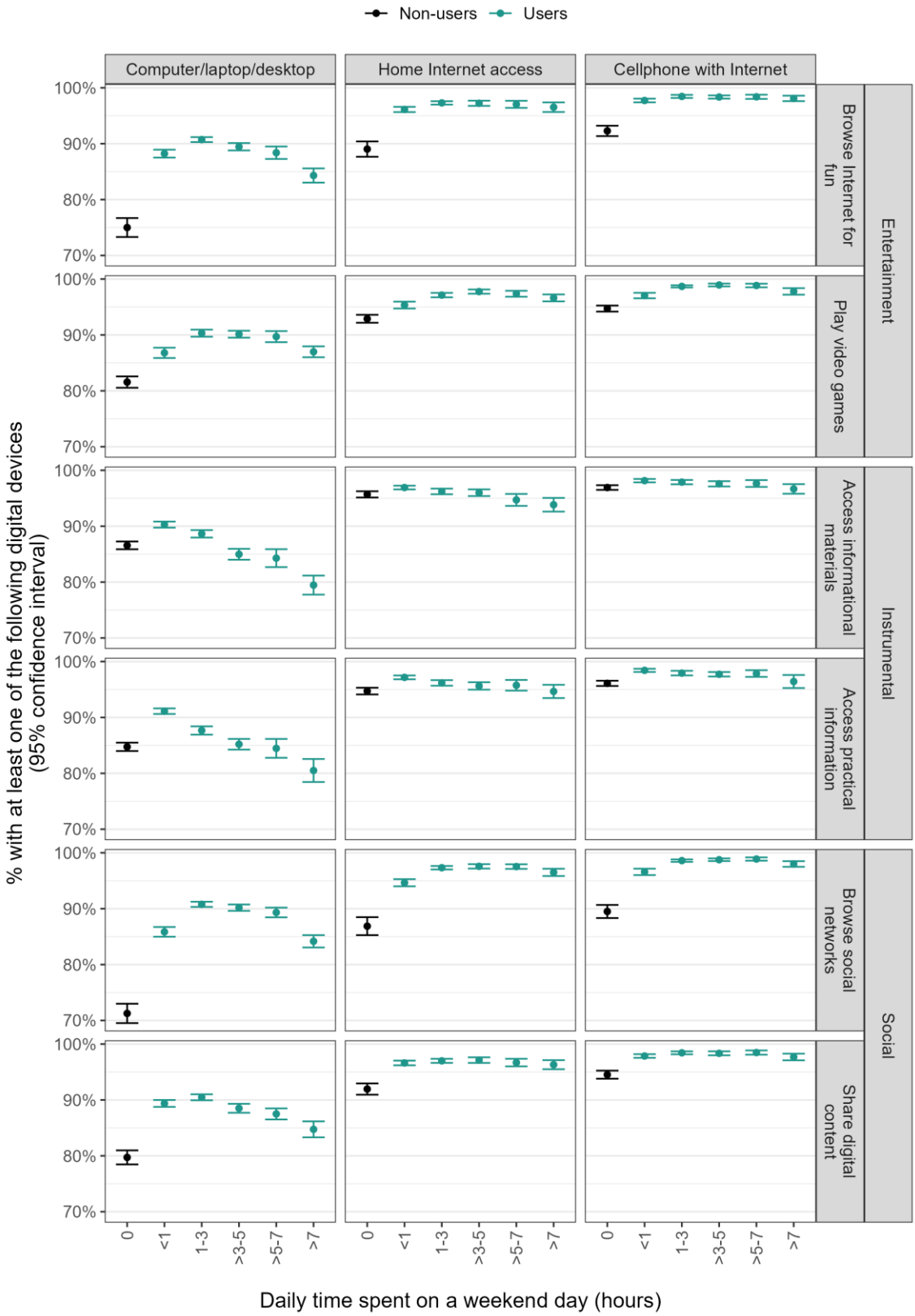

Figure 25. Percentage of students (after weighting) within each time spent category who reported having at least a computer (or similar devices), home Internet access (excluding through mobile phone) and a cellphone with Internet connectivity, by time spent on a typical **weekend day** on each digital activity.

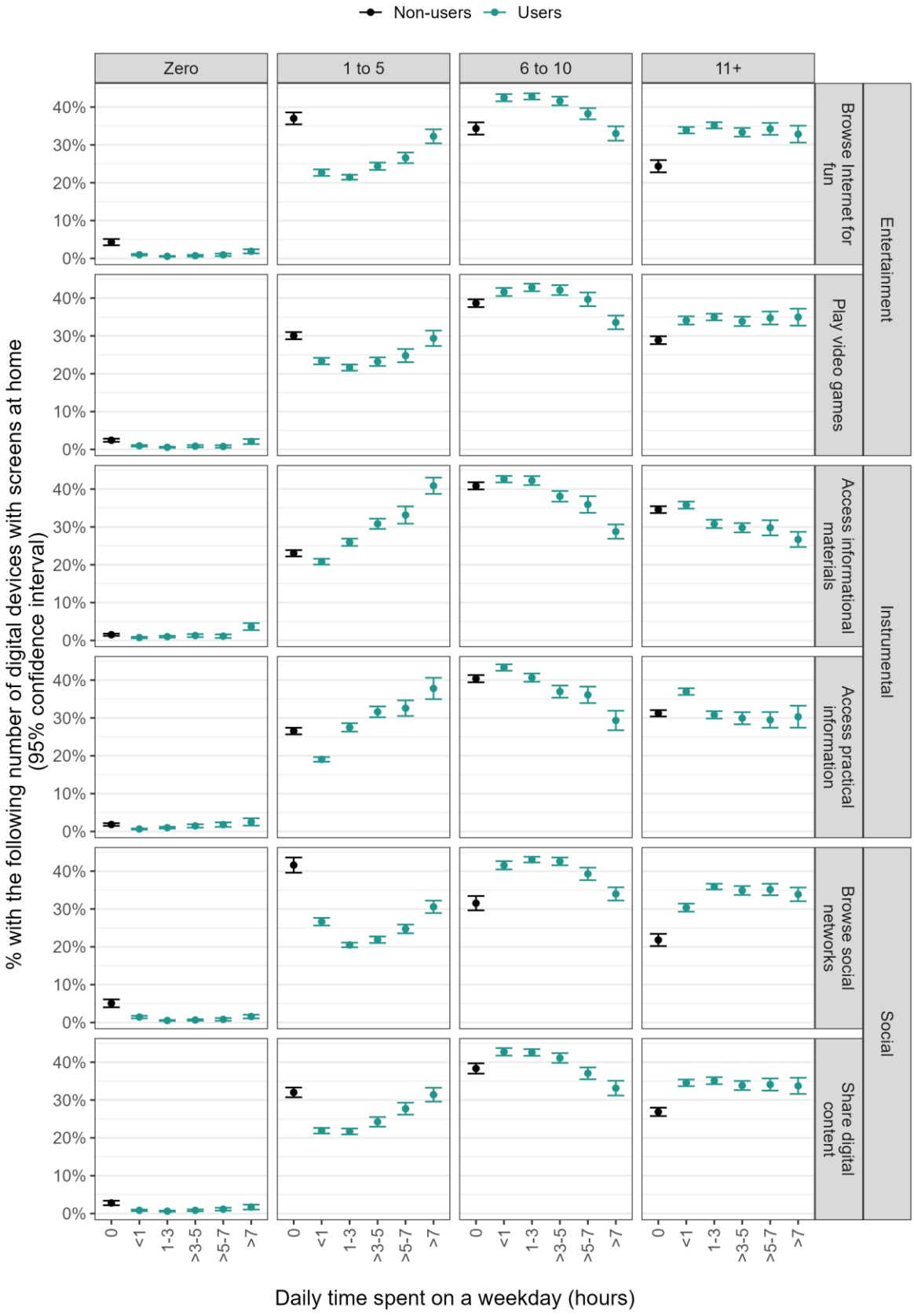

Figure 26. Percentage of students (after weighting) within each time spent category with zero, one to five, six to ten or eleven or more digital devices with screens at home, by time spent on each digital activity on a typical **weekday**.

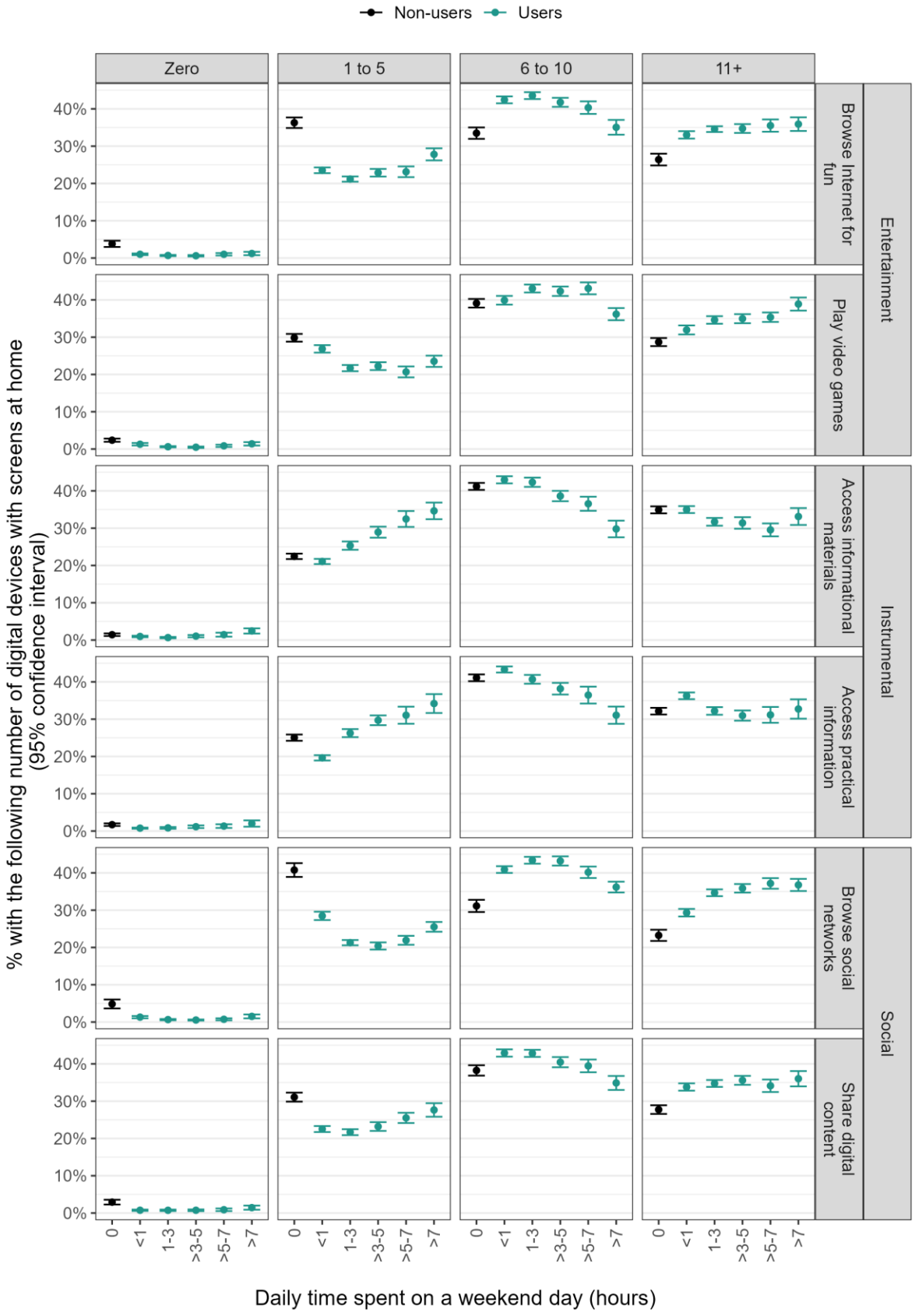

Figure 27. Percentage of students (after weighting) within each time spent category with zero, one to five, six to ten or eleven or more digital devices with screens at home, by time spent on each digital activity on a typical **weekend** day.