University of Bern
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Digital Technology Engagement During Childhood and Adolescence and the Reproduction of Educational Inequalities

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Abstract

This dissertation compiles four empirical studies that examine how children's and adolescents' engagement with contemporary digital technologies relates to the reproduction of socioeconomic and gender inequalities in education. Focusing on out-of-school engagement with digital technology and the role of parents, the empirical studies investigate how established mechanisms of social reproduction, like the intergenerational transmission of cultural capital, are transformed in the digital age.

The first study investigates the relationship between parental socioeconomic background and children's digital technology use in the Swiss context. Through a typological approach, the study reveals both a continuation of use patterns from the television era and the emergence of a new type of socioeconomic advantage based on the possession of digital (cultural) capital. The second study takes a comparative approach and examines cross-country differences in the association between socioeconomic background and adolescents' use of digital technologies for educational and recreational purposes. The results indicate that more universal access to ICT (information and communication technologies) at home and greater ICT integration in schools may exacerbate rather than mitigate socioeconomic inequalities in adolescent digital engagement. In contrast to mere digitalization efforts, educational reforms appear as a promising pathway to address digital inequalities in adolescence. The third study addresses the time-displacement hypothesis, analyzing how early adolescents' time allocation changes after they acquire their first personal mobile phone. Using longitudinal time-use data and a difference-in-differences design, the study demonstrates that mobile devices mostly compete with legacy media like television rather than displacing developmentally beneficial activities such as reading, physical activity, or sleep. The fourth study examines how Swiss adolescents' ICT interest and self-concept influence their selection into dual vocational education and training (VET) programs. Results indicate that ICT interest and self-concept contribute to gender differences in ICT-related career pathways.

By bridging the digital divide and educational inequality literatures, this dissertation advances sociological understanding of the role of digital technology engagement in the reproduction of educational inequalities. Even as disparities in ICT access diminish, inequalities in children's and adolescents' digital engagement remain and continue to produce unequal educational outcomes, as traditional forms of cultural capital interact with digital ones.

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Introduction

Point of departure

Since the 1990s, digital technologies have become deeply embedded in many aspects of daily life in industrialized societies (Allmann & Blank, 2021). Today, most children and adolescents grow up being constantly surrounded by digital technologies. In schools, digital tools are regularly integrated across subjects to prepare students for a future shaped by ongoing digitalization (Livingstone & Blum-Ross, 2020b). Beyond the classroom, digital engagement has become a default mode of spending time for many adolescents, ranging from educational activities to gaming, social interaction, media consumption, or creative expression (Ito et al., 2010). Much like the advent of the telephone, radio and television, the rise of digital technology has sparked concerns among parents, educators, and policymakers about its impact on the younger generation, a cyclic phenomenon known as a "moral panic" (Helsper, 2021, p. 132). Currently, fervent public debates focus on the possible links between mobile device and social media use and declines in adolescent mental health (Haidt, 2024) and academic performance (Schleicher, 2023). While many fears about digital technologies are likely overstated (Selwyn, 2011, pp. 40–41), the need for rigorous, evidence-based research is more urgent than ever. Recent policy measures, including Australia's federal ban on social media use for individuals under 16 (Archer, 2025), underscore the critical importance of robust scientific knowledge to inform public discourse and bring about effective decision-making.

The present dissertation adopts a sociological perspective on the topic of children's and adolescents' engagement with digital technologies. It begins with the premise that such engagement is heterogeneous and shaped by broader social structures and inequalities. Research on the "digital divide" highlights that systematic differences in terms of how individuals or groups use digital technologies remain even as access inequalities diminish within many countries (van Deursen & van Dijk, 2014). What remains less well understood, however, is how differences in digital engagement (digital inequalities) among children and adolescents translate into unequal life chances. In particular, there is limited research on how digital inequalities in childhood and adolescence intersect with and potentially reinforce educational inequalities. Do more privileged parents familiarize their children with digital technologies from an early age on in order to support their learning and digital skills, contributing to the reproduction of social inequalities (Bourdieu & Passeron, 1990;

Livingstone & Blum-Ross, 2020b)? Does extensive mobile phone use contribute to disadvantaged adolescents falling behind in terms of academic performance (Beland & Murphy, 2016)? How can policymakers and educators prevent “Matthew effects”, where previously advantaged families (the “usual suspects”; Selwyn, 2011) are better equipped to convert digital opportunities into further educational advantages for their children, leaving others behind (Helsper, 2021)? Why are female adolescents still much less likely to aspire for careers in information and communication technology (ICT), although their computational skills are similar to those of male adolescents (Fraillon, 2024), and what can be done about it? To date, sociological research has only partially addressed these important questions. In particular, research on digital inequalities remains largely disconnected from the educational inequality literature (Becker, 2023). The present dissertation aims to contribute to a better understanding of the role of children’s and adolescents’ digital engagement in the reproduction of educational inequalities by bridging these two separate strands of research.

Conceptual background

Socioeconomic and gender inequalities in education

Educational inequality refers to the unequal distribution of educational opportunities and educational outcomes according to ascribed characteristics, such as socioeconomic background or gender. Because education is a key determinant of life chances, including resources, power, and prestige (Barone, 2019), it is a core aim of educational sociology to understand the mechanisms through which educational inequalities arise and through which they are perpetuated (Becker, 2019). Despite educational expansion, educational attainment (defined as the highest level of formal education an individual has completed) remains strongly linked to socioeconomic background (Erikson, 2019; Shavit & Blossfeld, 1993). A key source of socioeconomic inequalities in education are disparities in children’s and adolescents’ academic achievement, which ultimately translate into unequal educational attainment. These disparities are often referred to as “primary effects” of social origin, in contrast to “secondary effects”, which describe socioeconomic disparities in the choice of different educational pathways net of disparities in academic achievement (Boudon, 1974). Disparities in academic achievement emerge already in early childhood, before children enter primary school, and increase throughout childhood and adolescence (Skopek & Passaretta, 2021).

Several well-established mechanisms contribute to the emergence of achievement disparities by socioeconomic background: First, family investment models describe how higher-SES parents (parents with higher socioeconomic status) possess more resources they can invest into their children’s development. These investments include the provision of learning materials, parental support with learning, general living standards, and residing in advantaged neighborhoods (Conger & Donnellan, 2007). Together, they contribute to socioeconomic differences in terms of children's cognitive and noncognitive skills and in terms of their academic performance (e.g., Biedinger, 2011). In a similar way, theories of cultural capital (Bourdieu & Passeron, 1990) emphasize the importance of parental reading behaviors, parental fostering of cognitively enriching cultural activities (e.g., visiting museums), the availability of cognitively stimulating objects in the home, and norms, aspirations and beliefs regarding the importance of education (Barone, 2006). As more advantaged parents possess more of this cultural capital, they are better able to positively influence their children's academic achievement (Jæger & Breen, 2016). Second, the family stress model emphasizes the role of economic pressure creating greater psychological stress for lower-SES families. This stress results in a greater risk for intra-family conflict, behavioral problems, and overall less involved parenting practices, which can all negatively affect children's development (Masarik & Conger, 2017). Third, in addition to environmental influences, achievement disparities also result to some extent from genetic inheritance and gene-environment interactions (Skopek & Passaretta, 2021; Uchikoshi & Conley, 2021). Finally, the role of schooling in the emergence of socioeconomic achievement disparities is still intensively debated (Skopek et al., 2024). While one influential strand of literature emphasizes how schools exacerbate inequalities, e.g., through tracking and unequal learning opportunities (Shavit & Blossfeld, 1993), or rewards to students' familiarity with highbrow culture (Bourdieu & Passeron, 1990), another strand of literature describes how schools function as equalizers (Coleman, 1966; Downey et al., 2004). The latter perspective emphasizes that inequalities resulting from schooling are generally smaller than inequalities resulting from time students spend outside of school (Skopek et al., 2024).

In contrast to educational inequalities by socioeconomic background, gender inequalities in education today remain mostly with regard to horizontal differences, that is, differences in the distribution of males and females across study programs and fields (Kriesi & Imdorf, 2019). Gender segregation can be observed on the level of secondary education, e.g., regarding the choice of mathematics and science classes or the selection into different vocational education and training (VET) programs (Kriesi & Imdorf, 2019), and on the tertiary level (Mann & DiPrete, 2013), e.g., regarding the selection into STEM fields (Science, Technology, Engineering and Mathematics). Although not inherently hierarchical, horizontal gender segregation in education translates into unequal life chances for women, as more technical occupations and occupations in STEM fields—where women are underrepresented—tend to offer higher wages. The mechanisms leading to this kind of educational gender segregation are highly complex. It is well-established that cultural environments play a crucial role in shaping gendered educational choices (Kriesi & Imdorf, 2019). Gender stereotypes are internalized through socialization processes, and lead to the emergence of gendered values, interests, and ability beliefs among children and adolescents, and to the perception of certain fields or occupations as gender-typical (Combet, 2024). Parents, peers, and gatekeepers (e.g., employers) play an important role in these socialization processes, as they often reinforce existing norms and stereotypes (Levanon & Grusky, 2016). The extent of gender segregation in education is further influenced by macro-level structures. For example, in countries with dual VET systems (e.g., Germany, Switzerland), gender segregation in secondary education is typically higher. One explanation is that a high differentiation of educational programs, which is typical for educational systems in which VET plays an important role, offers greater opportunities for gender-expressive choices (Charles & Bradley, 2009).

Inequalities in digital technology engagement

In light of the growing penetration of digital technologies into both educational institutions and students' leisure time, scholars have increasingly turned their attention to the implications of this trend for educational inequality. At the center of much research in this area are the questions of whether digital technologies affect the mechanisms through which educational inequalities emerge (e.g., Notten & Becker, 2017), and whether they have the potential to exacerbate or mitigate the level of inequalities in educational outcomes (Attewell & Battle, 1999). One important strand of research in this area investigates how the integration of technologies in educational institutions like schools affects students' learning processes and outcomes (Selwyn, 2011). Recently, results from the OECD's PISA study have triggered a worldwide debate on the distracting potential of students' private digital media use in the classroom, particularly for those students who are disadvantaged or struggle academically (Beland & Murphy, 2016; Schleicher, 2023). Irrespective of the significance of these debates, the focus of this dissertation is on children's and adolescents' digital engagement outside of school. Here, digital engagement refers to how children and adolescents use digital technologies (synonymous with information and communication technologies or ICT) in private settings (e.g., at home), and to their attitudes and perceived competence in using them (i.e., levels of enjoyment and self-perceived abilities).

The focus on out-of-school digital engagement shifts the theoretical emphasis towards the role of families as the main institution of out-of-school socialization, and specifically towards the role of parents. The main goal of this dissertation is to achieve a better understanding of the role of children's and adolescents' out-of-school digital engagement in the causal chain linking ascribed characteristics (like socioeconomic background, gender) and educational outcomes. We can analytically break this down into two sub-questions, which are elaborated on in the following sections: First, how do socioeconomic background and gender affect children's and adolescents' engagement with digital technologies (determinants of digital engagement)? And second, how does this digital engagement affect their educational outcomes (effects of digital engagement)?

Previous research on the determinants of digital engagement has been largely shaped by the concept of the "digital divide". According to van Dijk (2020, p. 1), the digital divide refers to "a division between people who have access to and use of digital media and those who do not". Access encompasses the availability and quality of physical and material resources, such as digital devices and Internet connectivity. Systematic disparities in access are typically referred to as the "first-level" digital divide. In contrast, the "second-level" digital divide captures disparities in the use of digital technologies that are not solely attributable to a lack of access (Attewell, 2001). The second-level digital divide also includes differences in the digital skills necessary for effective technology use (Hargittai, 2002). Over two decades of research on the second-level digital divide has demonstrated that individuals' engagement with digital technologies varies according to their social position—such as age, socioeconomic status, gender, and social networks—and that certain disparities in use persist even when opportunities to access the Internet become nearly universal (van Dijk, 2020).

From the very beginning of digital divide research, sociologists have been interested in the question of how digital divides affect educational inequalities. Many policymakers in the early 21st century had hoped that providing disadvantaged children with access to computers would overcome previously existing barriers to knowledge, certificates, and training, making them benefit disproportionately in terms of their academic performance (Attewell, 2001). More than two decades later, it is quite safe to say that this hope was not fulfilled. Although in many countries, access to the internet and computers at home and at school is near-universal today, educational inequalities are persistent, and in many cases, on the rise (Chmielewski, 2019; Schleicher, 2023). Moreover, regarding children and adolescents, the second-level digital divide is proving to be much more persistent than the first. Across many countries, adolescents from less advantaged backgrounds use digital technologies less for educational and information purposes (Becker, 2023; Ma et al., 2019; Notten et al., 2009; van de Werfhorst et al., 2022; Weber & Becker, 2019), and their digital skills are systematically lower, making them less able to benefit academically from their digital engagement (Helsper, 2012).

A fundamental reason why the second-level digital divide is so persistent, not least among children and adolescents, is that it represents a social and not merely a technological problem (Selwyn, 2004). How intensely, how confidently, and for which purposes digital technologies are used depends on a multitude of factors, including social, cultural, mental, material and time resources, skills, motivations and attitudes (van Dijk, 2020), and, to some extent, on aspects of technology access beyond Internet connectivity per se (van Deursen & van Dijk, 2019). For example, lower-SES adolescents' lower engagement with educational ICT can be empirically attributed to lower parental resources to support children in their digital use (Nikken & Opree, 2018), lower quality of technical infrastructure at home (Notten et al., 2009), and to selection into schools with lower quality of ICT-related infrastructure and teaching (Ma, 2021; Rafalow, 2018). These factors are related to larger social structures which cannot be changed by single policies (Selwyn, 2011).

Cultural reproduction in the digital age

Socioeconomic disparities in children's and adolescents' digital engagement have also been studied using theoretical frameworks that go beyond the digital divide. In particular, cultural reproduction theory in the tradition of French sociologist Pierre Bourdieu has been applied in this context (e.g., Weber & Becker, 2019). A particular strength of this theoretical approach is that it helps explain why it is particularly the educational domain in which children's and adolescents' digital engagement is so strongly dependent on their socioeconomic background. Another reason why it is a very useful framework for the subject matter is that Bourdieu's work puts a strong emphasis on the domestic sphere, and on the ways in which parents transmit advantage to their children.

According to Bourdieu, socioeconomic status is passed on from parents to their children through different forms of capital, including economic, social, cultural and symbolic capital (Bourdieu, 2011). Cultural capital in its embodied (or incorporated) form includes knowledge and skills but also tastes and mannerisms, which demonstrate a familiarity with the culture of the dominant social class (Jæger & Breen, 2016). This embodied cultural capital can be transformed into success within educational institutions, which, according to Bourdieu, are systematically biased to favor students who put their embodied cultural capital on display. A common interpretation of Bourdieu's relatively vague description of the cultural capital transmission process is that much of it takes place outside of educational institutions, through everyday interactions between parents and their children and through children's extracurricular activities (Bering & Schulz, 2024; Jæger & Breen, 2016; Lareau, 2011). Hence, inequalities in children's and adolescents' out-of-school activities, including digital engagement, have great implications for educational settings like schools, where the embodied cultural capital acquired at home is converted into tangible advantages in terms of educational attainment and future SES.

The role of digital technology engagement in cultural reproduction processes has been studied from different perspectives. Some scholars have conceptualized the digital as an additional, fifth form of capital in addition to economic, cultural, social, and symbolic capital (Ragnedda, 2018), others as a new sub-form of cultural capital (Ollier-Malaterre et al., 2019; Paino & Renzulli, 2012). Broadly speaking, these approaches conceptualize digital (cultural) capital as encompassing digital skills, attitudes toward technology, and the capacity to manage and selectively limit one's own digital engagement, all of which can be transmitted from parents to children. This specific form of capital enables individuals to maximize the benefits of digital engagement while minimizing potential harms (Ragnedda, 2018). It may also convey advantages by serving as a signal for familiarity with the culture of the dominant class in educational settings. In the digital age, this culture likely incorporates a certain familiarity with digital technology (Paino & Renzulli, 2012). Taking on a different perspective, an ethnographic study by Clark (2013) examined the role of digital technologies as tools in the transmission of cultural capital. The study illustrates how socioeconomically advantaged parents use digital technologies to facilitate this process—for example, by using mobile devices to coordinate their children's extracurricular activities. This perspective extends Lareau's (2011) seminal work on the "concerted cultivation" parenting style observed in middle-class families, which serves as a mechanism for transmitting cultural capital by fostering skills and behaviors that are especially valuable in educational settings.

What all of these studies have in common is the recognition that mechanisms of cultural reproduction are not simply "copy-pasted" into the digital age (Loh, 2024), rather, technology-related factors play a distinct role. Digital inequalities interact with non-digital inequalities in specific ways: Socioeconomically advantaged children and adolescents who also possess high levels of digital (cultural) capital are better positioned to benefit from digital engagement in terms of educational outcomes than their similarly advantaged peers who possess only little digital (cultural) capital (Becker, 2023). However, only very few studies so far have integrated these insights into research on children's and adolescents' digital engagement, leaving considerable room for further exploration in this dissertation. In particular, it remains unclear how children's engagement with digital technologies is embedded in the processes of cultural capital transmission from parents to children.

The role of time displacement effects

Turning from the determinants to the effects of digital engagement on children's and adolescents' educational outcomes, different mechanisms have been discussed in the empirical literature. Existing research in this area has largely concentrated on the relationship between digital media use and cognitive development, drawing mainly on neurobiological or psychological frameworks, or on learning theories (Hassinger-Das et al., 2020). From a sociological perspective, another mechanism that is often mentioned in studies of digital technology effects is more relevant, particularly in the context of cultural reproduction processes: time displacement. Time displacement is the notion that the introduction of new media, including digital technologies, displaces time that was previously spent on other activities (Bryant & Fondren, 2009). Time displacement has been an influential concept throughout the 20th century, inspiring extensive studies on the effects of television on children's reading behaviors (Himmelweit et al., 1958; Schramm et al., 1961; Williams, 1986), and Putnam's famous thesis of the detrimental effect of television on social capital and social integration in the United States ("Bowling Alone"; Putnam, 2000). At the center of time displacement research is the question of which activities are being displaced by new media or technologies. If the displaced activities are known to have positive developmental effects (e.g., reading), their displacement can be cause for concern, particularly if the displacing activity is considered as less beneficial than the one being displaced (Fiorini & Keane, 2014; Hernæs et al., 2019). The extensive digital technology engagement of adolescents in the age of smartphones and social media have led to a renewed interest in time displacement effects in recent years, e.g., regarding the displacement of nighttime sleep (Lemola et al., 2015; Schweizer et al., 2017).

Displacement effects are relevant for the study of educational inequalities for several reasons. New technologies challenge established processes of cultural reproduction through their potential to displace extracurricular activities that used to play a role in the transmission of cultural capital. Parents are confronted with the question whether their children's out-of-school activities should include targeted forms of digital engagement such as coding classes, in order to gain advantages in school or to increase their future chances of finding a high-paying job in the tech sector (Livingstone & Blum-Ross, 2020a). At the same time, smartphones and social media may decrease adolescents' interest in and time spent on enriching activities like reading, sports, and playing musical instruments (Fomby et al., 2021; Twenge, Martin, & Spitzberg, 2019), and could therefore pose a threat to their academic performance.

Displacement effects also represent a potential mechanism which strengthens or weakens the association between family background and children's and adolescents' academic achievement, e.g., when socioeconomically disadvantaged groups engage more intensively with an activity which displaces developmentally beneficial activities. However, it has hardly been studied before whether displacement effects of digital technologies on developmentally beneficial activities vary according to children's and adolescents' socioeconomic background. Given that children from higher-SES families tend to spend more time engaged in such activities, new media could theoretically displace a greater share of this time among the more advantaged (Hernæs et al., 2019). At the same time, because higher-SES parents are typically more involved in structuring and supervising their children's leisure time (Lareau, 2011), while lower-SES parents may lack the resources or time to do so, it is also plausible that any negative effects of digital technologies, such as displacement, may disproportionately affect disadvantaged adolescents, thereby exacerbating educational inequalities. With regard to contemporary digital technologies, particularly flexible mobile devices such as smartphones, empirical evidence remains rather limited.

Gender inequality and digital technologies

Digital technologies also have the potential to affect gender inequalities in education. How adolescents engage with digital technologies is strongly related to their gender. For example, it is well-established that girls use social media more than boys, but engage less in video gaming (Leonhardt & Overå, 2021), and that parents tend to be stricter and more controlling in mediating their daughters' digital technology use (Steinberg et al., 2024). For the study of educational inequality, the most relevant strand of research investigates gender differences in digital skills and in psychological dispositions towards digital technologies. According to the Informational Computer and Information Literacy Study (ICILS), girls in most countries possess significantly greater computer and information literacy than boys, while small gender differences in favor of boys are only found regarding computational thinking, which refers to more technical tasks (Fraillon, 2024). Nevertheless, boys across countries are more confident regarding their abilities to use ICT for technical tasks compared to girls (Gebhardt et al., 2019). Despite the great importance of ICT in modern labor markets, it remains poorly understood how these gender disparities in adolescents' digital engagement and related skills affect pathways into postsecondary education and the labor market. Of particular interest here are pathways into ICT professional positions, which pay high wages and tend to offer favorable working conditions (European Institute for Gender Equality, 2018). Selection processes into more or less "digital" careers are also relevant from a macro perspective, given the shortage of ICT professionals in many countries (Strohmeier et al., 2024). Computer science remains one of the most gender-imbalanced disciplines within STEM (Cheryan et al., 2017), which raises the question of how this inequality in vocational pathways is connected to gendered patterns of digital engagement in childhood and adolescence.

A well-established theoretical framework to explain how socialization processes affect educational and vocational choices is the (situated) expectancy value theory (SEVT) by Jacquelynne Eccles (Eccles, 1987; Eccles & Wigfield, 2020). It was specifically developed to explain the underrepresentation of women in the STEM domains. The SEVT explains achievement-related behavior (academic and occupational aspirations and choices) through the interplay of socialization influences (stereotypes, parenting, peer groups) and psychological processes (motivation, identity). The theory ascribes a core role to both subjective task values and expectancies for success, which jointly shape motivational behavior (Eccles & Wigfield, 2020). The SEVT provides an explanation for how stereotypes associating technology or mathematics with masculinity (Cheryan et al., 2017) translate into gendered vocational choices. The predictions of the SEVT are generally in line with empirically observed phenomena like lower self-perceived abilities of female adolescents regarding mathematics, despite their typically equal or even superior performance in standardized tests (Jann & Hupka-Brunner, 2020; Kriesi & Imdorf, 2019). Like other STEM disciplines, the SEVT can also be applied to the ICT domain (Strohmeier et al., 2024). Because computing is still generally perceived as a male domain, girls typically have lower self-perceived abilities regarding computers than boys (Ashlock et al., 2021; Beyer, 2014). Still, there is surprisingly little empirical evidence on the effects of these gender differences on choice of occupations, particularly in the context of vocational education and training (VET). Moreover, previous research also indicates that the ICT domain has several distinctive features in comparison to domains like mathematics. Importantly, there is a crucial difference between the technical aspects of ICT, such as programming and hardware, and the use of ICT as a tool for communication and information processing. As mirrored in the results from the ICILS study (Fraillon, 2024), this conceptual distinction must be acknowledged when analyzing gender differences in digital engagement.

Summaries of individual studies

At a time when a considerable share of children's and adolescents' out-of-school time is spent using digital devices, it is important to investigate how this digital engagement relates to the reproduction of educational inequalities. As outlined in the previous sections, systematic disparities in children's and adolescents' digital engagement according to their socioeconomic background and their gender remain despite the closing of the "first-level" digital divide in terms of access to technology in industrialized countries. These disparities are particularly relevant for inequalities in education, because according to family investment models, theories of cultural reproduction, and the situated expectancy-value theory, out-of-school activities in childhood and adolescence are an important source of educational inequalities. Inequalities in out-of-school activities, including digital engagement, can lead to disparities in academic achievement and to differing career pathways. Previous research shows that it is particularly the educational use of digital technologies in adolescence which is marked by significant socioeconomic disparities. However, it remains unclear to what extent digital inequalities only "digitalize" existing inequalities, or whether they open new areas of inequality, e.g., when high familiarity or (self-perceived) abilities regarding digital technologies are rewarded in educational institutions or on the labor market. Digital engagement may also affect well-established mechanisms of social reproduction in childhood and adolescence by competing with and potentially displacing other out-of-school activities that play an important role in the transmission of advantage. Bridging literatures on the digital divide and on educational inequalities, this dissertation aims to advance sociological understanding of the role of digital technologies in the reproduction of socioeconomic and gender inequalities in education. It is focused on how digital technologies change the mechanisms leading to educational inequalities, thus contributing to the broader question of whether digital technologies mitigate or exacerbate educational inequalities.

The dissertation compiles four empirical studies that examine the emergence of inequalities in digital engagement and the effects of digital engagement on educational outcomes (see conceptual overview in Figure I.1). Study 1 and Study 2 are focused on the roots of socioeconomic inequalities in digital technology use, while Study 3 and Study 4 examine the effects of digital engagement on two different educational outcomes. Study 1 dives into the complexity of socioeconomic differences in digital engagement patterns in the Swiss context. Study 2 takes a comparative approach and investigates how country-level home ICT access, educational returns, and school ICT integration moderate socioeconomic differences in adolescents' digital technology use across a large set of countries. Study 3 analyzes how mobile phone use in early adolescence affects time use for non-digital activities, addressing the time-displacement hypothesis. Study 4 focuses on gender inequality in ICT interest and self-concept and gender disparities in ICT-related vocational choices. While the first three studies contribute to advancing understanding of the role of digital engagement in social and cultural reproduction processes, the last study is focused on the role of digital engagement in the reproduction of gender segregation in modern labor markets. In the following, the four studies are briefly summarized and discussed in terms of their contribution to the overall topic of this dissertation.

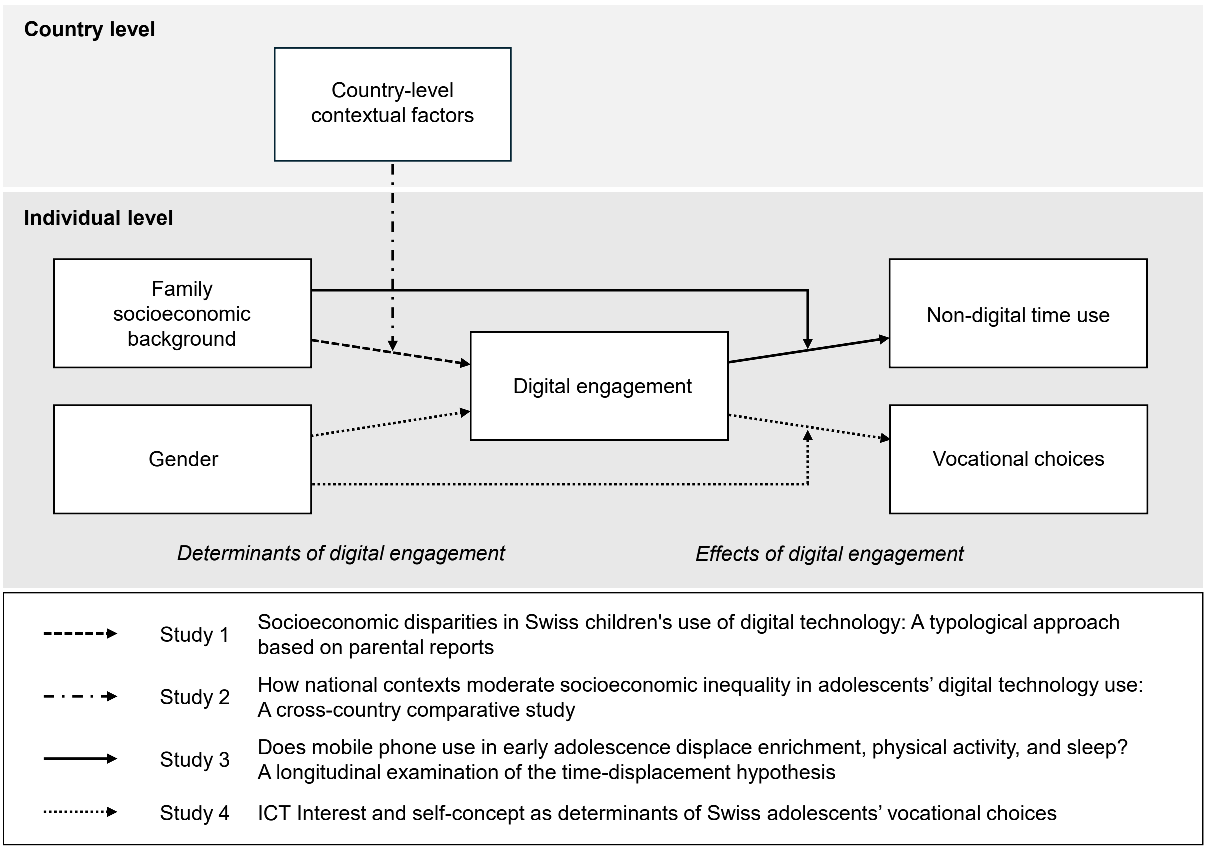

Figure I.1: Conceptual overview of the dissertation. Figure layout adapted from Loh (2024).

Study 1: Socioeconomic disparities in Swiss children's use of digital technology: A typological approach based on parental reports

The first study investigates the relationship between parental socioeconomic background and children’s digital technology use during middle childhood, a developmental stage that has received limited attention in previous research. In the era prior to home computers and mobile devices, children’s screen media use, such as watching television and playing early video games, was primarily recreational and offered limited value for cultural capital transmission. This contributed to the well-documented pattern of lower screen time among children from socioeconomically advantaged families (Grant, 2024). However, contemporary digital technologies can be used not only for purely recreational purposes, but also to support educational goals, including the development of ICT-related skills. From the perspective of cultural capital theory, it is therefore essential to examine not only whether socioeconomic differences exist in the amount of screen time, but also whether parental SES affects the types of activities children engage in using digital devices.

As a response to these new opportunities, patterns of children's digital technology use today may reflect shifting parental strategies, with higher-SES parents possibly recognizing digital media as tools for cultural capital transmission (Clark, 2013; Mollborn et al., 2022). However, effectively mediating children's digital engagement and guiding it towards educational activities requires both skills and resources on the part of parents, potentially giving rise to divergent digital parenting approaches (Livingstone & Blum-Ross, 2020b). To provide a more encompassing description of SES differences in children's digital use that also reflects heterogeneity between children of similar socioeconomic backgrounds, this study adopts a typological approach rather than focusing solely on individual activities. Based on online survey data from parents of Swiss children enrolled in second grade, the typology incorporates a broad spectrum of digital activities, including gaming, communication, and educational use, which reflects the multifaceted nature of modern digital technologies.

The results indicate that higher parental SES is associated with less intensive overall digital technology use among children, and particularly with a use type labeled "non-users". In the Swiss context, where the first-level digital divide has largely been overcome among younger cohorts (Camerini et al., 2018), patterns of screen time inequality thus resemble those of the television era: high levels of digital technology use among children continue to serve as markers of lower SES. At the same time, the study reveals that higher parental SES is also linked to a use type characterized by a diverse range of activities focused on education and information, referred to as "educational explorers". This type is strongly associated with greater parental ICT-related resources, including access to digital devices and higher self-assessed technological competence. These findings demonstrate that the new opportunities for the transmission of educational advantage are seized only by a minority of families, who are not only socioeconomically privileged but also possess high levels of digital (cultural) capital.

The study advances our understanding of cultural capital transmission in the digital age by demonstrating how new forms of inequality emerge based on the possession of digital (cultural) capital—even among traditionally privileged groups. This insight is a key contribution of the typological approach, which shifts attention to intra-class differences often overlooked in research that primarily focuses on children's screen time or on distinctions between educational and recreational digital activities (e.g., Camerini et al., 2018). However, the study also shares a common limitation with much of the existing literature in this area: it relies on parental reports of children's digital engagement. Such reports are prone to inaccuracies or even bias, particularly because screen media use among young children is frequently stigmatized. The implications of this limitation hinge on whether the measurement error varies systematically by parental SES, an issue that has received little attention in the literature to date. Finally, the findings are based on data from a single country (Switzerland), where digital technology access is exceptionally high. As further explored in Study 2, socioeconomic disparities in digital engagement are context-dependent, and shaped by macro-level factors like the level of technology access in a country.

Study 2: How national contexts moderate socioeconomic inequality in adolescents' digital technology use: A cross-country comparative study

The second study examines cross-country differences in the association between family socioeconomic background and adolescents' use of digital technologies for educational and recreational purposes. While such cross-national variation is frequently documented, it is rarely explained. Prior studies consistently report a positive association between family SES and adolescents' engagement with educational ICT; however, the strength of this relationship varies across countries. For instance, Ma et al. (2019) reported smaller SES gaps in educational ICT use in countries with higher GDP per capita. In contrast, the relationship between SES and recreational ICT use is generally negative—indicating more use among lower-SES adolescents—although positive associations have been observed in middle- and lower-income countries (Mielke et al., 2017). This study addresses the lack of explanation by theorizing and testing potential country-level moderators using PISA data from 44 countries. Its framework combines insights from social reproduction and digital divide research, focusing on home ICT access, educational returns, and school ICT integration quality as key moderators.

The results show that all three country-level variables significantly moderate the relationship between family SES and adolescents' ICT use, but the patterns differ markedly between educational and recreational use. Consistent with previous research, family SES is related to higher educational ICT use in all countries. However, contrary to earlier findings (Ma et al., 2019), this gap is not significantly associated with either national gross domestic product per capita or levels of home ICT access. Instead, the size of the SES gap is positively related to country-level educational returns, i.e., the extent to which additional years of schooling translate into higher income. This finding aligns with recent evidence showing that higher educational returns are linked to greater socioeconomic disparities in the uptake of shadow education (Entrich, 2020). Educational ICT use may thus be understood as part of a broader set of extracurricular investments that are more common among advantaged families. Importantly, these findings suggest that the design of national education systems plays a key role: where educational returns are high, advantaged families may face stronger incentives to secure their children's status through additional investments, including both shadow education and educational ICT use (Zwier et al., 2020). Finally, the average quality of ICT integration in a country's schools is associated with a slightly larger SES gap in educational ICT use. This finding clearly contradicts the theoretical expectation that high-quality school ICT integration should help mitigate these disparities (Loh et al., 2025). It raises important questions about whether the benefits of investments into school ICT infrastructure disproportionately serve socioeconomically advantaged students.

By contrast, the SES gap in recreational ICT use is strongly associated with national levels of home ICT access. Notably, this relationship persists even after controlling for GDP per capita. At least part of the variation in the direction of the SES gap between lower- and higher-income countries can be attributed to differences in home ICT access across countries. Importantly, the results indicate that mitigating the first-level digital divide does not necessarily lead to more equitable educational ICT engagement. Instead, in many contexts, it appears to facilitate higher recreational use among disadvantaged adolescents, echoing patterns observed during the television era. Despite the high policy relevance of the topic of this study, the study's cross-sectional design and the limited set of control variables constrain the ability to draw causal inferences. To determine under which conditions high-quality ICT integration in schools can effectively reduce SES disparities in educational ICT use, future research should employ longitudinal and, ideally, experimental designs. Further research is particularly needed to disentangle how the quality and quantity of school ICT integration affect SES gaps in educational ICT use.

Study 3: Does mobile phone use in early adolescence displace enrichment, physical activity, and sleep? A longitudinal examination of the time-displacement hypothesis

The third study addresses the time-displacement hypothesis, analyzing how early adolescents' time allocation changes after they acquire their first own mobile phone. The study focuses on the potential displacement of activities with established positive effects on adolescent development, including enrichment (homework, reading, cultural activities), physical activity (structured sports and unstructured physical activity), and sleep (nighttime sleep). Such displacement effects would be cause for concern, as resulting net effects on developmental outcomes would likely be negative, considering that mobile phones are hardly used for developmentally beneficial activities (Goudeau et al., 2021). Due to the multifunctional nature of contemporary mobile phones, it is difficult to predict which activities are likely to be displaced. Part of the explanation for the absence of robust empirical evidence on displacement effects of digital technologies is that it is very difficult to empirically isolate causal effects. Most previous studies have either employed cross-sectional designs (e.g., Schweizer et al., 2017), which are prone to unobserved variable bias, or trend analyses (e.g., Fomby et al., 2021; Twenge, Hisler, & Krizan, 2019), which make it difficult to attribute cohort-level behavioral changes to certain causes.

Addressing the methodological limitations of previous research, the third study introduces an innovative identification strategy. It uses a weighted difference-in-differences design and longitudinal time use data from Australia. The analysis exploits variation in the timing of early adolescents' acquisition of their first personal mobile phone to analyze how their time allocation changes after this event. Early adolescents who do not (yet) own a mobile phone function as a control group. This design, which has been previously applied in a similar way to test how mobile phone acquisition affects academic performance (Gerosa & Gui, 2023), allows for a causal interpretation of the resulting coefficients under much weaker assumptions than previous studies on displacement effects, because it mitigates bias resulting from unobserved confounding and reverse causality. The results show that early adolescents allocate significantly less time to television, movies, and videos after acquiring their first mobile phone, but time spent on developmentally beneficial activities remains unaffected. The results further indicate that displacement effects of mobile phones do not depend on early adolescents' socioeconomic background.

Recent studies estimate that adolescents worldwide spend an average of four daily hours on their mobile phones (Tkaczyk et al., 2024; Tomczyk & Lizde, 2023). This extensive use has fueled debates about the role of mobile phones in declining academic performance and mental health (Haidt, 2024). The findings from the third study suggest that the changes in adolescents' time allocation induced by the rise of mobile phones hardly extend beyond recreational screen media use: The study's robust empirical design highlights that mobile phones are part of a continuously evolving set of screen-based technologies (Hall & Liu, 2022). Even before the rise of mobile devices, screen media use was already extensive among early adolescents in industrialized countries. Rather than focusing on changes in net time use, future studies should attend to how mobile phones affect the developmental quality of activities depending on the ways in which mobile phones are used (e.g., passive scrolling versus active engagement). The generalizability of the study's findings is limited by the age of the dataset, which was collected between 2014 and 2016. Moreover, Australia may be a special case considering the relatively late age of phone acquisition and recent attempts to restrict adolescents' social media use through federal legislation (Archer, 2025). While the study is replicable in principle, only few longitudinal time use studies on children and adolescents currently exist. Finally, because the focus is on the period of initial phone acquisition, displacement effects at older ages, when adolescents typically engage with their phones more intensively, cannot be ruled out.

Study 4: ICT interest and self-concept as determinants of Swiss adolescents' vocational choices

The fourth and final study examines how adolescents' ICT interest and self-concept influence their selection into dual vocational education and training (VET) programs. It uses longitudinal data on Swiss compulsory school leavers, linked to a European database that measures the average intensity of ICT use across occupations. The study offers a novel perspective on how digital engagement contributes to the reproduction of occupational gender segregation in three respects: First, it explores pathways into firm-based dual VET, an area less studied than tertiary education or occupational aspirations. Because the transition into VET typically occurs at a younger age, it is marked by a high share of gender-stereotypical choices (Hupka-Brunner & Meyer, 2023). In contrast to the choice of tertiary study programs, VET choice is also more closely linked to specific career pathways: In the Swiss context, a majority of trainees continue working in their training occupation long term (Bundesamt für Statistik, 2020). Second, the study uses a novel database on job task content that distinguishes between the intensity of basic and more advanced ICT use (Fernández-Macías & Bisello, 2022), offering a more nuanced differentiation of digital skill demands. Third, the study investigates how gender moderates the associations between ICT interest and self-concept and the occupational task content of adolescents' future occupations, which has rarely been done before.

The results show that ICT interest predicts selection into training occupations (VET programs) involving both higher use of basic and advanced ICT, while a more positive ICT self-concept predicts the level of advanced, but not the level of basic ICT use. This aligns with the SEVT, which posits that domain-specific interests and self-concepts independently influence vocational choices (Eccles, 1987). As expected, ICT self-concept was less predictive of basic ICT use, likely because tasks such as email or word processing require minimal technical expertise. Using decomposition techniques, the study finds that girls' lower average ICT interest and self-concept explain nearly half of the gender gap in advanced ICT use. However, raising girls' ICT self-concept to match boys' levels would have little impact on closing this gap. Moderation analyses clarify this finding: for girls, only ICT interest predicts both basic and advanced ICT use in future occupations, whereas for boys, only ICT self-concept serves as a significant predictor. Finally, the study shows that ICT self-concept, but not interest, is significantly associated with entry into occupations such as systems administrators, programmers, and web developers. Taken together, these findings suggest that increasing girls' ICT interest alone is unlikely to reduce gender segregation in the ICT sector.

The fourth study shows that adolescents' psychological dispositions toward ICT shape their vocational choices in the context of dual VET. These choices are strongly gendered not only in the likelihood of selecting occupations with intensive advanced ICT use, but also in the differing impact of intrinsic motivation (interest) versus self-perceived competence (self-concept). Notably, the absence of a link between ICT self-concept and advanced ICT use among girls contrasts with much of the STEM literature, which often attributes female underrepresentation in STEM fields to girls' less positive domain-specific self-concepts (Kriesi & Imdorf, 2019). However, this finding aligns with more recent research suggesting that domain-specific self-concepts matter more for boys than for girls when making occupational choices (Kang et al., 2021). These results highlight the need for future SEVT-based studies to consider gender as a moderator, to avoid misinterpreting the drivers of gendered occupational selection. For policy and intervention design, however, further research is needed to disentangle the role of individual preferences from external influences, particularly employer decisions, which are critical in the Swiss VET context (Duc & Lamamra, 2022). As this study is based on correlational data, observed relationships may be partially shaped by such external selection processes.

Reflections and future directions

Sociological research on inequalities in children's media consumption predates the introduction of home television (e.g., Macdonald et al., 1949). A dissertation on inequalities in children's and adolescents' engagement with screen media in the year 2025 therefore needs to explicitly address the question "what's new?". The key sociological argument motivating this dissertation, which is outlined in Study 1 in more detail, is that the role of modern digital technology engagement in childhood and adolescence goes far beyond what movies, television, and early video games largely represented for decades: that is, mere recreational activities with the potential to distract children from learning and sedate adolescents during their spare time. For a long time, due to their limited developmental benefits, growing up in more advantaged circumstances was therefore associated with less extensive screen media use (Grant, 2024; Lareau, 2011). However, since the 1990s, industrialized societies have entered what Allmann and Blank (2021) call the "age of compulsory computing". Citizens in these societies are required to engage with digital technologies regularly and frequently to be able to fully participate in civic, economic, social, and cultural life. The compulsory mode of digital engagement has also entered schools that are expected to teach children and adolescents "digital skills", while also using digital technologies to change the style of teaching. These developments have the potential to affect the role of digital engagement in the reproduction of broader societal inequalities. When screen media engagement becomes a potential way to acquire human capital, it is likely that this affects how it is related to children's and adolescents' socioeconomic background and gender. This dissertation presents four empirical studies that aim to advance sociological understanding of these inequalities by addressing different aspects of the relationship between ascribed characteristics (socioeconomic background and gender), digital engagement, and educational outcomes. Three key insights from these studies are discussed in the following, before turning to remaining open questions and directions for future research.

First, sociological understanding of socioeconomic and gender inequalities in children's and adolescents' digital engagement today can be advanced through combining insights from "traditional" theories on social and cultural reproduction (e.g., Bourdieu & Passeron, 1990; Eccles, 1987) and insights from digital inequalities research (e.g., van Dijk, 2020). In Study 1, the social reproduction perspective explains why less intensive ICT use types are more common among more advantaged children and why educational ICT use is so strongly associated with higher parental education. However, the digital inequality perspective helps us understand why education-centered use is limited to only a specific minority of more advantaged children: Helping children develop capital-enhancing and responsible ICT habits requires that parents possess specific ICT-related resources, or "digital capital" (Ragnedda, 2018). While both perspectives on their own are unable to capture the entire complexity of socioeconomic inequalities in children's digital engagement, their combination has proven to be fruitful, as they shed light on new inequalities between individuals with similar socioeconomic backgrounds (see also: Becker, 2023).

Second, the closing of the first-level digital divide in access to digital technologies does not eliminate socioeconomic inequalities in children's and adolescents' digital engagement (see Study 1 and Study 2). Although technical barriers to online educational content for disadvantaged adolescents are largely overcome in many countries, it appears that countries with more universal home access to ICT do not display smaller socioeconomic gaps in adolescents' educational ICT use (Study 2). Instead, these high-access countries are marked by greater recreational ICT use among the less advantaged adolescents compared to their more advantaged peers. This supports the general argument from the early literature on digital inequalities that socioeconomic differences in digital engagement represent a social and not a technical problem (Selwyn, 2004) and therefore require practical solutions that go beyond providing technological infrastructure. Accordingly, Study 2 shows that the design of educational regimes, as expressed by the economic returns to education, affects the extent of socioeconomic inequality in digital engagement. This highlights how the political design of institutions can mitigate or exacerbate inequalities also with respect to adolescents' digital engagement. Reducing societal pressure on adolescents' academic performance through institutional adjustments may represent a pathway towards reducing disparities not only regarding extracurricular activities like private tutoring (Entrich, 2020), but also regarding adolescents' digital engagement.

Third, when studying socioeconomic differences in children's and adolescents' digital engagement, scholars need to acknowledge differences in types of content. Still, many studies analyze differences regarding overall screen time, which is an easy variable to collect through surveys. However, as Study 1 and Study 2 demonstrate, SES differences in screen time conceal complex patterns of activities that have different implications for educational inequalities. While educational ICT use is widely acknowledged as a capital enhancing activity, recreational ICT use is not, and instead the latter is often associated with time-wasting or perceived as a risky behavior (Jorge et al., 2022; Livingstone & Blum-Ross, 2020b). Hence, educational and recreational ICT have different theoretical implications from a social stratification perspective and, as Study 2 demonstrates, associations with family SES can look quite different depending on the regional context. In addition, although the overall time adolescents currently spend using their mobile phones is extensive, this screen time per se is unlikely to affect educational outcomes at a larger scale. As Study 3 shows, mobile devices mostly compete with and displace legacy media like television, which aligns with previous results from trend analyses (Fomby et al., 2021; Twenge, Hisler, & Krizan, 2019). If inequalities in mobile phone use are found, like higher use times among disadvantaged adolescents, this does not necessarily imply greater inequalities in outcomes, as similar inequalities have existed before regarding television or video games (Grant, 2024).

Although the four studies address critical gaps in sociological understanding of the role of children's and adolescents' digital engagement in the reproduction of educational inequalities, important questions remain. In particular, still relatively little is known about whether and how socioeconomic and gender inequalities in digital engagement translate into inequalities in educational outcomes. This is a critical area for future research, because, as Ellen Helsper puts it: "Differences in ICT access, skills, and use are not what primarily matters when it comes to inequality. The real issue is the continuation or exacerbation of existing inequalities in everyday life that impact our well-being" (Helsper, 2021, p. 34). One major barrier to understanding the effects of children's and adolescents' digital engagement on educational outcomes is the lack of high-quality data. Most large-scale educational datasets contain only superficial and often outdated measures of digital engagement. This limitation reflects both the rapid pace of technological change and the diversity of ways in which individuals engage with digital technologies, making it difficult for empirical research to keep up. For instance, when work for this dissertation—including the collection of primary data on children's digital engagement in the Swiss context—began in early 2022, generative artificial intelligence tools like ChatGPT were not yet available to the public. Today, millions of children and adolescents use these tools regularly both for recreational and educational purposes, potentially reshaping the role of digital engagement in the reproduction of educational inequalities once again (Yu et al., 2024).

Nevertheless, for research in this area to progress, it is critical to integrate high-quality data collection on digital engagement in studies on education, preferably, using technical solutions or experience sampling methods to overcome limitations of single, self-reported survey items in the age of mobile devices (Barr et al., 2020). Given the current limitations of available data, the state of research in this area is too premature to derive robust recommendations for practical interventions or policymaking. However, the findings from this dissertation suggest that successful interventions must take into account the broader sociological dimensions of digital inequalities and established insights from the literature on educational inequalities. Efforts that focus solely on mitigating inequalities in digital access, parental digital literacy, school ICT integration quality, or other factors emphasized by literature on the digital divide, are unlikely to be sufficient to eliminate socioeconomic and gender inequalities in children's and adolescents' digital engagement. Instead, structural reforms, such as reducing early tracking or minimizing institutional differentiation in secondary school, hold lots of promise, as they are known to reduce educational inequality more broadly (Entrich, 2020; van de Werfhorst & Mijs, 2010), and may have spillover effects on inequalities in digital engagement as well.

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Study 1:

Socioeconomic disparities in Swiss children's use of digital technology: A typological approach based on parental reports

Abstract. For decades, higher parental socioeconomic status (SES) has been linked to less screen time among children. However, the spread of mobile devices and digital learning tools may be altering the relationship between parental SES and children's technology use, as parents reassess the potentials of children's use of ICT (information and communication technologies) for acquiring skills and knowledge. Drawing on Bourdieu's theory of cultural reproduction, this study examines how parental SES relates to ICT use in middle childhood (ages 7–10). By applying latent class analysis to parental survey data from Switzerland ($N = 2{,}490$), four distinct ICT use types were identified: "heavy users", "moderate entertainment users", "educational explorers", and "non-users". Higher parental SES was associated with both limited (non-users) and education-centered ICT use (educational explorers), while lower SES was linked to more intensive, entertainment-oriented use (heavy users). The findings underscore how socioeconomic disparities extend beyond children's screen time to include qualitative differences in ICT use. Among higher-SES families, a divide emerges between those limiting ICT use and ICT-resourceful families leveraging technology to transmit cultural capital, reflecting traditional and evolving class-specific attitudes towards ICT. The typological approach uncovered the heterogeneity of parental responses to the ambiguities of ICT across the socioeconomic spectrum.

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Introduction

Socioeconomic gradients in children's time use are well-established (Macdonald et al., 1949). For example, children from more advantaged backgrounds spend more time on structured leisure activities, like music practice or sports (Covay & Carbonaro, 2010), book reading (Aikens & Barbarin, 2008), and studying (OECD, 2014). These differences perpetuate socioeconomic inequalities by directly affecting children's development and by fostering a distinctive "habitus" (Bourdieu, 2000; Lareau, 2011). Socioeconomic gradients also affect children's consumption of broadcast media and their use of other information and communication technologies (ICT): More advantaged children watch less entertainment television (Gershenson, 2013), and spend less time on online entertainment and communication (Camerini et al., 2018).

However, the role ICT play in children's lives has changed significantly in recent years, questioning previous results and theoretical assumptions. Intuitive touchscreen and voice interfaces and mobile devices enable children to actively use ICT before learning to read and write (Kabali et al., 2015), contributing to the recent worldwide increase in preadolescent children's ICT use (Goode et al., 2020; Mullan, 2018). ICT are also increasingly used to support learning in primary schools and in private settings (Meyer et al., 2021; Vanderlinde et al., 2015). Finally, families and schools are expected to help children attain "digital literacy" from an early age (OECD, 2021). These developments have sparked controversial debates about children's ICT use among parents, educators, policymakers, and the broader public (Livingstone & Blum-Ross, 2020b).

Nevertheless, empirical research on ICT use at primary school age is lacking (Graafland, 2018), in particular with regard to socioeconomic differences (Mollborn et al., 2021). Although children in middle childhood are usually able to read and therefore able to use ICT in functionally similar ways compared to adolescents, their use of social media or texting is much lower (Coyne et al., 2018) and parental oversight is stronger (Suárez-Álvarez et al., 2022). Potential effects on children's development, and the resulting parental and pediatric guidelines are highly age-dependent as well (Mollborn et al., 2021; World Health Organization, 2019). It therefore remains uncertain whether previous findings on socioeconomic differences in adolescence apply to middle childhood.

The aim of this study is to advance understanding of the role of children's ICT use in the reproduction of social inequalities in the digital age. Examining early inequalities in children's ICT experience represents an important foundation for designing effective curricula and targeted interventions, as primary schools and families are faced with the challenge to teach children how to make the most of their ICT use. To achieve this aim, socioeconomic disparities in children's parent-reported ICT use are analyzed through the lens of Bourdieu's theory of cultural reproduction (Bourdieu & Passeron, 1990), drawing on a survey dataset collected in Switzerland in 2022. Switzerland is an interesting context for this study because paradoxically, despite the almost universal access to high-speed internet, computers, and mobile devices (Bundesamt für Statistik, 2023; Camerini et al., 2018), Swiss children start using computers at older ages and use the Internet less than children in most other European countries (Juhanák et al., 2019; Smahel et al., 2020).

Background

French sociologist Pierre Bourdieu's theory of cultural reproduction posits that parents transmit socioeconomic advantage to their children through their higher cultural capital (Bourdieu & Passeron, 1990). Cultural capital appears in three different states (Bourdieu, 2011): embodied (e.g., skills, tastes, behaviors), objectified (e.g., books and other cultural objects), and institutionalized (e.g., educational and other credentials). According to Bourdieu, more advantaged children maintain their socioeconomic position in society by converting their embodied cultural capital into success in the educational system (Jæger & Breen, 2016). Socially stratified parenting styles represent one important way in which embodied cultural capital is transmitted from parents to children. For instance, the seminal study by Lareau (2011) showed how the "concerted cultivation" parenting style of US middle-class parents helped their children to develop their individual talents and interests and fostered their ability to negotiate with adults, contributing to a sense of entitlement that was often rewarded by their teachers. Working-class parenting was characterized by lower parental involvement in children's leisure activities and a greater emphasis on parental authority ("natural growth").

Changing class-specific parental views on screen media?

It is well-established that higher-SES children in Western countries spend less time watching television than their lower-SES counterparts. This pattern strongly reflects socioeconomic differences in parental perceptions of the developmental value of screen media (Grant, 2024; Huston et al., 1999). From a cultural capital perspective, watching television is barely useful to transmit embodied cultural capital, particularly in comparison with alternative leisure activities like book reading. Consequently, middle-class parents traditionally associate television with lowbrow culture (Grant, 2024), and perceive it as a threat to healthy child development (Wartella & Jennings, 2000). Lareau (2011) also noticed many middle-class parents' critical view on children's television watching, deeming it incompatible with the concerted cultivation style of parenting. For working-class parents, however, television traditionally offered a low-cost and low-risk opportunity for shared family time (Clark, 2013).

Contemporary digital technologies may be shifting these established socioeconomic disparities in parental attitudes towards children's ICT use (Ito et al., 2020). Nearly unlimited individualization opportunities through apps, websites, and videos enable parents to customize their children's use of ICT towards their developmental stage, individual interests, and potentially, towards more educational content (e.g., mobile learning apps). Modern ICT, therefore, offer more opportunities for the transmission of embodied cultural capital and are more compatible with concerted cultivation than linear television. Moreover, ICT skills can be seen as being as a form of embodied cultural capital, promising tangible advantages in the education system and on the labor market (Paino & Renzulli, 2012). Fostering children's ICT skills by letting them use ICT in specific ways can therefore appear as an investment in their cultural capital (Livingstone & Blum-Ross, 2020b). Hence, children's strict abstinence from ICT is not only practically difficult to realize for many parents, but may even threaten children's educational and economic success (Mascheroni et al., 2016), which was much less the case before the introduction of mobile touchscreen devices.

Prior quantitative studies on children's ICT use typically report only small SES differences in screen time (Bohnert & Gracia, 2023), but a gap in the type of activities. Higher parental SES is associated with more learning- and information-oriented ICT use (Clark, 2013; Weber & Becker, 2019), and with lower recreational ICT use (Camerini et al., 2018; Corkin et al., 2023). Research on mediation practices finds that contrary to established socioeconomic disparities around television watching, lower-SES parents are more focused on restriction of contemporary ICT use, while higher-SES parents tend to prefer co-use practices (Mascheroni et al., 2016).

However, socioeconomically stratified parental attitudes and mediation strategies do not necessarily translate into differences in children's ICT use patterns. In practice, educational apps are often of limited quality (Meyer et al., 2021) and many children quickly lose interest in electronic games targeting school content (Mascheroni et al., 2016). Higher-SES parents often express frustration regarding the inconsistence between their ideals and their children's actual ICT use (Clark, 2013; Mascheroni et al., 2016; Mollborn et al., 2022).

Research questions

While the focus of the theoretical arguments is on parental strategies and attitudes, the following research questions emphasize children's actual ICT use as a product of changing parenting strategies and families' complex configurations of resources and constraints. The fact that children's ICT use is measured indirectly via parental reports in this study is acknowledged explicitly in the formulation of all research questions. Furthermore, because SES differences in children's ICT use may follow nonlinear patterns and ICT use is highly diverse and individualized, a typological approach was chosen. It avoids a priori assumptions regarding different ICT-based activities (e.g., whether learning games represent a recreational or educational activity) and has the potential to reveal unexpected combinations of ICT-related activities across different socioeconomic groups. Hence, the first research question reads:

> **RQ1:** What types of children's ICT use emerge based on parental reports when diverse use purposes of ICT are considered?

Despite the new opportunities promised by modern ICT, children's ICT use is still widely perceived as potentially harmful (Mollborn et al., 2022). Consequently, higher-SES parents' desire to limit their children's ICT use due to development, health, or status concerns (in line with the "traditional" view) may conflict with the need to foster their children's ICT skills and prepare them for life in a digital world (the "new" view; Mollborn et al., 2022). For lower-SES parents, there are conflicting arguments as well: While television used to represent an opportunity to spend family time, the more solitary use facilitated by mobile devices offers less of this benefit. In general, higher-SES children are expected to use ICT less for recreational, and more for educational purposes than lower-SES children, but it is unclear how parental SES relates to different combinations of children's digital activities. This yields the second research question:

> **RQ2:** Is parental SES associated with certain types of children's ICT use as reported by their parents?

In addition to parental SES, unequal parental resources and family conditions regarding ICT skills (Livingstone et al., 2017; Nikken & Opree, 2018), associated self-perceptions (Mascheroni et al., 2016), attitudes towards ICT (Cingel & Krcmar, 2013), or aspects of family structure like the presence of siblings or a second parent can affect parental mediation strategies (Koch et al., 2024), which may result in heterogeneity between families with similar SES (Mascheroni et al., 2016). As theoretical arguments suggest a dilemma for parents, understanding which factors lead children with similar SES to using ICT in different ways can provide important insights into the mechanisms involved. This leads to the final research question:

> **RQ3:** Which factors explain children's selection into different ICT use types based on parental reports, independent of parental SES?

Data and Methods

Data

The parent survey data was collected as part of a pilot study of the Swiss National Educational Monitoring Program, conducted between May and July 2022 (Assessment of the Achievement of Basic Educational Competences; Herzing, Röhlke, & Erzinger, 2023; Herzing, Röhlke, Seiler, & Erzinger, 2023). For the pilot study, Swiss second-year students (typically around 8 years of age) were sampled and then tested in different domains. All parents of the 4,822 children eligible for the assessment were subsequently invited to voluntarily complete a self-administered, multilingual online survey (Röhlke & Herzing, 2023). The data used in this study stems exclusively from the parent survey.

Because no health-related or other sensible information was collected in the parent survey, the study did not fall under the national or cantonal laws regarding human research and did not require ethical approval. The Swiss educational monitoring program is anchored in the Swiss constitution and regulated by the Intercantonal Agreement on Harmonization of Compulsory Education (HarmoS Agreement). Parents received detailed information about the student assessment and the parent survey several weeks in advance in written form. This document included information on the study purpose, data protection and anonymization, data use for publication, and voluntariness of participation. Parents were explicitly informed that schools would receive no feedback on student performance. Throughout the whole field stage, telephone contacts were offered to answer parents' questions and enable them to withdraw their children from the assessment if requested. Parental participation in the online survey was voluntary, as explicitly stated in the parental information letter, the invitation with the login details, and the introduction to the online survey. The latter also informed parents that they could skip any question they felt uncomfortable with. The active participation of parents in the online survey after receiving the outlined information was treated as implied informed consent.

A total of 2,606 parents filled in the main questionnaire. After excluding responses from parents who indicated that their child mostly lives in another household ($n = 12$), and observations without valid information in any ICT use indicator variable ($n = 104$), 2,490 observations remained in the main sample (weighted mean age: 8.4 years). A subsample used for predicting latent class membership (RQ3) contained 2,146 observations (dropping $n = 344$ observations with missing values in one of the predictor variables).

Variables

Indicators of children's ICT use

Measuring children's ICT use is challenging, due to unreliable child reports and practical hurdles with technology-based methods (Vandewater & Lee, 2009). This study relies on parental reports, the most common measurement approach. Although parental reports are prone to some measurement error, related to social desirability, limited knowledge, and children's active and covert undermining of parental restrictions (Vittrup, 2009), parental and child reports of children's media use generally align well for younger children (Wood et al., 2019).

Parental reports of children's ICT-related leisure activities were surveyed based on an adapted scale from PISA 2022, covering the time the child spends on such activities on a normal week day (Programme for International Student Assessment; OECD, 2023b). The original scale ranged from 1 (*never or almost never*) to 6 (*more than 4 h a day*). To account for very small group sizes, some response categories were collapsed. In addition, parents were asked about the frequency of children's use of the Internet to support studying or homework outside of school (OECD, 2023b), with the original scale ranging from 1 (*never or almost never*) to 5 (*every day or almost every day*). The original wording and response categories as well as the final indicators are presented in Table 1.A1 (Appendix). Weighted sample distributions of all indicator variables are shown in Table 1.1.

To fully capture children's ICT use including activities not covered by any of the other indicator variables, the use frequency of the three most flexible and popular digital devices (mobile phones, tablets, and desktop PCs) was also included. The original scale ranging from 1 (*never or almost never*) to 5 (*every day or almost every day*) was dichotomized, capturing weekly use. A more differentiated scale would have led to identification problems (Visser & Depaoli, 2022) due to strong residual correlations (because some activities were strongly linked to a specific device).

Predictor variables

In line with previous research (e.g., Camerini et al., 2018; Corkin et al., 2023; Mascheroni et al., 2016; Mollborn et al., 2022), this study uses parental educational attainment as the main indicator of parental SES. Theoretical arguments on cultural capital transmission processes and SES differences in parenting styles closely link to parental education (Mollborn et al., 2022). The highest educational attainment of both parents (if available) was measured using five categories: "lower secondary education or less", "upper-secondary /lower vocational degree", "higher vocational/bachelor's degree", "master's degree", and "doctorate". Parents' joint income is used to test the robustness of the findings, as income may influence parental mediation and children's ICT use independently of parental education, due to the cost of maintaining high-quality digital devices and tools (Camerini et al., 2018; Clark, 2013).

Regarding parental ICT-related resources, parental occupations were categorized as "ICT-specialist" (e.g., software and applications developers and analysts), "ICT-task intensive occupation" (except ICT-specialists; e.g., business services and administration managers, marketing professionals), or none of those (Grundke et al., 2017). Parental ICT self-efficacy was measured using a z-standardized scale (Cronbach's $\alpha = .87$) adapted from PISA 2022 (OECD, 2023b). The question stated: "To what extent can you do the following tasks using digital resources?", with 12 tasks to be rated on a five-point scale. Parental attitudes regarding children and technology were measured as their agreement to two statements ("children can learn a lot of new things by using PCs" and "the internet is dangerous for children") on a four-point scale. The answers were z-standardized individually for each attitude, with higher values indicating higher agreement. Availability of digital devices was measured as the number of personal computers (PCs) at home (including laptops and tablets). A second variable covered the variety of available devices in the household (⍰ = .72).

Single parent status as an indicator for the family structure was measured based on the number of parents or legal guardians living in the child's main household (either one or two). To capture additional, work-related parental time constraints, parental full-time employment was coded as "yes" if all parents in the household worked more than 80% of a full-time job. Sibling constellation was categorized into four groups: No siblings, child only has older siblings, child only has younger siblings, and other. Descriptive statistics of the predictor variables are presented in Table 1.A4 (Appendix).

Method

Latent Class Analysis (LCA) is a statistical method that identifies subgroups (classes) of observations based on multivariate data. The goal of LCA is to identify a categorical latent variable of class membership based on the empirical patterns in a set of indicator variables, minimizing the statistical association of the indicator variables within the latent classes. The optimal number of classes in every LCA must be selected by the researcher(s) based on goodness-of-fit measures and the interpretability of the classes. The Bayesian Information Criterion (BIC), which evaluates model fit, rewarding more parsimonious models, is one of the most established goodness-of-fit measures for LCA.

LCA was performed using Mplus, version 8.4 (Muthén & Muthén, 2017). Models were estimated using a maximum likelihood estimator which imputes missing values in the indicator variables. Following the approach suggested by Visser and Depaoli (2022), local dependencies in nine pairs of indicator variables were identified based on high bivariate residual correlations and modeled in the final latent class models, because unmodeled residual correlations can bias the estimates. The full Mplus syntax used to identify the latent classes is presented in the Appendix.

Bivariate associations between latent classes and parental education were calculated using the Bolck-Croon-Hagenaars method (BCH; Bakk & Kuha, 2021). For the multivariate model predicting latent class membership, the 3-step method as implemented in Mplus 8.4 was used (Asparouhov & Muthén, 2014). Both the BCH-method and the 3-step method consider the uncertainty of class assignment, excluding the predictors from the identification of the latent classes. All analyses included a nonresponse-adjusted sampling weight (Herzing, Röhlke, & Erzinger, 2023).

Results

Model parameters from latent class models with two to six latent classes based on the 12 indicator variables (see Table 1.1) are presented in the Appendix (Table 1.A2). The 4-class solution was optimal, combining the lowest BIC value with clear interpretability and no insubstantial classes. The quality of class separation for the final 4-class solution as indicated by the relative entropy measure was 0.62, which is usually considered as medium, but acceptable (Wang & Wang, 2020, p. 346).

Model selection

The 4-class solution: A typology of ICT use in middle childhood

Table 1.1 displays the class profiles of the four latent classes including class sizes as well as the weighted distributions of all indicator variables based on the full sample (column on the left). In addition, Figure 1.1 visualizes the 4-class solution yielded by the LCA in a simplified and reader-friendly way. In Figure 1.1, the categories were collapsed to metric scales from zero to one, with zero indicating that 100% of children were in the lowest category, and one indicating that 100% of children were in the highest category. All interpretations are based on the original values from Table 1.1.

"Heavy users", the smallest class (class size: 11%), were characterized by the most frequent and time-intensive ICT use across most activities and devices, according to their parents. Particularly, the intensive use of video games and recreational Internet browsing stood out in comparison to the other classes. However, children's ICT use in this class was not restricted to entertainment activities, many children also used ICT for educational purposes, such as using learning software or games. Only a minority of children used the Internet for schoolwork, but this share was still much higher than in the other classes. The smartphone stood out among the devices, with almost three quarters of heavy users using it every week.

The largest class with 43%, *"Moderate entertainment users"*, was characterized by moderate use intensity across a largely entertainment-focused repertoire of activities often performed on mobile devices, such as playing video or computer games and browsing the Internet for pleasure. The use of learning software or games was the only education-related activity performed by a substantial share of children in this class. Other activities were hardly performed.

Children in the *"Educational explorers"* class (20%) engaged in diverse activities, often focusing on learning and information. Most children played video or computer games and browsed the Internet for pleasure regularly, but with limited use times. Using learning software and looking up online information were common activities in this class. Diverse

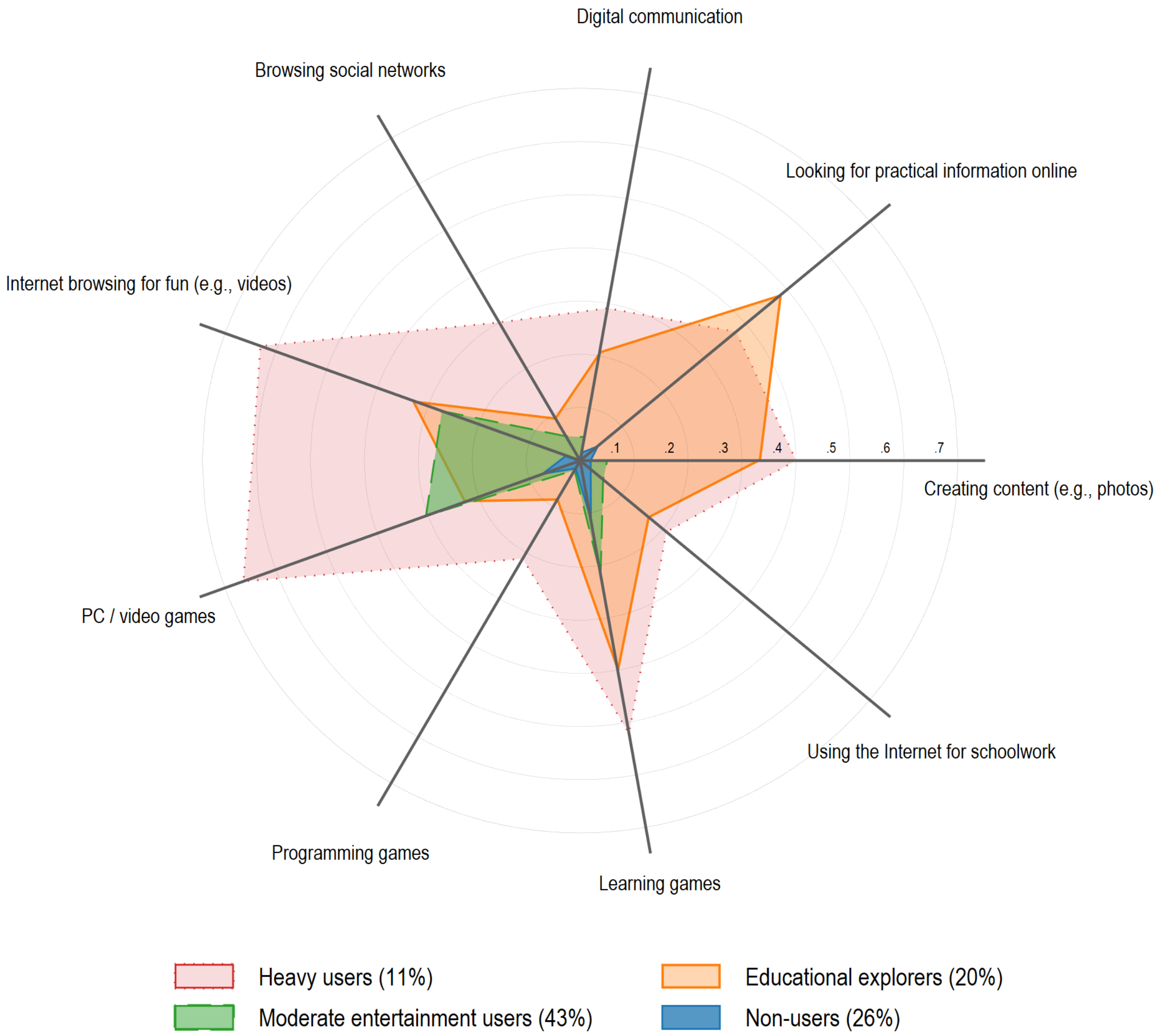

Figure 1.1: Simplified visualization of 4-class solution

Note. Weekly device use (smartphone, PC, tablet) not displayed to increase interpretability.

activities like digital communication, generating their own content and using the Internet to support schoolwork were also relatively common compared to the other classes. Device use was very diverse in this class, with relatively many children using a PC.

Children in the second-largest latent class, the *"Non-users"* (26%), hardly used any ICT. Some children in this class played video or computer games with limited use times. A minority of the children in this class used learning software for at least a couple of minutes per day. The remaining activities were performed only by a very small share of children. Among the devices, tablets were the most used one.

In sum, RQ1 can be answered as follows: Four ICT use types were identified based on parental reports of their children's activities, which differed both regarding use intensity (with non-users as the least and heavy users as the most intensive use type) and regarding the type of activities (moderate entertainment focusing on entertainment, educational explorers focusing on learning- and information-centered activities). To provide more context, Table 1.A3 (Appendix) presents a cross-tabulation of basic demographic variables across latent classes. Age, gender, and urbanity level were only weakly associated with latent class assignment, while migration background was strongly associated with assignment to the heavy users class (not controlling for parental education). Overall, factors indicating cultural influences (migration background, language region) were more strongly related to the use types than other demographics.

Distribution of latent classes by parental education

Figure 1.2 displays the distribution of latent classes by highest formal parental education (bivariate analysis based on the BCH-method). Overall, differences by parental education were substantial. The *heavy users* type was much more common among children of parents with low educational attainment compared to children of parents with moderate or high educational attainment. Already in the second lowest category ("upper secondary school/lower vocational degree"), children were much less likely to be categorized as heavy users. This share decreased further among children whose parents had a higher vocational or bachelor's degree and a master's degree. It was again slightly higher when one of the parents held a doctoral degree. *Moderate entertainment users* represented the most common use type across all levels of parental education. However, it was slightly more common when parental education was lower, being most dominant among children whose parents held an upper secondary school or lower vocational degree.

The likelihood of children falling into the *educational explorers* class increased steadily with higher parental education. This use type was very rare among children of the lowest educated parents. Nevertheless, even among children of the highest educated parents, the educational explorers type was not the dominant use type. The *non-users* type was strongly associated with parents holding a tertiary degree. Only few children whose parents had a lower secondary school degree were categorized as non-users. Higher tertiary degrees did not considerably increase the likelihood of children being classified as non-users.

To answer RQ2, higher parental education was associated with a higher likelihood for children to be classified as both educational explorers and non-users based on parental reports of their ICT-related activities. Moreover, a variety of use types was found across all levels of parental education. For children of the highest educated parents, three use types were almost equally common: moderate entertainment users, educational explorers, and non-users. For children of parents with lower education, two use types, the heavy users and the moderate entertainment users, were most common. Repeating the bivariate analysis using parental income instead of educational attainment yielded the same patterns and substantive conclusions (see Figure 1.A1, Appendix).

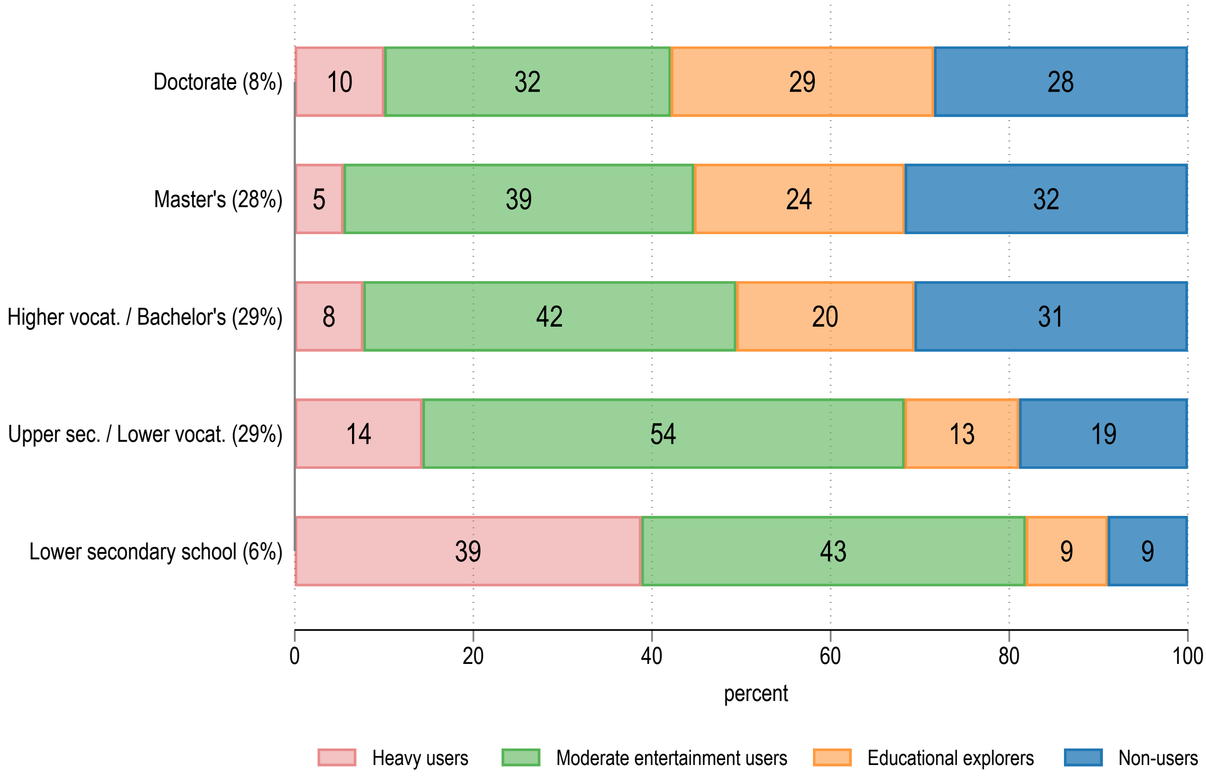

Figure 1.2: Distribution of latent classes by highest level of parental education

Exploring other predictors of latent class assignment

Although parental education was strongly associated with certain ICT use types among children, a large heterogeneity of use types across all levels of parental education remained. Which factors explain this heterogeneity empirically (RQ3)? Table 1.2 displays results from a multinomial logistic regression model predicting latent class assignment (logit coefficients). The regression coefficients in Table 1.2 refer to the six pairwise contrasts of the four latent classes, indicating the association of each variable with assignment to one latent class as opposed to one of the other three latent classes. This presentation of the multinomial results is particularly useful to investigate RQ3, asking: Which variables predict assignment to one latent class (e.g., educational explorers) in contrast to another class (e.g., non-users), when parental education and other demographic variables are held constant?

Even under the statistical control of parental level of education, several groups of variables were significantly associated with latent class assignment. Regarding parental ICT resources, a low variety of digital devices at home was significantly associated with assignment to the non-user class over the moderate entertainment users ($p = .028$) and the heavy users class ($p = .008$). Higher parental ICT self-efficacy significantly predicted assignment to the educational explorers over the moderate entertainment users ($p = .011$) and the non-users class ($p = .008$). Surprisingly, a parent working as an ICT specialist was associated with assignment to the non-users as opposed to the educational explorers class ($p = .015$). Negative parental attitudes towards children's ICT use significantly predicted assignment to the non-users class as opposed to the three other latent classes. Hence, more positive parental attitudes and higher parental ICT self-efficacy were associated with children being classified as educational explorers rather than non-users.

Among the indicators of family structure, only the sibling constellation was significantly associated with latent class assignment. As opposed to non-users, educational explorers were more likely to be an only child (the reference category), and less likely to have only younger siblings ($p = .001$). Being an only child as opposed to having older siblings was also positively related to the educational explorers as opposed to the moderate entertainment users class ($p = .047$).

Regarding RQ3, differences in ICT-related resources and attitudes towards ICT were the most important predictors of latent class assignment based on parental reports, holding parental education constant. The implications of this result are discussed in the following section. Finally, Table 1.A4 (Appendix) presents a cross-tabulation of the substantive predictors by level of parental education. Higher-educated parents scored higher on all ICT-related variables: They had a higher ICT self-efficacy, more devices in the household, and held more positive attitudes towards children's ICT use. These resources and attitudes may partly explain the overrepresentation of educational explorers among children of high-SES parents. However, they cannot explain why the non-users type was associated with higher parental education, which was negatively associated with the same predictors overall.

Discussion

This study analyzed children's ICT use from a socio-cultural reproduction perspective (Bourdieu & Passeron, 1990), using a typological approach based on parental survey data. It was argued that prior to the massive spread of new mobile touchscreen devices and software applications in recent years, screen media use in middle childhood held limited value for cultural capital transmission, explaining the well-established negative association between parental SES and children's television time. However, new opportunities to support cultural capital transmission through ICT and to integrate ICT use in a "concerted cultivation" style of parenting may change the value parents with differing SES assign to their children's ICT use, affecting the relationship between parental SES and children's screen media use (Ito et al., 2020; Mollborn et al., 2022). As prior empirical research on ICT use in middle childhood is limited, it was previously unknown whether empirical patterns support either one or both interpretations of cultural reproduction theory.

Empirical analyses based on parental reports revealed no dominant ICT use type for either higher-SES or lower-SES families, supporting the idea that "cultures and structures related to children's technology use are in flux" (Mollborn et al., 2022, p. 19). Higher parental SES was simultaneously associated with two fundamentally different use types ("non-users" and "educational explorers"), indicating a divide among more advantaged families that may reflect the conflict between "traditional" and "new" class-specific views on ICT. In fact, among families with the highest SES, three similarly large latent classes were observed (additionally including "moderate entertainment users"). The fourth use type ("heavy users") was hardly present among families with high parental SES.

These results have several implications for socio-cultural reproduction processes in the digital age. First, the negative association between parental SES and the heavy users type alongside the positive association with the non-users type suggest that despite new technological opportunities, many higher-SES parents maintain the traditional view on screen media as less valuable for cultural capital transmission compared to other leisure activities, resembling the well-established social stratification in children's television consumption (Grant, 2024). This finding contrasts interestingly with a recent study of 8-year-olds in New Zealand, which found "limited use" to be associated with lower, rather than higher, parental education (Corkin et al., 2023).

Second, the finding that the educational explorers type was strongly associated with higher SES partly supports the idea of a new class-specific view on ICT. A subgroup of mostly higher-SES parents apparently lets their children use ICT in a broad way that may both help them develop general skills (e.g., through learning software and games) and give them a head start regarding ICT skills (Juhanák et al., 2019) by using ICT for more advanced and diverse activities (e.g., finding information). However, multivariate analyses demonstrated that this "new" approach was adopted only by a specific subgroup of parents: those with both higher SES and higher ICT-related resources. Higher-SES parents may lean towards different digital parenting strategies depending on their own capabilities of guiding their children's ICT use. Parents with higher SES, but lower ICT-related resources and more critical attitudes apparently resort to fostering other, more established leisure activities, which may constitute a "safer bet" in light of the uncertainties surrounding children's ICT use (Livingstone & Blum-Ross, 2020b; Meyer et al., 2021).

Third, although lower-SES parents expressed more critical views on children's ICT use, their children were less likely to be labeled non-users, suggesting that non-use may be harder to realize for them (Kuntsman & Miyake, 2022). Instead, lower-SES children were more likely to be assigned to the heavy users class. This pattern may be explained by higher levels of unstructured leisure time among lower-SES children (Lareau, 2011) or by the high prevalence of smartphone use in this group. Smartphone-centric ICT use is related to more entertainment- and social media-focused use types, which particularly affects lower-SES youth and children who are more likely to access the internet mainly via mobile phones (Lim & Loh, 2019).

Limitations and conclusions

The most important limitation of this study is the potential inaccuracy of parental reporting of children's ICT use due to limited parental knowledge or social desirability effects (Vittrup, 2009). Because this study focused mainly on socioeconomic disparities, mere limitations of accuracy are relatively unproblematic. However, if parental reports were biased according to SES, e.g., if higher-SES parents disproportionately underreported their children's ICT use, this would question some of the conclusions. The main consequence would be an overestimation of actual SES differences in children's ICT use and hence, of the attributed importance of children's ICT use for processes of socioeconomic reproduction via tangible effects on outcomes like cognitive development. However, even with this hypothetical bias, the results would still be informative regarding the presumed shift in class-specific parental perceptions of the value of children's ICT use. As argued in the background section and supported by the observed heterogeneity among higher-SES families, current norms about children's ICT use are conflicting (Mollborn et al., 2022), which makes a uniform bias less likely. Unfortunately, the available data offer no way to empirically assess such a bias.

Second, the online mode of the data collection may have caused an underrepresentation of children from digitally excluded parents (Herzing & Blom, 2019). However, external nonresponse analyses indicated only a small underrepresentation of households owning less than two computers (Röhlke & Herzing, 2023). Third, the quality of class separation indicated by the entropy measure was medium, which may result from imperfect indicators. It may also indicate a variety of gradually differing use patterns that is difficult to capture with a typology. Fourth, the focus on a specific age group implies that the relevance for children's further life course is unclear: How many of the non-users are simply "late starters"? ICT use types may change considerably with increasing age (Mollborn et al., 2021).

Finally, children's perspectives and agency regarding their own ICT use were not investigated because digital parenting strategies and parental resources in the context of social reproduction were the primary focus of this study. In Western countries, children are encouraged to voice their opinions and can therefore influence their ICT use, even if their preferences contradict their parents' ideals (Livingstone & Blum-Ross, 2020b; Mollborn et al., 2022). Higher parental SES is positively related to active parental mediation (Koch et al., 2024), which increases children's agency regarding ICT use. How the presented use types and the heterogeneity across levels of parental education relate to children's agency is an interesting starting point for further research.

The typological approach followed in this study revealed systematic heterogeneity in children's ICT use between and within SES levels, underscoring its advantages compared to the variable-based approach, which is more common in prior quantitative studies. A typology offers a more comprehensive description of socioeconomic disparities in children's ICT use and can help researchers to better understand the complex processes of social reproduction in the digital age. Follow-up studies should explore whether different types of children's ICT use are related to outcomes such as cognitive or digital skills, health, and wellbeing, potentially widening or narrowing social inequalities.

Identifying children's ICT use patterns linked to parental SES can guide nuanced and targeted approaches to promoting beneficial ICT use and reducing digital inequalities. Because primary schools are now starting to integrate ICT increasingly early (Vanderlinde et al., 2015), teaching with and about ICT must reflect children's diverse out-of-school experiences with ICT. As this study has shown, socioeconomic disparities in ICT use extend beyond screen time already in middle childhood and are strongly related to differing use purposes. These qualitative differences matter more than differences in screen time, as using ICT for playful learning rather than pure entertainment may benefit children's cognitive development and the development of important media-related skills (Livingstone et al., 2017; Sanders et al., 2019). As a potential school-based intervention, teaching children how to use ICT for playful learning may particularly support lower-SES students, who are less likely to pursue such activities at home. Interventions also need to consider the different device types that are prevalent across SES groups. For lower-SES students, school-based digital literacy training could be particularly effective if smartphone applications are included, overcoming possible stigma around early use. In Switzerland, many higher-SES children have rather limited ICT experience by second grade, particularly when their parents are cautious about ICT. School and civil society initiatives could help these families balance a safe and healthy childhood with preparing for a future in a digital world.

Table 1.1: Distribution of indicator variables in the main sample and across latent classes

Latent class number		I	II	III	IV
Variables	Over-all %	Heavy users (%)	Moderate entertain-ment users (%)	Educa-tional explorers (%)	Non-users (%)
Play video or computer games (on any device or platform)					
(Almost) Never	48	17	39	40	80
<30 min. per day	31	3	36	54	17
30-60 min. per day	14	43	19	5	2
>60 min. per day	7	37	6	2	1
Browse the Internet for pleasure (except social networks, e.g., listening to podcasts or music, watching videos)					
(Almost) Never	49	17	44	21	91
<30 min. per day	30	9	35	59	9
30-60 min. per day	16	40	18	18	0
>60 min. per day	6	33	4	2	0
Look for practical information online					
(Almost) Never	85	62	100	51	95
At least a few minutes per day	15	38	0	49	5
Browse social networks					
(Almost) Never	93	70	95	91	100
At least a few minutes per day	7	30	5	9	0
Communicate digitally (e.g., email, chat, messenger)					
(Almost) Never	91	71	96	79	98
At least a few minutes per day	9	29	5	21	2
Create or edit their own digital content (e.g., photos, videos, music)					
(Almost) Never	87	60	95	67	98
At least a few minutes per day	13	40	5	34	2
Play programming games (e.g., Scratch)					
(Almost) Never	93	79	98	91	98
At least a few minutes per day	5	21	2	9	2
Use the Internet to support studying or homework					
(Almost) Never	88	77	92	76	97
At least once a year	6	5	6	13	1
At least once a month	6	19	3	10	2
Use learning software, games, apps, or other learning tools					
(Almost) Never	57	35	64	26	77
<30 min. per day	34	26	29	65	21
>30 min. per day	9	39	7	8	2
Use a smartphone					
(Almost) Never	59	26	52	44	96
At least once a week	41	74	49	56	4
Use a tablet computer					
(Almost) Never	44	31	34	34	73
At least once a week	56	69	66	67	27
Use a PC or laptop					
(Almost) Never	78	67	81	62	90
At least once a week	22	33	19	38	10
Latent class size (%)		11	43	20	26

Note. $N = 2{,}490$; weighted.

Table 1.2: Multinomial logistic regression predicting latent class assignment (3-step-method, logit coefficients)

	I	II	III	IV	V	VI
	Ref.: Moderate entertainment users			*Ref.: Non-users*		*Ref.: Heavy users*
Outcome: Latent class assignment	Non-users	Heavy users	Educational explorers	Heavy users	Educational explorers	Educational explorers
Parental ICT resources						
Number of PCs at home (count)	-0.27^{**}	-0.10	-0.07	0.17	0.20^{+}	0.03
Variety of digital devices at home (z)	-0.29^{*}	0.28	-0.14	0.57^{**}	0.15	-0.42
Parent is neither ICT specialist nor has ICT task-intensive occupation (ref.)						
Parent is ICT specialist	0.21	0.58	-0.98^{+}	0.37	-1.18^{*}	-1.56^{+}
Parent has ICT task-intensive occupation	0.35	0.36	0.01	0.02	-0.34	-0.35
Parental ICT self-efficacy (z)	0.04	0.34	0.69^{*}	0.31	0.65^{**}	0.34
Parental attitudes						
Children can learn a lot by using PCs (z)	-0.21^{+}	0.35	0.30^{*}	0.57^{*}	0.51^{**}	-0.06
The Internet is dangerous for children (z)	0.26^{+}	-0.21	0.02	-0.47^{**}	-0.28^{+}	0.19
Family structure						
Single parent (ref. two-parent)	-1.02	-0.58	-0.65	0.43	0.37	-0.07
All parents work full time (ref. part time or less)	-0.20	0.54	-0.15	0.34	-0.35	-0.69
Sibling constellation: Only child (ref.)						
Older siblings only	-0.74	-0.15	-1.10^{*}	0.59	-0.37	-0.96
Younger siblings only	0.83	-0.69	-0.81	-1.52^{**}	-1.64^{**}	-0.13
Other	0.18	-0.54	-1.14^{+}	-0.72	-1.33^{*}	-0.61
Highest parental education						
Doctorate	0.57	-0.68	-0.19	-1.26	-0.76	0.50
Master's degree	0.36	-1.25	0.00	-1.61^{*}	-0.36	1.25
Bachelor's or upper vocational degree (ref.)						
Upper sec. or lower voc. degree	-0.80^{*}	0.41	-0.93^{*}	1.21^{*}	-0.14	-1.34^{*}
Lower secondary school	-2.01^{**}	1.29^{+}	-1.34	3.30^{**}	0.67	-2.63

Note. $n = 2{,}146$. Weighted. Additional controls: child's gender, age, generational status, school language, level of urbanity.
"Ref." indicates the reference category or reference class. z = z-standardized: scale rescaled to mean = 0, SD = 1. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

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Appendix

Table 1.A1: Documentation of the recoding of the original indicator variables prior to LCA

Original wording question	Original items corresponding to the indicators used in the LCA	Final indicators used for the LCA
During a typical week day, how much time does your child spend doing the following leisure activities?	”Play video-games (using a smartphone, a gaming console or an online platform or Apps)”	Play video or computer games (on any device or platform)
	”never or almost never	(Almost) Never
	”less than 30 minutes”	< 30 min. per day
	”up to 1 hour”	30-60 min. per day
	”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	> 60 min. per day
	Browse the Internet (excluding social networks) for fun (e.g., reading news, listening to podcasts and music or watching videos)	Browse the Internet for pleasure (except social networks, e.g., listening to podcasts or music, watching videos)
	”never or almost never”	(Almost) Never
	”less than 30 minutes”	< 30 min. per day
	”up to 1 hour”	30-60 min. per day
	”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	< 60 min. per day
	Look for practical information online (e.g., find a place, book a train ticket, buy a product)	Look for practical information online
	”never or almost never”	(Almost) Never
	”less than 30 minutes”, ”up to 1 hour”, ”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	At least a few minutes per day
	Browse social networks (e.g., Instagram, Facebook)	Browse social networks
	”never or almost never”	(Almost) Never
	”less than 30 minutes”, ”up to 1 hour”, ”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	At least a few minutes per day
	Communicate digitally (e.g., emails, chat, WhatsApp)	Communicate digitally (e.g., email, chat, messenger)
	”never or almost never”	(Almost) Never

Table 1.A1 (continued): Documentation of recoding

Original wording question	Original items corresponding to the indicators used in the LCA	Final indicators used for the LCA
	”less than 30 minutes”, ”up to 1 hour”, ”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	At least a few minutes per day
	Create or edit their own digital content (photos, videos, music, computer programs)	Create or edit their own digital content (e.g., photos, videos, music)
	”never or almost never”	(Almost) Never
	”less than 30 minutes”, ”up to 1 hour”, ”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	At least a few minutes per day
	Play programming games (e.g., Scratch, Spark from Code Camp)	Play programming games (e.g., Scratch)
	”never or almost never”	(Almost) Never
	”less than 30 minutes”, ”up to 1 hour”, ”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	At least a few minutes per day
	Learning software, games or apps, other learning tools (e.g., Appolino or Mindsteps online support)	Use learning software, games, apps, or other learning tools
	”never or almost never”	(Almost) Never
	”less than 30 minutes”	$<$ 30 min. per day
	”up to 1 hour”, ”1 to 2 hours”, ”2 to 4 hours”, ”more than 4 hours”	$>$ 30 min. per day
How often has your child used the following digital resources outside of school this school year (e.g. at home or at a place where he/she normally has access to digital resources)?	Smartphone (e.g. Mobile phone with internet access)	Use a smartphone
	”never or almost never”, ”about once or twice a month”	(Almost) Never
	”about once or twice a week”, ”every day or almost every day”, ”multiple times a day”	At least once a week
	Tablets (e.g. iPad, Samsung Galaxy Tab)	Use a tablet computer
	”never or almost never”, ”about once or twice a month”	(Almost) Never
	”about once or twice a week”, ”every day or almost every day”, ”multiple times a day”	At least once a week
	PC or laptop	Use a PC or laptop

Table 1.A1 (continued): Documentation of recoding

Original wording question	Original items corresponding to the indicators used in the LCA	Final indicators used for the LCA
	”never or almost never”, ”about once or twice a month”	(Almost) Never
	”about once or twice a week”, ”every day or almost every day”, ”multiple times a day”	At least once a week
This school year, how often has your child used digital resources for the following school activities outside of class?	”Browsed the internet to follow up lessons (e.g., for finding explanations)”, ”Communicate with other students about school assignments (e.g., via video call or messenger service)”	Use the Internet to support studying or homework
	”never or almost never”	(Almost) Never
	”about once or twice a year”	At least once a year
	”about once or twice a month”, ”about once or twice a week”, ”every day or almost every day”	At least once a month

Table 1.A2: Goodness of fit of latent class models with two to six classes (N = 2,490)

Class #	npar	LL	AIC	BIC	Entropy
2	46	−16, 501	33,094	33,362	0.56
3	65	−16, 371	32,871	33,249	0.60
4	84	−16, 254	32,675	33,164	0.62
5	103	−16, 200	32,607	33,206	0.63
6	122	−16, 159	32,561	33,271	0.66

Note. Weighted. Class # = number of latent classes; npar = number of parameters; LL = Log-likelihood; AIC = Aikake’s Information Criterion; BIC = Bayesian Information Criterion.

Table 1.A3: Cross-tabulation of latent classes and demographic variables

		I	II	III	IV	
	Full sample % / mean (weighted)	Heavy users	Moderate entertain-ment users	Educa-tional explorers	Non-users	Overall chi-square test
Child age (months)	101	102	101	101	100	16.3**
Child is female (%)	48	40	45	57	50	7.2
Child is native Swiss (%)	81	57	84	78	87	38.7***
Child is second-generation immigrant (%)	15	34	13	16	11	24.4***
Child is first-generation immigrant (%)	4	9	3	6	2	13.1**
Settlement structure: Urban (%)	55	65	52	61	50	10.4*
School main language: (Swiss-) German (%)	68	52	67	89	59	96.1***
School main language: French (%)	27	41	28	8	35	86.4***
School main language: Italian (%)	5	7	5	3	6	16.5**
Latent class size (%)		11	43	20	26	

Note. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. All results are weighted.

Table 1.A4: Cross-tabulation of explanatory factors by parental education

	Overall % / mean	Lower secondary school (n = 104)	Upper sec. / Lower vocat. (n = 629)	Higher vocat. / Bachelor's (n = 596)	Master's (n = 617)	Doctorate (n = 223)
Device availability						
Number of PCs at home (mean)	3.13	1.89	2.59	3.12	3.50	4.20
Variety of digital devices at home (z-standardized, mean)	0.02	−0.40	−0.05	0.11	0.05	0.04
Parental ICT resources						
Parent is ICT specialist (%)	12	2	5	12	18	16
Parent has ICT task-intensive occupation (%)	23	4	11	23	34	31
Parental ICT self-efficacy (z-standardized, mean)	0.01	−0.48	−0.18	−0.03	0.21	0.37
Parental attitudes						
Children can learn a lot of new things by using PCs (z-standardized agreement, mean)	−0.01	−0.22	−0.06	−0.05	0.07	0.16
The Internet is dangerous for children (z-standardized agreement, mean)	−0.01	0.25	0.17	−0.04	−0.10	−0.25
Family structure						
Single parent (%)	7	20	12	6	3	6
All parents work full time (%)	19	28	25	18	16	14
Sibling constellation: Only child (%)	12	11	15	9	11	16
Sibling constellation: Older siblings only (%)	34	33	35	33	34	37
Sibling constellation: Younger siblings only (%)	39	37	35	44	39	33
Sibling constellation: Other (%)	15	19	15	13	16	15
Group size parental education (%)		4	27	31	29	9

Note. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. All results are weighted.

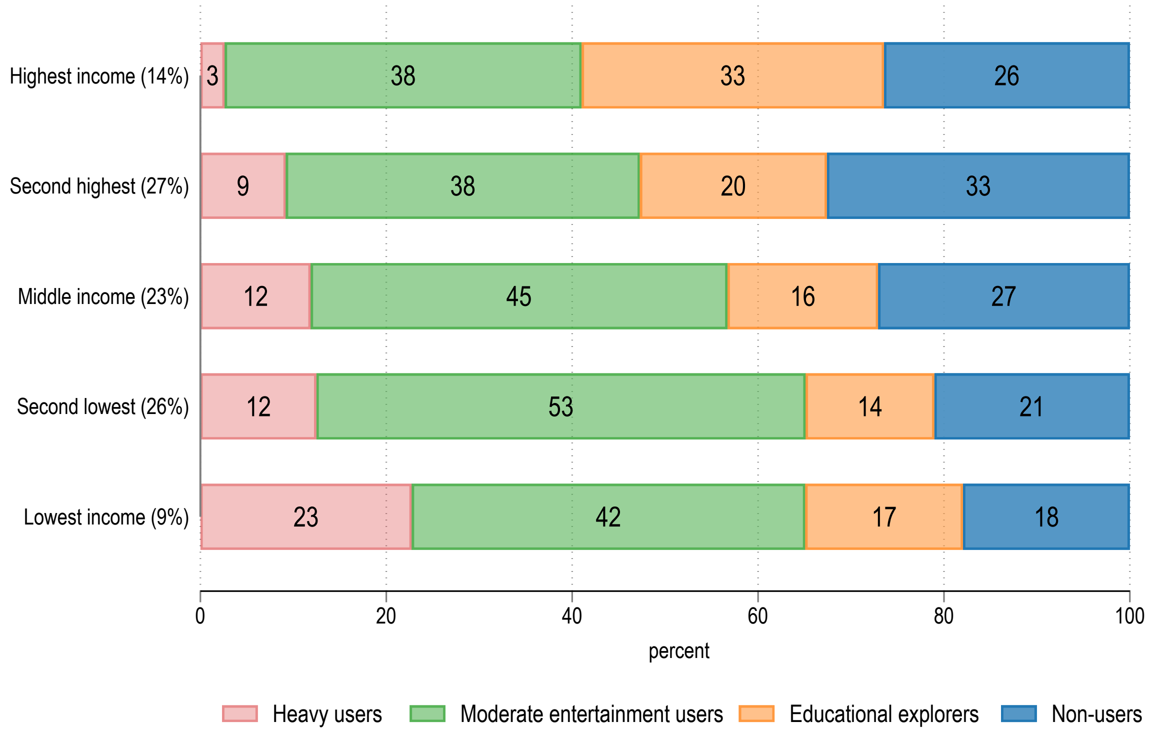

Figure 1.A1: Distribution of latent classes by total parental income

Mplus Syntax

Main model (4-classes):

```
INPUT INSTRUCTIONS
  TITLE:
    Variable List -

    game_ind : Daily minutes of playing video or computer games
      0: (Almost) Never
      1: At least a few minutes (<30 min.)
      2: 30-60 min.
      3: >60 min.
    browse_ind : Daily minutes of browsing the Internet for pleasure
      0: (Almost) Never
      1: At least a few minutes (<30 min.)
      2: 30-60 min.
      3: >60 min.
    search_ind : Daily minutes of looking up online information
      0: (Almost) Never
      1: At least a few minutes
    socmed_ind : Daily minutes of using social media
      0: (Almost) Never
      1: At least a few minutes
    chat_ind : Daily minutes of digital communication
      0: (Almost) Never
      1: At least a few minutes
    create_ind : Daily minutes of creating own content
      0: (Almost) Never
      1: At least a few minutes
    program_ind : Daily minutes of playing programming games
      0: (Almost) Never
      1: At least a few minutes
    schint_ind : Frequency of using the Internet for studying
      0: (Almost) Never
      1: At least once a year (< once a month)
      2: At least once a month
    learng_ind : Daily minutes of playing learning games
      0: (Almost) Never
      1: At least a few minutes (<30 min.)
      2: >60 min.
    phone_ind : Regular use of a mobile phone
      0: (Almost) Never
      1: At least once a week
    tablet_ind : Regular use of a tablet computer
      0: (Almost) Never
      1: At least once a week
```

```
    pc_ind : Regular use of a personal computer
      0: (Almost) Never
      1: At least once a week
    smp_w_nrapqw : Sampling: Parent questionnaire weight, non-response adjusted
DATA:
    FILE = __000002.dat ;
  VARIABLE:
    NAMES =
      game_ind browse_ind search_ind socmed_ind chat_ind create_ind
  program_ind schint_ind learng_ind phone_ind tablet_ind pc_ind
  smp_w_nrapqw ;
    MISSING ARE ALL (-9999) ;
    CLASSES = c(4) ;
  weight=smp_w_nrapqw  ;
  categorical = game_ind browse_ind search_ind socmed_ind chat_ind
  create_ind program_ind schint_ind learng_ind phone_ind tablet_ind
  pc_ind  ;

  ANALYSIS:
     PARAMETERIZATION = rescov ;
     ALGORITHM = integration ;
  type=mixture ;
  proc=16(starts)  ;
  starts= 3000 400  ;
  estimator=mlr  ;
  stiterations = 30  ;

  OUTPUT:
  MODEL:
  %overall%
  browse_ind WITH game_ind  ;
  game_ind WITH learng_ind  ;
  socmed_ind WITH chat_ind  ;
  program_ind WITH pc_ind  ;
  schint_ind WITH pc_ind  ;
  tablet_ind WITH learng_ind  ;
  phone_ind WITH socmed_ind  ;
  phone_ind WITH tablet_ind  ;
  chat_ind WITH phone_ind  ;
```

Study 2:

How national contexts moderate socioeconomic inequality in adolescents' digital technology use: A cross-country comparative study

Abstract. This study examines how national contexts moderate the association between adolescents' socioeconomic background and their out-of-school use of information and communication technologies (ICT). Prior research shows that socioeconomically advantaged adolescents use ICT more for educational (i.e., school-related) and less for recreational purposes (e.g., gaming, social media). However, little is known about how these socioeconomic gaps vary across countries. Bridging social reproduction and digital divide literatures, we develop and test different country-level moderators. Using survey data from the 2022 Programme for International Student Assessment (PISA) on 15-year-olds from 44 countries, we find that higher family socioeconomic status (SES) is related to more educational ICT use in all examined countries. This SES gap is wider in countries with greater educational returns and higher quality of school ICT integration, but unrelated to countries' home ICT access levels. For recreational ICT use, however, home ICT access is the main driver of cross-country differences in the SES gap. A negative association between SES and recreational use is only found for countries where home ICT access is high, while the association is positive in countries with low access. Overall, cross-country patterns of digital use inequality in adolescence differ fundamentally between educational and recreational ICT use.

This study is co-authored by Renae Sze Ming Loh. It is currently under review.

Introduction

Interactive information and communication technologies (ICT) have reshaped adolescents' free time, with digital activities such as electronic games or social media supplanting activities like reading, sports and watching television as activities of choice (Fomby et al., 2021). Across many countries, adolescents spend multiple hours daily on digital devices outside school. The digital activities that make up these hours differ vary by socioeconomic background, with those from higher socioeconomic status (SES) families using ICT more for educational purposes (e.g., Notten et al., 2009; van de Werfhorst et al., 2022) and less for recreational purposes (e.g., gaming, social media, and digital communication; Camerini et al., 2018; Weber & Becker, 2019). However, these socioeconomic gaps vary considerably across countries in magnitude and sometimes even in direction (Gracia et al., 2020, 2023; Ma et al., 2019; Mielke et al., 2017; van de Werfhorst et al., 2022).[1]

And while such cross-national differences in SES gaps are noted, a systematic explanation is still lacking. As a result, the generalizability of these patterns and their theoretical underpinnings remain uncertain. As inequalities in ICT use are connected to inequalities in life outcomes such as adolescents' wellbeing and mental health (Gracia et al., 2023), their physical health (Stiglic & Viner, 2019), but also their cognitive development and related educational outcomes (Black et al., 2024), understanding which country-level factors may narrow or widen SES gaps in ICT use has important implications for inequalities in other domains. This is particularly so as countries continue to invest significantly in ICT within education (OECD, 2023a), and the nature of work and leisure continues to digitalize, thus amplifying the role ICT and ICT use has in life outcomes (Allmann & Blank, 2021).

In this study, we therefore examine how national contexts moderate the relationship between adolescents' socioeconomic background and their out-of-school use of ICT – making an effort to distinguish between educational and recreational ICT use rather than overall out-of-school screen-time. We analyze data from the Programme of International Student Assessment (PISA) 2022 on 44 countries (N = 332,822) with different levels of country affluence and varying educational systems. PISA 2022 offers a wide range of items that cover the variety of activities that make up adolescents' ICT use today, as well as further contextual information that enables the up-to-date measurement of relevant country-level conditions.

A key contribution of our study is the theorizing of potential country-level moderators beyond affluence. We bring together several arguments that were previously scattered across different bodies of literature: First, from digital divide literature comes the argument that when the "first-level digital divide" is closed, i.e., when home ICT access in a country

[1] For instance, Mielke et al. (2017) reported reversed SES gaps in screen-time in high-income countries, but positive SES gaps in low-income countries, while van de Werfhorst et al. (2022) reported positive SES gaps regarding school-related ICT use across all investigates countries, which varied strongly in terms of magnitude.

becomes nearly universal, home access is less likely to represents a barrier to ICT use for disadvantaged households (Camerini et al., 2018). Therefore, SES gaps in adolescents' ICT use may narrow or even reverse in countries with greater home ICT access levels. Second, social reproduction scholarship highlights how greater educational returns in a country place more pressure on and shape higher-SES adolescents' out-of-school activities (Doepke & Zilibotti, 2019). Educational returns may consequently widen the SES gap in educational ICT use and narrow or reverse the SES gap in recreational ICT use. Finally, digital education scholarship posits that schools with high-quality ICT-supported teaching may mitigate socioeconomic inequality in adolescents' digital skills which in turn support their educational ICT use (Loh et al., 2025). We therefore expect smaller SES gaps in educational ICT use in countries with greater average school ICT integration quality.

Theoretical background

According to social reproduction theories (Bourdieu & Passeron, 1990), adolescents' out-of-school activities can function as a mechanism of intergenerational status transmission (Jæger & Breen, 2016; Lareau, 2011). The pursuit of capital enhancing activities like reading, going to the museum, or certain extracurricular activities such as private tutoring, sports practice, and music lessons, can foster cognitive or noncognitive skills (Jürges & Khanam, 2021) as a form of "embodied cultural capital" (Bourdieu, 2011). As adolescents from higher-SES backgrounds engage more frequently in these capital-enhancing activities than their less-advantaged peers (Bering & Schulz, 2024), they accumulate more embodied cultural capital that they can ultimately translate into educational and occupational success (Jæger & Breen, 2016).

Today, using ICT dominates adolescents' out-of-school activities, but its role in social reproduction remains unclear. Rather, the dominant rhetoric is one of distraction – that screen-time is necessarily detrimental and not capital-enhancing as reading or going to the museum (Jorge et al., 2022). Moreover, many previous studies have examined inequalities in overall screen-time (i.e., time using ICT) rather than distinguishing between educational and recreational use (e.g., Gracia et al., 2020; Mielke et al., 2017; OECD, 2015), typically yielding mixed patterns of positive and negative associations with SES across countries. Furthermore, such a stance washes over the different activities that make up screen-time, which may also be disparate over social lines; this disparity in use is referred to as the "second-level digital divide" (van Dijk, 2020). To understand the role ICT use plays in today's social reproduction processes calls for a distinction between different forms of ICT use.

In this study, we differentiate between educational and recreational ICT use. While other delineations are possible, we opt for the educational and recreational distinction as it mirrors the demarcation between educational (capital enhancing) and recreational (or non-capital enhancing) leisure activities in social reproduction traditions, and aligns with distinctions drawn in prior research on SES differences in adolescents' ICT use (Weber & Becker, 2019). Educational ICT use, such as completing homework, studying for an exam, or watching educational videos, may improve school performance and therefore serves towards status reproduction and is typically more common among advantaged adolescents. In contrast, recreational ICT use, like playing electronic games, using social media, or streaming, lacks direct benefits and may even be detrimental to human-capital outcomes (Bohnert & Gracia, 2023). It is therefore problematized in many families (Mollborn et al., 2022) and typically less pursued by adolescents with higher-SES backgrounds.

Family socioeconomic background and ICT use (individual level)

In this section, we briefly summarize the leading individual-level mechanisms from social production and digital divide literatures (Becker, 2023; Loh et al., 2023b; van Dijk, 2020), which underlie socioeconomic inequalities in adolescents' educational and recreational ICT use. These individual-level mechanisms form the theoretical foundation for our hypotheses on country-level moderators, but we will not test them in this study.

Firstly, home access to ICT, which includes the availability of hard- and software and internet access, forms the basis for engaging in digital activities (van Deursen & van Dijk, 2019). While the first-level digital divide of socioeconomic disparities in household access is narrowing (van Dijk, 2020), low-SES adolescents typically still have access to fewer and lower-quality digital devices at home and, in many countries, are still less likely to have access to a personal computer (Goudeau et al., 2021). Many rely primarily on mobile phones (Correa et al., 2020), which lend better to recreational rather than educational use due to their affordances (Goudeau et al., 2021; van Deursen & van Dijk, 2019). Consequently, socioeconomic inequality in home ICT access leads to socioeconomic disparities in educational ICT use (Hargittai, 2010; Notten et al., 2009), and arguably recreational ICT use as well.

Secondly, as mentioned, engagement with enriching activities (e.g., homework and studying, tutoring and structured extracurricular activities like music or sports practice) differ by socioeconomic background (Bering & Schulz, 2024). This has differing implications for educational and recreational ICT use opportunities. Since educational ICT use is seen and aligns with enrichment, while recreational ICT use does not, higher-SES adolescents are more likely to, when using ICT during their out-of-school time, engage in educational ICT use rather than recreational. This tendency is reinforced by unequal parental mediation strategies (Mascheroni et al., 2016).

Lastly, digital skills are almost a prerequisite to ICT use (Hargittai, 2010), and positively associated with socioeconomic background (Fraillon, 2024). In addition to higher parental support with ICT (Nikken & Opree, 2018), higher-SES adolescents may be more likely to attend schools which foster their digital skills and show them how to use ICT productively and in advanced ways (González-Betancor et al., 2021; Rafalow, 2018). With higher skills, adolescents are more likely to engage in more diverse (Hargittai, 2010), and potentially capital-enhancing ICT use, like using ICT to find information or support studying (van Dijk, 2020). As recreational ICT use among adolescents (e.g., watching videos, social media) typically requires largely basic digital skills, adolescents' digital skills may be more strongly related to their educational than their recreational ICT use.

In summary, due to socioeconomic inequalities in home ICT access, engagement with enriching activities, and digital skills, adolescents' family SES is generally considered to be positively associated with educational ICT use and negatively associated with recreational ICT use. Indeed, multi-country studies consistently find family SES to be positively associated with adolescents' educational ICT use, regardless of form, like school-related ICT use (Becker, 2023), use of educational software (Ma et al., 2019), informational internet use (Notten et al., 2009; OECD, 2015), informational online reading (Notten & Becker, 2017), school-related ICT use (van de Werfhorst et al., 2022), and browsing the Internet for school or sharing school-related materials (Weber & Becker, 2019). However, the magnitude of the SES gap in educational ICT use varies considerably across countries (e.g., Ma et al., 2019; van de Werfhorst et al., 2022) and the "typical" associations are largely established based on high-income countries.

SES gaps in recreational ICT use are less consistent, and vary across countries not only in magnitude, but also in direction (Mielke et al., 2017; Trucco et al., 2022; Weber & Becker, 2019). The association between SES and recreational ICT use was found to be positive in studies examining middle- or lower-income countries (e.g., Trucco et al., 2022), but reversed in studies on high-income countries (e.g., Camerini et al., 2018). This evinces that inconsistencies in SES and ICT use associations are, at least in part, due to country differences.

The role of national contexts: Developing cross-level moderation hypotheses

Theoretical arguments are scant on the sources of country-level differences beyond theorizing differences in affluence. Furthermore, only a handful of studies have sought to explain cross-country differences in ICT use inequalities among adolescents. Of note is Ma et al. (2019), who found that the SES gap in educational ICT use was smaller in high-income countries, and in low-income countries with higher national investment in research and development. They did not find significant moderation effects of income inequality and political freedom levels after controlling for national income. Notten and Becker (2017) reported no significant differences in the relationship between family cultural capital levels and educational ICT use (informational online reading) between countries with differing levels of digitalization and development. Finally, Mielke et al. (2017) found a reversed SES gap (negative association with SES) in recreational ICT use only in high-income countries, while the association turned positive for lower-income countries.

In the following, we build upon prior work and the individual-level arguments discussed above to elaborate on how three key facets of national context that are specifically relevant to adolescents and their ICT use –- (1) average home ICT access, (2) educational returns, and (3) school ICT integration –- moderate the relationship between SES and educational and recreational ICT use. This gives us the opportunity to also understand differences between high-income countries. Figure 2.1 visualizes our conceptual model.

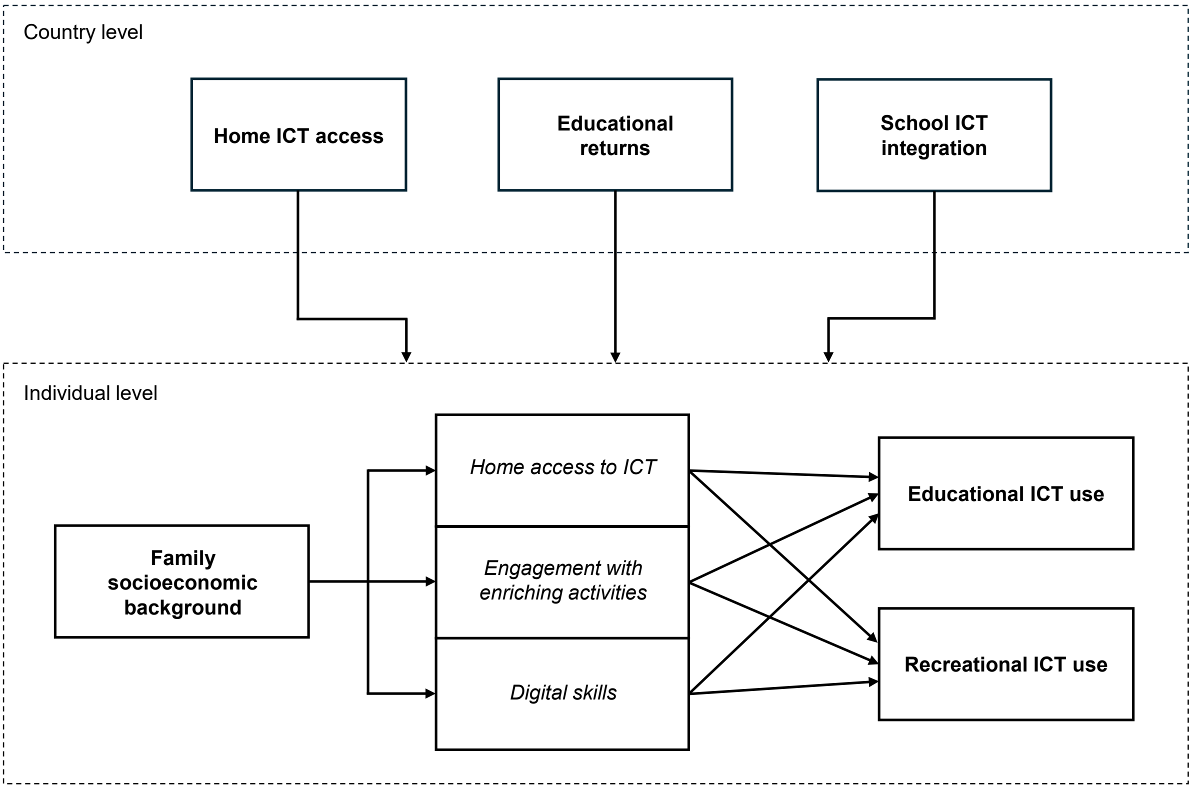

Figure 2.1: Conceptual model

Country-level home access to ICT: In countries with higher average access levels to ICT, higher-SES adolescents possess a smaller advantage in terms of ICT use opportunities over their lower-SES peers. This could be due to two different, albeit related, sub-mechanisms. The first is a ceiling effect, where near-universal access reduces SES disparities and thereby limits the sway access at home has on ICT use (Camerini et al., 2018), even if the remaining "disconnected" families are mostly low-SES (Goudeau et al., 2021). Second, any remaining socioeconomic differences in ICT access may be less likely to affect adolescents' use behavior, as these tend to refer to secondary characteristics such as brands or actuality of devices. These characteristics are likely to have a smaller effect on usage than more fundamental aspects of access such as the availability of a computer. As such, greater national average of home ICT access would dampen the mediating effect of individual-level home ICT access (Figure 2.1).

Following the argument made further above, that better individual-level access to ICT at home is positively related to both educational and recreational ICT use, we posit that greater country access levels increase lower-SES adolescents' relative intensity of ICT use both regarding educational and recreational ICT use.[2] We therefore expect higher access to be related to a smaller SES gap in educational ICT use:

> **Hypothesis 1:** In countries with greater average ICT access levels, the SES gap in educational ICT use is narrower.

For recreational ICT use, while the mathematical implication of our hypothesis is the same (implying a negative moderation effect of access levels on the association between SES and ICT use), the formulation of a hypothesis is more complicated because, according to previous studies, the direction of the relationship between SES and recreational ICT use differs between countries. Higher access levels may therefore be related not only to a narrowed positive SES gap, but to the SES gap reversing from being positive in lower-access countries to negative in high-access countries:

> **Hypothesis 2:** In countries with greater average ICT access levels, the SES gap in recreational ICT use is narrower or reversed.

Country-level educational returns: Next, in countries with greater private educational returns, socioeconomic stratification in adolescents' ICT use will be more pronounced. Higher educational returns (i.e., a student's success in the educational system is more consequential for future earnings) typically result in more pressure on students to perform well in school. This spurs stricter parenting styles and more investment in out-of-school enrichment activities like private tutoring (Doepke & Zilibotti, 2019). In contrast, in countries with lower educational returns, e.g., in countries with strong welfare redistribution systems, pressure on students is lower and parenting tends to be less strict. As a consequence, in high-pressure contexts, adolescents are likely to engage more with enriching and less with purely recreational activities (Doepke & Zilibotti, 2019).

Furthermore, higher educational returns exacerbate socioeconomic inequalities in out-of-school activities, as additional pressure induced by greater educational returns will disproportionately affect higher-SES adolescents. Social reproduction literature illuminates this, arguing that intergenerational maintenance of social status is a powerful motivational driving socially stratified investments in children's educational success (Breen & Goldthorpe, 1997; Lucas, 2001). According to this literature, higher-SES adolescents have a greater incentive to invest in their educational success, e.g., through enriching out-of-school activities

[2] We deliberately make no assumptions about heterogeneity in the individual-level effect of home access on use behavior by socioeconomic background in order to not overcomplicate the hypotheses.

(Entrich, 2020), because they have more to lose in terms of their future economic position. Consequently, educational ICT use represents a greater opportunity for higher-SES adolescents to help maintaining their social status in countries where school success is more strongly related to future earnings:[3]

> **Hypothesis 3:** In countries with greater educational returns, the SES gap in educational ICT use is wider.

Similarly, in countries with higher educational returns, recreational ICT use poses a greater risk to adolescents' future economic success, due to potential problems in school from intensive recreational ICT use (Bohnert & Gracia, 2023) negatively impacting future income in these contexts. Thus, higher-SES adolescents are expected to engage less in recreation use compared to lower-SES adolescents, narrowing the SES gap in recreational use or leading to a more strongly reversed SES gap (greater negative association), depending on countries' differing baseline levels in this relationship:

> **Hypothesis 4:** In countries with greater educational returns, the SES gap in recreational ICT use is narrower or reversed.

Country-level school ICT integration: Finally, higher ICT integration quality in a country's schools –- in terms of their technical infrastructure, teacher digital skills and motivation and curriculum emphasis on ICT use in the classroom (Loh et al., 2025) – may mitigate socioeconomic inequalities in adolescents' educational ICT use. This is done by compensating for disadvantaged students' relative lack in digital skills through high-quality ICT integration in school (González-Betancor et al., 2021; Loh et al., 2025) providing opportunities and guidance on more advanced ICT use in their school, which they often lack at home (Warschauer & Matuchniak, 2010). Countries differ in the average quality of their schools' ICT integration, with some countries heavily relying on ICT-supported education as a part of a broader economic strategy around ICT (Loh et al., 2023a), while other countries set different goals or struggle with the practical complexities of school ICT implementation (Fraillon, 2024).

Because students' digital skills are an important prerequisite for diverse and capital-enhancing ICT use which includes educational activities (van Dijk, 2020), greater digital skills and knowledge about how to use ICT for education obtained in school may therefore lead to lower-SES adolescents using ICT more for educational purposes, or matching the level of use of their higher-SES peers. Hence, we hypothesize that:

> **Hypothesis 5:** In countries with greater average quality of school ICT integration, the SES gap in educational ICT use is narrower.

[3] A similar argument has been tested in two studies recently, which argued that the existence of high-stakes exams may lead to higher social stratification in the uptake of shadow education (Entrich, 2020; Zwier et al., 2020).

As most recreational ICT use does not require higher levels of digital skills, we do not expect school ICT integration quality to be related to SES gaps in recreational ICT use:

> **Hypothesis 6:** The SES gap in recreational ICT use is not significantly related to countries' average quality of school ICT integration.

Data and Methods

Data

We analyze OECD PISA 2022 data, which is primarily concerned with assessing 15-year-old students' performance in mathematics, reading, and science towards the end of compulsory schooling. PISA 2022 additionally offers current and comparable indicators of adolescents' ICT use across a large number of countries. Students were sampled in a two-stage stratified sampling process, with the first stage consisting of individual schools having 15-year-old students, and the second stage consisting of students within schools (OECD, 2024). Self-reports of adolescents' ICT use were surveyed as part of the ICT familiarity questionnaire, which was administered in 51 countries (N = 393,607). We further use PISA 2022 data to create two country-level moderator variables (indicators for country-level home ICT access and school ICT integration quality). In addition, we use an external database by Montenegro and Patrinos (2021) for internationally comparable estimates of country-level educational returns, and data from the World Bank for GDP per capita in 2022 (as a control variable). Information on country-level educational returns was not available for seven countries[4], and they are thus excluded, leaving a final analysis sample of 332,822 students from 44 countries.

Measures

Dependent variables

Adolescents' out-of-school educational and recreational ICT use is based on three self-report questions from the ICT familiarity questionnaire. All items are listed in Table 2.1. The exact wording of the questions is presented in Table 2.A1 (Appendix). We set implausible responses to missing values prior to calculations. We consider responses as clearly implausible when students indicated to spend "7 hours or more" every day on all seven leisure activities (e.g., video games; see Table 2.A1), which applied to 6,509 students (1.96%) in total. Retaining these large outlier answers could potentially cause bias.

[4] Brunei Darussalam, Hong Kong, Israel, Kazakhstan, Macao, Saudi Arabia, and Taiwan.

Because categorizing diverse ICT-related activities as either recreational or educational is not always straightforward, we conduct an exploratory factor analysis (principal components). Applying orthogonal rotation yields the factor loadings presented in Table 2.1. As the factor scores for Factors 1 and 2 align very well with our theoretical distinction between educational and recreational ICT use, the predicted values obtained from these factors are used as our dependent variables for the subsequent empirical analyses. Factor 3 refers to ICT use for largely school-unrelated information gathering as well as content creation ("creative-explorative use"), which does not fit our theoretical framework and is excluded from analysis.

Table 2.1: Rotated factor loadings

	Factor 1	Factor 2	Factor 3
Factor label	Educational ICT use	Recreational ICT use	Creative-explorative ICT use
See school grades or assignment results	**0.76**	0.13	−0.08
Browse the web for school	**0.82**	0.08	−0.01
Follow up on school lessons	**0.81**	0.04	0.11
Receive / download school assignments	**0.80**	0.01	0.11
Upload school-related work	**0.80**	0.05	0.09
Communicate with teacher	**0.72**	0.03	0.16
Communicate with other students about schoolwork	**0.71**	0.07	0.08
Search for information on school-related activities or assignments	**0.80**	0.04	0.11
Play video games	−0.04	**0.63**	0.14
Browse social networks	0.11	**0.82**	0.18
Browse the internet for fun	0.10	**0.76**	0.30
Look for practical information online	0.07	0.33	**0.76**
Communicate/share content on social networks	0.11	**0.63**	0.49
Read/listen to/watch informational materials	0.06	0.25	**0.80**
Create or edit digital content (photos, videos)	0.04	0.29	**0.76**
Educational software / educational game use	0.25	−0.24	**0.58**

Note. N = 221,223 students (complete cases). Loadings greater than |.50| are shown in boldface.

Socioeconomic background

For socioeconomic background, we use the PISA index of economic, social and cultural status (ESCS), a composite index of three indicators derived from the student questionnaire (OECD, 2024): Highest parental occupational status (HISEI), highest education of parents in years (PAREDINT), and home possessions (HOMEPOS). HOMEPOS includes the number of books, the availability of an own room for the student and the availability of digital devices and software available in the student's main household.

Country-level moderating variables

Country-level home ICT access is reflected as the percentage of adolescents with self-reported home access to all of the following: a computer (including tablets), Internet access (excluding mobile access), their own cell phone with Internet access, and educational software or apps. Our measure represents a country-level aggregation of students' responses in the general student questionnaire of PISA 2022. It acknowledges that both physical and material ICT access affect individuals' opportunities to use ICT (van Deursen & van Dijk, 2019). For a robustness check, we instead use the average number of digital devices available in adolescents' homes (see Table 2.3 for descriptive statistics).

Country-level educational returns is measured as percentage income returns to an additional year of schooling, as estimated by Montenegro and Patrinos (2021). Measuring private educational returns is challenging, and hardly any international databases exist except for the one used in this study. The actuality of indicators in the database differs across countries as they were compiled from different cross-sectional surveys. However, private educational returns to schooling are usually relatively stable over time (Montenegro & Patrinos, 2021). We use the latest information available for each country in the database.

Country-level school ICT integration is indicated by an average of students' perceptions of the quality of ICT infrastructure and related teaching in their current school. This is derived through the ICTQUAL scale from PISA 2022, which we average within countries, and finally rescale to the range 0–10 (Cronbach's $\alpha = 0.91$). Conceptually, this scale combines aspects of school ICT infrastructure, availability of technical support, and ICT use in education (for details, see Table 2.A1), all of which are key facets of school ICT integration.

As a control variable on the country level, we use gross domestic product (GDP) per capita (in 2020 USD), as provided by the World Bank. We control for GDP per capita as it is likely correlated with ICT access at home and school ICT integration levels, as well as SES gaps in ICT use (Ma et al., 2019; Mielke et al., 2017). Furthermore, it captures other unobserved aspects of country affluence. If associations hold when controlling for GDP per capita, this makes our results more credible in representing theoretically meaningful associations rather than an undefined correlate of countries' wealth.

Table 2.2 presents bivariate correlations between the country-level moderating variables. As expected, home ICT access and school ICT integration quality are positively related to GDP per capita, while the level of educational returns is only weakly correlated. Home ICT access and school ICT integration quality also show a large positive correlation.

Table 2.2: Bivariate correlations between country-level moderator variables ($N = 44$)

		(1)	(2)	(3)	(4)
(1)	GDP per capita (logged)	1.00			
(2)	Home ICT access (%)	.68	1.00		
(3)	Educational returns	.19	.05	1.00	
(4)	School ICT integration (scale 0-10)	.57	.68	.06	1.00

Multiple imputation

The self-reported indicators of students' ICT use that constitute our dependent variables contained a considerable amount of missing data, which varies across countries (see Table 2.3).[5] As missingness here results not from design but from students' response behaviors, missingness is likely influenced by student characteristics and hence not missing completely at random (MCAR). Thus, applying listwise deletion may potentially bias our estimates. To address this, we apply multiple imputation by chained equations (MICE; Azur et al., 2011), using a categorization and regression tree (CART) algorithm as implemented in the mice package of R version 4.4.2 (van Buuren & Groothuis-Oudshoorn, 2011). We generate 20 imputed datasets separately for each country, merge them into one dataset and pool the estimates and standard errors of our main analyses using Rubin's rules (Rubin, 2004). To enhance imputation quality, we include gender, availability of digital devices, and students' ICT self-efficacy as auxiliary variables.

Statistical modeling

To test our hypotheses, we apply a two-step modeling approach (Giesecke & Kohler, 2024). First, we estimate the first-level association between adolescents' socioeconomic background (ESCS) and the intensity of educational [recreational] ICT use separately for all 44 countries (the second-level units), using ordinary least squares (OLS) regression models. We adjust all standard errors for clustering on the school level. Second, we use the regression coefficients of ESCS across all countries obtained from the first step as the dependent variable in another set of OLS regression models, where we regress this variable on the country-level predictors. The resulting coefficients of the country-level variables represent cross-level interactions (interaction between a first- and a second-level variable), showing how country-level factors moderate SES effects on the individual level. The two-step approach is well-suited for analyzing cross-level interactions in two-level data, especially when the dataset contains many observations at the first and a limited number of observations at the second level

[5]Note: The percentage of students in the analysis sample with entirely missing information across all ICT use indicators is smaller (10.7%) than the percentage of students with partial information (22.8%).

(Giesecke & Kohler, 2024).[6] These conditions are all met in the present case. Results from multilevel models are presented under "Robustness checks".

[6]For a discussion of the performance of the two-step model in terms of statistical inference and other general properties, see Giesecke and Kohler (2024).

Table 2.3: Sample overview and descriptive statistics of country-level variables

Country/Society	Sample size	Missing values	GPD per capita	Home ICT access[a]		Educational returns	School ICT integration[a]	
		% of adolescents with missing or incomplete data on ICT use	(In 1,000 US$, 2022)	% of adolescents with access to computer, smartphone, Wi-Fi, educational software	Alternative measure: Average number of digital devices in the household	% income increase associated with one additional year of schooling	Student-perceived quality of ICT infrastructure and related teaching, scale 0-10	Alternative measure: Average number of computers per student
Albania	6,129	65.0	5.2	48.2	7.7	2.9	6.0	0.3
Argentina	12,111	62.4	12.9	44.2	6.9	8.8	1.5	0.4
Australia	13,437	23.1	61.0	85.9	12.4	12.8	7.8	1.8
Austria	6,151	28.4	46.7	76.2	10.9	9.9	5.4	–
Belgium	8,286	34.8	44.2	67.2	10.8	6.4	4.1	1.2
Brazil	10,798	54.5	8.8	32.3	5.6	10.5	1.7	0.4
Bulgaria	6,107	52.9	9.6	65.5	8.7	7.8	4.4	1.5
Chile	6,488	39.4	14.2	57.9	8.2	12.3	4.7	1.3
Croatia	6,135	26.9	16.7	86.8	9.0	11.6	5.9	0.7
Czech Republic	8,460	25.6	20.2	77.8	9.6	10.5	4.3	1.5
Denmark	6,200	34.1	60.3	88.0	12.6	7.7	7.5	1.3
Dominican Republic	6,868	57.7	8.7	34.0	6.5	10.0	1.8	0.5
Estonia	6,392	21.5	21.1	84.4	9.4	6.5	6.3	2.3
Finland	10,239	32.6	46.7	60.2	10.4	7.9	7.0	1.3
Georgia	6,583	64.6	5.7	43.2	6.8	11.4	3.1	0.9

(continued at the next page)

Table 2.3 (continued): Sample overview and descriptive statistics of country-level variables

Country/Society	Sample size	Missing values	GPD per capita	Home ICT access[a]		Educational returns	School ICT integration[a]	
		% of adolescents with missing or incomplete data on ICT use	(In 1,000 US$, 2022)	% of adolescents with access to computer, smartphone, Wi-Fi, educational software	Alternative measure: Average number of digital devices in the household	% income increase associated with one additional year of schooling	Student-perceived quality of ICT infrastructure and related teaching, scale 0-10	Alternative measure: Average number of computers per student
Germany	6,116	36.5	43.4	57.7	10.8	14.5	1.6	1.3
Greece	6,403	28.1	20.3	54.7	8.6	6.4	2.5	0.5
Hungary	6,198	23.0	16.3	72.1	9.5	13.2	5.4	1.3
Iceland	3,360	37.0	57.8	88.1	11.4	7.2	6.9	–
Ireland	5,569	21.1	97.3	79.5	10.9	8.1	5.7	1.4
Italy	10,552	24.4	33.4	80.1	9.3	6.6	3.5	1.0
Japan	5,760	9.0	36.2	63.0	8.6	14.0	7.3	2.2
Jordan	7,799	58.6	3.9	39.6	6.6	8.9	2.4	0.4
Korea	6,454	12.1	33.7	71.6	9.2	13.2	6.2	1.2
Latvia	5,373	20.2	17.0	83.4	9.0	11.4	5.1	1.8
Lithuania	7,257	23.4	18.5	82.8	8.9	12.9	6.1	2.6
Malaysia	7,069	17.4	11.4	35.5	7.0	12.0	4.5	0.7
Malta	3,127	35.5	30.8	85.7	10.7	9.8	4.0	0.8
Morocco	6,867	45.9	3.3	23.1	5.2	10.0	0.1	0.3
Panama	4,544	54.8	15.4	35.4	6.5	10.0	1.7	0.4
Poland	6,011	28.0	17.2	71.1	9.5	10.5	2.8	1.6

(continued at the next page)

Table 2.3 (continued): Sample overview and descriptive statistics of country-level variables

Country/Society	Sample size	Missing values	GPD per capita	Home ICT access[a]		Educational returns	School ICT integration[a]	
		% of adolescents with missing or incomplete data on ICT use	(In 1,000 US$, 2022)	% of adolescents with access to computer, smartphone, Wi-Fi, educational software	Alternative measure: Average number of digital devices in the household	% income increase associated with one additional year of schooling	Student-perceived quality of ICT infrastructure and related teaching, scale 0-10	Alternative measure: Average number of computers per student
Romania	7,364	33.4	12.1	71.0	8.0	10.3	6.1	1.7
Singapore	6,606	9.5	67.9	88.4	11.3	12.5	10.0	2.0
Slovak Republic	5,824	32.4	18.9	74.3	8.6	8.5	4.0	1.4
Slovenia	6,721	24.9	25.3	82.2	10.1	9.6	6.2	1.0
Spain	30,800	24.6	27.7	64.4	9.7	7.8	4.7	1.3
Sweden	6,072	31.1	55.9	83.2	11.4	4.7	8.4	–
Switzerland	6,829	32.4	90.1	72.3	11.0	11.6	8.4	1.4
Thailand	8,495	18.5	6.3	32.9	4.9	9.4	6.1	0.7
Türkiye	7,250	17.3	14.1	36.5	6.0	9.3	2.4	0.6
Ukraine (18 regions)	3,876	39.6	2.0	61.3	7.5	5.7	5.1	0.8
United Kingdom	12,972	39.8	47.3	83.7	11.2	11.9	5.3	1.5
United States	4,552	27.8	63.7	80.5	10.6	13.3	8.0	1.8
Uruguay	6,618	59.7	18.0	69.3	7.2	9.8	5.2	0.6
Total/Mean	332,822	33.5	29.3	65.3	9.0	9.8	4.9	1.2

Note. [a] Based on imputed datasets, mean values across imputed datasets ($m = 20$).
Sources: PISA 2022; World Bank, Montenegro and Patrinos (2021); own calculations.

Results

Descriptive results

Figure 2.2 presents the bivariate associations between socioeconomic background (ESCS) and ICT use intensity (educational on the left, and recreational on the right) for the 44 countries, sorted by coefficient size. Exact values are provided in Table 2.A2 (Appendix). The coefficients indicate the estimated change in the intensity of educational or recreational ICT use per standard deviation increase in ESCS. Positive coefficients indicate that higher SES is related to more intense ICT use, negative values indicate the opposite. For instance, in Korea, a one standard deviation increase in ESCS corresponds to 0.34 standard deviation rise in educational ICT use.

For *educational ICT use*, statistically significant positive SES gaps ($p < .05$) are found in all examined countries. The coefficient magnitude varies considerably across countries, from 0.06 (Albania) to 0.34 (Korea). At first glance, no clear trend based on country affluence emerges as high-income countries appear both at the top (e.g., Korea, Japan) and the bottom (e.g., Croatia, Germany, Spain) of the coefficient distribution. Notably, the four largest SES gaps in educational ICT use are all located in East or Southeast Asia (Korea, Japan, Singapore, Malaysia).

For *recreational ICT use*, most countries show a reversed SES gap, indicating less intense use among higher-SES adolescents ($p < .05$). However, in 12 out of 44 countries, the SES gap is positive ($p < .05$) and several countries have coefficients that are not significantly non-zero. On this score, there is an obvious correlation with country affluence, with many of the (upper- and lower-) middle-income countries being among those with a positive SES gap (Dominican Republic, Morocco, Brazil, Thailand, Argentina, Jordan, Türkiye, Malaysia). For several Eastern European countries, we find a near-zero coefficient (Bulgaria, Georgia, Croatia, Romania, Poland, Slovak Republic). Again, (South-)East Asian countries stand out, showing the largest negative associations (Singapore, Japan, Korea). Overall, these patterns underscore that the association between adolescents' socioeconomic background and their recreational ICT use differs in both size and direction across countries.

Multivariate analyses of cross-level interactions

Table 2.4 presents several OLS regression models, in which we regress SES gaps in educational ICT use (Figure 2.2, left panel) on different combinations of country-level predictors. Models 1–3 assess the moderators separately, Model 4 includes all three simultaneously, and Model 5 adds GDP per capita as a control variable. The resulting coefficients indicate cross-level interactions, i.e., how the individual-level association between ESCS and educational ICT use is moderated by the country-level predictors. Table 2.5 follows the same logic as Table 2.4, referring to SES gaps in recreational instead of educational ICT use.

Looking at Table 2.4, there is no significant association between countries' home ICT access levels and the SES gap in educational ICT use in any of the models (Models 1, 4, 5). Thus home ICT access level does not contribute to explaining the variance in the SES gap across countries at all, as indicated by the negative adjusted R-squared in Model 1. Hence, we find no support for Hypothesis 1. However, we do find that the level of educational returns is associated with a significantly wider SES gap in educational ICT use (Model 2). The positive coefficient remains stable when controlling for other moderators (Models 4 and 5). Notably, the contribution of educational returns to the explained variance in the bivariate model is higher (Model 2) compared to home ICT access and school ICT integration quality (see Models 1 and 3). Therefore, Hypothesis 3 is supported. Finally, the quality of school ICT integration in a country is related to a significantly wider SES gap in educational ICT use. The result is stable across the bivariate model (Model 3), the model that includes other moderators (Model 4), and when including GDP per capita (Model 5), which is strongly correlated with school ICT integration quality (see Table 2.2). Hence, we find evidence for a significantly wider SES gap in countries with greater school ICT integration quality, thereby contradicting and rejecting Hypothesis 5.

Table 2.4: OLS regression coefficients predicting SES gaps in educational ICT use ($N = 44$)

DV: SES gap in **educational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	.0004			−.0006	−.0004
Educational returns (% income per add. year)		.0093**		.0091**	.0095**
School ICT integration quality (scale 0-10)			.0086*	.0116*	.0122*
GDP per capita (logged, in 1,000 USD [2022])					−.0078
Constant	.1150***	.0473*	.0966***	.0324	.0361
R-squared (adjusted)	−.0076	.1704	.0944	.2637	.2539

Note. DV = dependent variable. Results based on 20 imputed datasets. Coefficients indicate the estimated change in the slope of ESCS across all countries.
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Turning to recreational ICT use (Table 2.5), home ICT access levels are by far the strongest predictor of the SES gap, accounting for 61.7% of the cross-country variance (Model 1). As expected (Hypothesis 2), the moderating coefficient is negative, indicating that a higher percentage of adolescents with access to ICT at home in a country is related to a narrower or reversed SES gap in recreational ICT use. In Models 4 and 5, the negative coefficient of home ICT access becomes smaller, but it remains clearly significant ($p < .001$) when controlling for the other country-level variables despite home ICT access level being strongly correlated with both school ICT integration quality and GDP per capita (see Table 2.2).[7]

While we expected the SES gap in recreational ICT use to narrow or reverse in countries where educational returns are greater, none of the models (Table 2.5) return a statistically significant coefficient ($p < .05$) and the contribution to the explained variance is minute (Model 2). Hypothesis 4 is therefore rejected. Finally, we find that school ICT integration quality is associated with a narrower or reversed SES gap in recreational ICT use (Model 3), but this association diminishes to statistical insignificance once we control for the remaining predictors (Models 4 and 5). This is likely due to the strong correlations particularly with GDP per capita. Therefore, the results support the expected null effect (Hypothesis 6).

Table 2.5: OLS regression coefficients predicting SES gaps in recreational ICT use ($N = 44$)

DV: SES gap in **recreational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	$-.0042^{***}$			$-.0036^{***}$	$-.0027^{***}$
Educational returns (% income per add. year)		$-.0080$		$-.0063^{+}$	$-.0045$
School ICT integration quality (scale 0-10)			$-.0286^{***}$	$-.0071$	$-.0043$
GDP per capita (logged, in 1,000 USD [2022])					$-.0350^{*}$
Constant	$.2304^{***}$	.0357	$.0989^{**}$	$.2878^{***}$	$.3038^{***}$
R-squared (adjusted)	.6169	.0198	.3769	.6413	.6863

Note. DV = dependent variable. Results based on 20 imputed datasets. Coefficients indicate the estimated change in the slope of ESCS across all countries.
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

[7]We computed variance inflation factors (VIFs) for Model 5 in Tables 2.4 and 2.4 to test for multicollinearity problems. The VIFs do not indicate severe multicollinearity, as all VIFs are below 2.5, which is clearly below conventional thresholds (Chatterjee & Hadi, 1986).

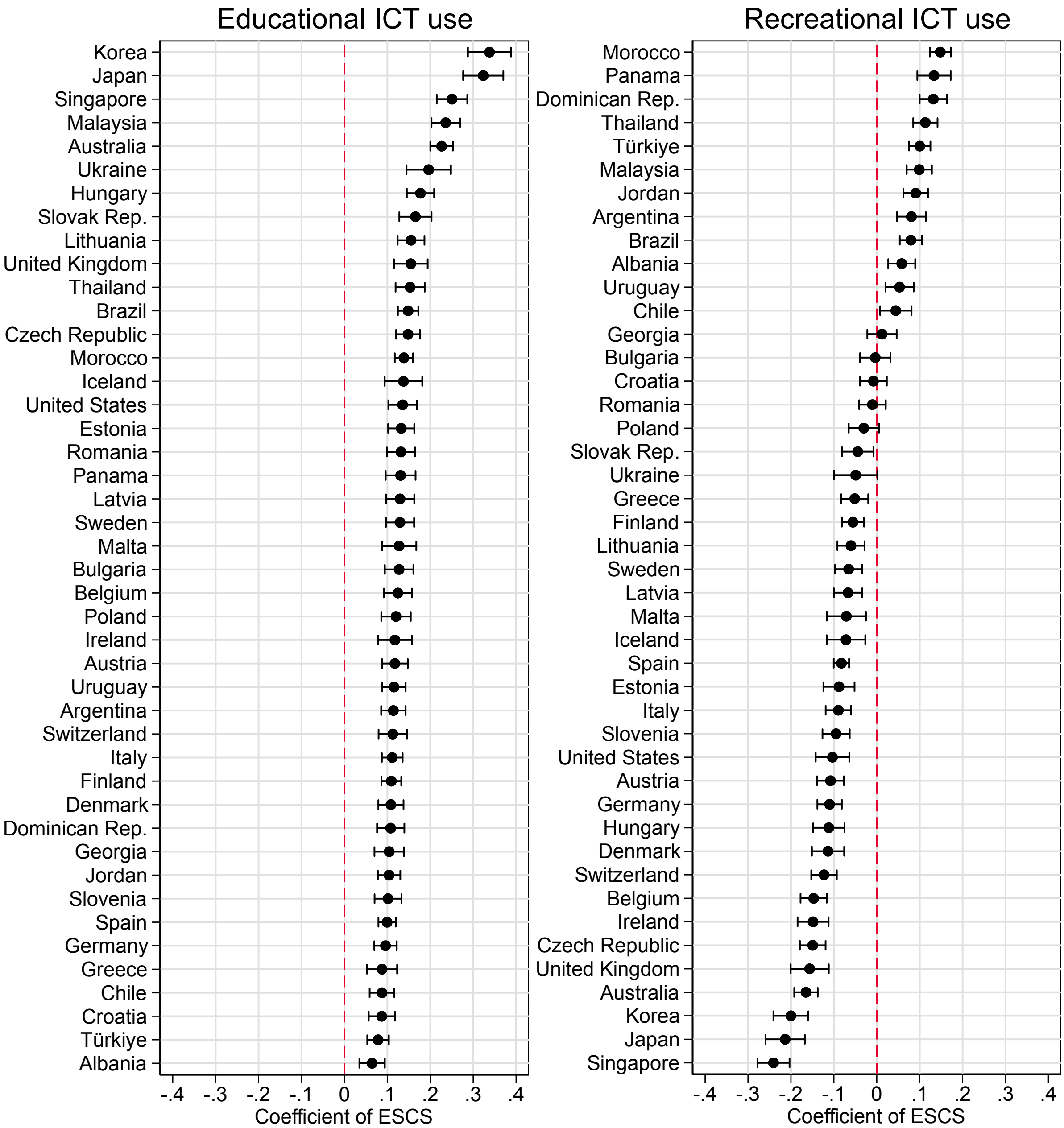

Figure 2.2: Association between ECSC and ICT use intensity across countries

Robustness checks

We run several robustness checks to address potential concerns regarding missing data, measurement and modeling. All results are presented in the Appendix. First, as multiple imputation (MI) relies on several assumptions about missingness and on the availability of high-quality predictors (Rubin, 2004), we repeat our main analyses using listwise deletion instead (n = 220,142). This yields no considerable differences in results (comparing Table 2.A3 and Table 2.A4 (Appendix) to Table 2.4 and Table 2.5). The only exception being a slightly diminished coefficient for school ICT integration quality (see Table 2.A3), which still does not change our conclusions (Table 2.4), and the rejection of Hypothesis 5.

Second, we test an alternative measure of home ICT access levels across countries: the average number of digital devices available in the household, which was surveyed in the PISA 2022 student questionnaire. Doing so, we address possible concerns around the inclusion of educational software and the exclusion of peripheral devices in our main measure of home ICT access levels. The results and conclusions remain stable (see Table 2.A5). For school ICT integration quality, the use of students' subjective assessments may raise concerns, as these assessments could be inaccurate or biased across countries. Therefore, we use the aggregated number of computers per student as reported by the school principal in the PISA 2022 school questionnaire as an alternative, more objective measure. This ratio has often been used in prior studies as a proxy, although it glosses over other important aspects of school ICT integration quality, like teachers' competencies and motivation (Loh et al., 2025). Repeating the analyses using this alternative measure (Table 2.A6) yields one notable difference. The positive coefficient of school integration on the SES gap in educational ICT use (Table 2.A6, Models 1–3) is no longer statistically significant (compared to Table 2.4, Models 3–5). This finding suggests together with the results from Table 2.A3, that the finding of a wider SES gap in educational ICT use in countries with greater school ICT integration (Table 2.5) should be treated with some caution. Still, Hypothesis 5 clearly receives no support across all our models.

Next, we test an alternative version of the ESCS index. The HOMEPOS component of the original ESCS variable in PISA 2022 includes variables that we simultaneously use to calculate our indicator of country-level home ICT access (availability of digital devices and software in the household; OECD, 2024), which could in principle lead to bias. We generate our alternative ESCS variable by replacing the HOMEPOS component in the calculation of the ESCS with the number of books in the household. All results remain stable (Table 2.A7 and Table 2.A8). Third and finally, we repeat our main analyses using multilevel models with three levels (students, schools, countries). The findings presented in Table 2.A9 and Table 2.A10 remain unchanged compared to our main results.

Discussion

In this study, we systematically described socioeconomic inequalities in adolescents' out-of-school ICT use across 44 countries and provided one of the first systematic attempts to explain the cross-country variation in the extent and direction of these inequalities. In line with previous research (Notten et al., 2009; van de Werfhorst et al., 2022), we found that the SES gap in educational ICT use was positive across all studied countries and varied only in size. In contrast to earlier studies, we found no significant association between national income levels and the size of the SES gap in educational use (Ma et al., 2019). Our results looked quite different regarding recreational ICT use: The SES gap in recreational ICT use was reversed (negative association) in most high-income countries, but several middle-income countries displayed a positive SES gap as well. Overall, greater national income levels were strongly correlated with a narrower or reversed SES gap in adolescents' recreational ICT use.

Extending previous knowledge in the field, we found that the SES gap in educational ICT use was significantly associated with the level of educational returns, and the overall quality of school ICT integration. While, as hypothesized, higher educational returns were associated with a wider SES gap in educational ICT use, the finding that the SES gap in educational ICT use was slightly wider in countries with higher quality of school ICT integration was unexpected. SES-based school selection effects might explain this, although evidence for such selection is mixed (Ma, 2021; van de Werfhorst et al., 2022). Alternatively, there might be a flooring effect as low ICT integration in schools may mean lower educational (school-related) ICT use at home, therefore producing lower SES gaps in educational ICT use. This is not to suggest, off the back of our results which represent correlations only, that countries should adopt policies of low school ICT integration to narrow educational ICT use disparities.

We also found that average home ICT access levels were unrelated to the SES gap in educational ICT use but related to a smaller or reversed gap in recreational ICT use. This may be counterintuitive as prior studies have often cited low-SES adolescents' lack of (full) ICT access at home as an important reason for their lower use of educational technologies (Goudeau et al., 2021). Our results suggest near-universal home ICT access at home does not guarantee the mitigation of the SES gap in educational ICT use. Indeed, our sample included several countries with high levels of home ICT access (e.g., Denmark, Singapore, Switzerland), but these countries did not show significantly smaller SES gaps in educational ICT use.

Furthermore, our results indicated that the negative association between socioeconomic background and recreational ICT use is largely limited to countries with the highest levels of home access to ICT. Some studies have already noted the strong dependence of this relationship with GDP per capita or national income (Mielke et al., 2017). The fact that the large association with home ICT access remained when we controlled for GDP per capita in our model emphasizes that it is about access in these more affluent countries. Lastly, by distinguishing between educational and recreational out-of-school ICT use, our results also illuminate that the previously reported inconsistency in SES gaps regarding overall ICT use intensity (Gracia et al., 2020, 2023; OECD, 2015) is partly due to how the associations between SES and educational and recreational ICT use often, while not always, go in opposite directions and vary by national contexts.

Limitations

Our cross-sectional design prevents the drawing of causal conclusions. This invites future studies equipped with longitudinal data or using natural experiments to ascertain whether, for example, advancing ICT integration in schools augments SES gaps in students' ICT use. Additionally, while the number of countries included on our sample is high compared to similar comparative studies (Bryan & Jenkins, 2016), our study is still limited by the number of predictors we can include in our models. We cannot rule out the possibility that some of the associations reported in our study are driven by other country-level factors which we did not include.

Our results are also based on a selective group of countries, namely as PISA was conducted among OECD members and select partner countries (OECD, 2024). As such the countries included many high-income, some middle-income, and no low-income countries. Thus, our theoretical arguments and findings are, in the strictest sense, applicable to high- and middle-income countries. The arguments may not hold for low-income countries where certain cross-level associations, like the association between country home ICT access levels and SES gaps in recreational ICT use, are likely weaker or even reversed. In these contexts, ceiling effects are unlikely to occur, and associations may even reverse when higher-SES households act as "first-movers" like they did in high-income countries at the beginning of the 21st century, when the digital divide first emerged (van Dijk, 2020).

Finally, our findings rely on adolescents' self-reported ICT use instead of objective measures, e.g., using tracking technologies (Parry et al., 2021). Socioeconomic inequalities in these self-reports may be affected by selective social desirability effects, e.g., when higher-SES or lower-SES adolescents systematically over- or underreport certain activities. However, little is known about SES bias in the accuracy of adolescents' self-reported ICT use to date, much less if these biases also differ across countries owing to differing educational returns and related norms. Internationally comparable objective datasets on ICT use will be required for further investigation on this score.

Conclusions

Adolescents' extensive ICT use has drawn significant attention for its supposed negative effects on mental health (Haidt, 2024) and school performance (OECD, 2023c), particularly among more vulnerable individuals (Odgers, 2018). Understanding the emergence of socioeconomic disparities in this domain is thus crucial to prevent the deepening of broader socioeconomic inequalities. Our results suggest that integrating social reproduction and digital divide perspectives represents a promising approach towards understanding SES inequalities in adolescents' ICT use (in line with Becker, 2023). Our study advances the digital inequalities literature by showing that the extent of inequalities in adolescents' ICT use is related to institutional factors beyond technology access—specifically, educational returns and school ICT integration.

We also contribute to a growing sociological and economic literature which studies how different educational regimes shape class-based investments in students' school success (Doepke & Zilibotti, 2019). Similar to educational investments like shadow education (Entrich, 2020; Zwier et al., 2020), a more intense use of educational ICT may represent a way for higher-SES adolescents to maintain their family's SES. Our results suggest that this is particularly relevant in contexts where school success is highly consequential for future income. In this regard, our results align with those of Entrich (2020), who showed that the SES gap in shadow education participation was highest in (South-)East Asian countries like Korea and Singapore, where educational returns are exceptionally high. The same group of countries also stood out in our study, showing the largest SES gap in educational ICT use and the largest reversed SES gap in recreational ICT use. Comparative research in this fashion underscores that SES inequalities in adolescents' out-of-school activities are no law of nature: The design of countries' educational institutions is related to the extent of inequality.

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Appendix

Table 2.A1: Question wording in the ICT familiarity questionnaire

PISA 2022 question and categories	Item
IC176: "The following statements are about the use of digital resources for school-related activities outside of classroom hours. **This school year, how often did you use digital resources for the following activities?"** 1 (*Never or almost never*) – 5 (*Every day or almost every day*)	See school grades or assignment results Browse the web for school Follow up on school lessons Receive / download school assignments Upload school-related work Communicate with teacher Communicate with other students about schoolwork Search for information on school-related activities or assignments
IC177/IC178: **"During a typical week / weekend day, how much time do you spend doing the following leisure activities?"** 1 (*No time at all*) – 7 (*More than 7 hours a day*)	See school grades or assignment results Browse social networks Browse the internet for fun Look for practical information online Communicate/share content on social networks Read/listen to/watch informational materials Create or edit digital content (photos, videos)
IC171: **"This school year, how often did you use the following digital resources outside of school (e.g., at home or where you usually access digital resources)?"** 1 (*Never or almost never / Resource unavailable*) – 5 (*Every day or almost every day*)	Educational software / educational game use
IC172: "The following question is about the availability, accessibility and quality of digital resources at your school. **To what extent do you agree or disagree with the following statements?"** 1 (*Strongly disagree*) – 4 (*Strongly agree*)	There are enough digital resources for every student. There are enough digital devices with access to the Internet at my school. The school's Internet speed is sufficient. Digital resources function properly at my school. Digital resources are easily accessible within the classroom. Digital learning resources available at my school make learning interesting. The school provides sufficient technical support to help students in their use of digital resources. Teachers at my school have the necessary skills to use digital devices during instruction. Teachers at my school are willing to use digital resources for teaching.

Note. "Digital resources" are defined as digital devices, software, and online resources.

Table 2.A2: Estimated SES gaps in ICT use intensity across countries

Country/Society	SES gap in educational ICT use	SES gap in recreational ICT use
Albania	.06***	.06***
Argentina	.11***	.08***
Australia	.23***	−.16***
Austria	.12***	−.11***
Belgium	.12***	−.15***
Brazil	.15***	.08***
Bulgaria	.13***	−.00
Chile	.09***	.04*
Croatia	.09***	−.01
Czech Republic	.15***	−.15***
Denmark	.11***	−.11***
Dominican Republic	.11***	.13***
Estonia	.13***	−.09***
Finland	.11***	−.06***
Georgia	.10***	.01
Germany	.10***	−.11***
Greece	.09***	−.05**
Hungary	.18***	−.11***
Iceland	.14***	−.07***
Ireland	.12***	−.15***
Italy	.11***	−.09***
Japan	.32***	−.21***
Jordan	.10***	.09***
Korea	.34***	−.20***
Latvia	.13***	−.07***
Lithuania	.16***	−.06***
Malaysia	.24***	.10***
Malta	.13***	−.07***
Morocco	.14***	.15***
Panama	.13***	.13***
Poland	.12***	−.03+
Romania	.13***	−.01
Singapore	.25***	−.24***
Slovak Republic	.17***	−.04*
Slovenia	.10***	−.09***
Spain	.10***	−.08***
Sweden	.13***	−.07***
Switzerland	.11***	−.12***
Thailand	.15***	.11***
Türkiye	.08***	.10***
Ukraine (18 regions)	.20***	−.05+
United Kingdom	.15***	−.16***

Table 2.A2 (continued): Estimated SES gaps in ICT use intensity across countries

Country/Society	SES gap in educational ICT use	SES gap in recreational ICT use
United States	.14***	−.10***
Uruguay	.12***	.05**

Note. MI applied with 20 datasets. Sources: PISA 2022, World Bank, Montenegro and Patrinos, 2021; own calculations. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A3: Listwise deletion: SES gaps in educational ICT use ($N = 44$)

DV: SES gap in **educational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	.0000			−.0007	−.0006
Educational returns (% income per add. year)		.0088**		.0085**	.0088**
School ICT integration quality (scale 0-10)			.0059	.0092+	.0099+
GDP per capita (logged, in 1,000 USD [2022])					−.0067
Constant	.1705***	.0852*	.1447***	.0324	.0979
R-squared (adjusted)	−.0237	.1385	.0302	.1746	.1591

Note. DV = dependent variable. Listwise deletion applied. Coefficients indicate the estimated change in the slope of ESCS across all countries (OLS regression coefficients).
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A4: Listwise deletion: SES gaps in recreational ICT use ($N = 44$)

DV: SES gap in **recreational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	−.0051***			−.0043***	−.0032***
Educational returns (% income per add. year)		−.0091		−.0068+	−.0048
School ICT integration quality (scale 0-10)			−.0346***	−.0099	−.0059
GDP per capita (logged, in 1,000 USD [2022])					−.0418*
Constant	.2895***	.0478	.1177**	.3494***	.3718***
R-squared (adjusted)	.6296	.0148	.3853	.6569	.6997

Note. DV = dependent variable. Listwise deletion applied. Coefficients indicate the estimated change in the slope of ESCS across all countries (OLS regression coefficients).
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A5: Alternative measure home ICT access ($N = 44$)

	DV: SES gap in educational ICT use			DV: SES gap in recreational ICT use		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Home ICT access (Average number of devices in the household)	−.0165	−.0063	−.0050	−.0428***	−.0374***	−.0377***
Educational returns (% income per add. year)		.0090**	.0092**		−.0064*	−.0064+
School ICT integration quality (scale 0-10)		.0116**	.0116*		−.0071	−.0072
GDP per capita (logged, in 1,000 USD [2022])			−.0035			.0007
Constant	.1177**	.0496	.0465	.3416***	.3913***	.3920***
R-squared (adjusted)	−.0165	.2707	.2534	.6899	.7221	.7148

Note. DV = dependent variable. MI applied with 20 datasets. Coefficients indicate the estimated change in the slope of ESCS across all countries (OLS regression coefficients).
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A6: Alternative measure school ICT integration ($N = 41$)

	DV: SES gap in educational ICT use			DV: SES gap in recreational ICT use		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Home ICT access (% with full access)		−.0004	−.0004		−.0033***	−.0022***
Educational returns (% income per add. year)		.0081*	.0081*		−.0025	.0002
School ICT integration quality (Computer-to-student ratio)	.0353*	.0324	.0323	−.1256***	−.0462+	−.0432+
GDP per capita (logged, in 1,000 USD [2022])			.0000			−.0403**
Constant	.0986***	.0478	.0482	.1065***	.2501***	.2658***
R-squared (adjusted)	.1071	.2024	.1806	.4936	.6607	.7229

Note. DV = dependent variable. MI applied with 20 datasets. Coefficients indicate the estimated change in the slope of ESCS across all countries (OLS regression coefficients). Three countries (Austria, Iceland, Sweden) dropped from the analysis because the school questionnaire was not administered in PISA 2022. Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A7: Alternative measure ESCS: SES gaps in educational ICT use ($N = 44$)

DV: SES gap in **educational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	.0002			−.0007	−.0004
Educational returns (% income per add. year)		.0087**		.0085**	.0090**
School ICT integration quality (scale 0-10)			.0072*	.0108*	.0116*
GDP per capita (logged, in 1,000 USD [2022])					−.0105
Constant	.1156***	.0438	.0940***	.0380	.0433
R-squared (adjusted)	−.0171	.1806	.0761	.2705	.2710

Note. DV = dependent variable. MI applied with 20 datasets. Coefficients indicate the estimated change in the slope of ESCS (alternative measure excluding ICT-related home possessions) across all countries (OLS regression coefficients).
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A8: Alternative measure ESCS: SES gaps in recreational ICT use ($N = 44$)

DV: SES gap in **recreational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	$-.0042^{***}$			$-.0036^{***}$	$-.0027^{***}$
Educational returns (% income per add. year)		$-.0084$		$-.0067^{+}$	$-.0048$
School ICT integration quality (scale 0-10)			$-.0290^{***}$	$-.0071$	$-.0040$
GDP per capita (logged, in 1,000 USD [2022])					$-.0381^{**}$
Constant	$.2198^{***}$	.0246	$.0860^{**}$	$.2807^{***}$	$.2984^{***}$
R-squared (adjusted)	.6126	.0222	.3734	.6387	.6911

Note. DV = dependent variable. MI applied with 20 datasets. Coefficients indicate the estimated change in the slope of ESCS (alternative measure excluding ICT-related home possessions) across all countries (OLS regression coefficients).
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A9: Multilevel regression coefficients predicting SES gaps in educational ICT use

DV: SES gap in **educational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	.0002			$-.0006$	$-.0005$
Educational returns (% income per add. year)		$.0069^{*}$		$.0067^{*}$	$.0069^{*}$
School ICT integration quality (scale 0-10)			$.0064^{*}$	$.0093^{*}$	$.0105^{**}$
GDP per capita (logged, in 1,000 USD [2022])					$-.0003$
Constant	$.1088^{***}$	$.0478^{+}$	$.0840^{***}$	.0415	.0351

Note. DV = dependent variable. MI applied with 20 datasets. Coefficients indicate the estimated change in the slope of ESCS across all countries. Three-level model with students (level 1), schools (level 2), and countries (level 3). $N = 332{,}822$ (12,438 schools, 44 countries). Sampling weights were rescaled so that all 44 countries contributed equally to the final estimate.
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.A10: Multilevel regression coefficients predicting SES gaps in recreational ICT use

DV: SES gap in **recreational** ICT use	Model 1	Model 2	Model 3	Model 4	Model 5
Home ICT access (% with full access)	−.0040***			−.0034***	−.0029***
Educational returns (% income per add. year)		−.0073		−.0057+	−.0049
School ICT integration quality (scale 0-10)			−.0268***	−.0063	−.0009
GDP per capita (logged, in 1,000 USD [2022])					−.0013**
Constant	.2193***	.0328	.0936**	.2719***	.2437***

Note. DV = dependent variable. MI applied with 20 datasets. Coefficients indicate the estimated change in the slope of ESCS across all countries. Three-level model with students (level 1), schools (level 2), and countries (level 3). N = 332,822 (12,438 schools, 44 countries). Sampling weights were rescaled so that all 44 countries contributed equally to the final estimate.
Sources: PISA 2022, World Bank, Montenegro & Patrinos (2021); own calculations.
$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Study 3:

Does mobile phone use in early adolescence displace enrichment, physical activity, and sleep? A longitudinal examination of the time-displacement hypothesis

Abstract. This study empirically tests the time-displacement hypothesis, examining if early adolescents' mobile phone use displaces time spent on developmentally beneficial activities. Time displacement is often considered a key mechanism by which mobile phone use negatively impacts developmental outcomes in adolescence, but robust empirical evidence on this hypothesis is lacking. This study overcomes several methodological limitations of prior studies on time displacement through a specific research design. Using longitudinal time-use data from a sample of Australian early adolescents (ages 10-13) in combination with a weighted difference-in-differences (DID) design, the effect of first mobile phone acquisition on allocation of time to various activities is examined. The results challenge the time-displacement hypothesis, providing no evidence that early adolescents spend less time on enrichment, physical activity, or sleep after acquiring their first mobile phone. Instead, acquiring their first mobile phone is associated with a significant reduction in time spent watching TV, movies, or videos. This suggests that the historic rise in adolescent mobile phone use may partly reflect a shift away from traditional screen-based activities rather than a displacement of developmentally beneficial activities. Parental guidelines recommending later ages of mobile phone acquisition are unlikely to impact early adolescents' engagement in non-screen activities.

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Introduction

The rapid rise of smartphones has allowed adolescents to spend more time on screens outside of school than ever before (Fomby et al., 2021; Radesky et al., 2023). Recent estimates across different contexts indicate that adolescents spend an average of four hours per day engaged with their mobile devices (Radesky et al., 2023; Tkaczyk et al., 2024; Tomczyk & Lizde, 2023)[8] The extensive use of mobile phones has caused concerns among educators, parents and researchers regarding its effects on critical areas of adolescent development (George & Odgers, 2015). Of particular worry are potential negative effects on cognitive performance (Amez et al., 2023; Gerosa & Gui, 2023), and on health and wellbeing (Dempsey et al., 2020; Stiglic & Viner, 2019). The rise of mobile phones has been discussed as a possible driving force behind historic declines in academic performance (Schleicher, 2023) and mental health (Haidt, 2024).[9] In response, schools around the world have implemented mobile phone bans on school grounds, despite inconclusive evidence of the effectiveness of such bans (Kessel et al., 2020; Selwyn & Aagaard, 2021). As public discourse intensifies around protecting youth from supposed harms of mobile devices, research on the effects of mobile phone use on adolescent development is still underdeveloped (Amez & Baert, 2020; Odgers, 2018). Most studies on developmental effects of mobile phone use rely on correlational designs, thus many results may be biased due to imperfect control of confounding variables (Amez & Baert, 2020).

A central argument for negative effects of mobile phone use in adolescence is that time spent using the device displaces time spent on other, developmentally more beneficial activities (Kushlev & Leitao, 2020; Marciano & Camerini, 2021; Neuman, 1988). This "time-displacement hypothesis" also underpins many debates in the public and in families around the world as a more or less implicit allegation: What could adolescents have done with all the time spent on their phones (Jorge et al., 2022)? The basic idea of time displacement is that individuals possess a fixed time budget. Hence, if they want to increase the time spent on a certain activity, e.g., using new technology like the mobile phone, they have to reduce the amount of time spent on other activities (Bryant & Fondren, 2009). The net effect of such shifts in time use on the outcome of interest depends on the effects of both the displacing and the displaced activity (Fiorini & Keane, 2014). Despite being frequently used as one of the main explanations for hypothesized negative effects of mobile phone use on adolescents' academic performance (e.g., Dempsey et al., 2019; Gerosa & Gui, 2023; Marciano & Camerini, 2021) and despite many studies investigating displacement and disruption of adolescents' sleep due to mobile phone use (Lemola et al., 2015; Schweizer

[8]Yet, obtaining reliable estimates of adolescents' phone use times is challenging, as data collection methods are complex and use times vary by context and age (grosse Deters & Schoedel, 2023).

[9]Particularly regarding mental health, the evidence base for widespread international downward trends is controversial. Nevertheless, debates regarding the role of mobile phones already influence policymaking (e.g., phone bans in schools) and therefore call for robust empirical evidence.

et al., 2017), robust empirical evidence for time displacement effects of mobile phones is lacking.

In general, previous studies have applied three types of designs to study time displacement effects of screen media use in the era of mobile technologies: First, most studies rely on correlational designs, in which respondents report both screen time and time spent on other activities. However, reverse causality and unobserved confounding can strongly bias the results. For example, some studies have found that surprisingly, heavier Internet users more actively participate in sports, which is likely because these individuals are generally more active (Robinson, 2011). Studies using longitudinal data can mitigate this problem to some extent (e.g., Lizandra et al., 2019), but these designs are still prone to the risk of reversed causality (i.e., more extensive media use as an effect of the outcome of interest). Second, studies comparing adolescent time use across different cohorts show important trends, like the increase of mobile device use across cohorts, and the decrease of certain other activities like television watching (Fomby et al., 2021; Twenge, Hisler, & Krizan, 2019). Nevertheless, these trends represent only aggregate changes in time use which cannot clearly be attributed to a certain cause (like the rise of mobile phones), because many historical changes occur at the same time. Third, very few studies have conducted experiments, reducing participants' screen time or social media use for a certain period in order to study what the additional time is used for (Hall et al., 2019). While these designs are very effective in eliminating confounding bias, they are difficult to conduct regarding mobile phones and to some extent prone to expectancy bias (i.e., because participants expect that reductions in screen time will benefit them in certain ways, they change behavior or respond differently in surveys).

This study presents a different approach to studying time displacement effects of mobile phone use in adolescence that overcomes several limitations of the previously discussed approaches at once. Using high-quality longitudinal time use data, this study examines how early adolescents' (aged 10-13 years) time use changes in the first two years after these adolescents acquire their first own mobile phone. A weighted difference-in-differences analysis is applied to control for time trends and to consider the non-randomized assignment to the treatment (mobile phone acquisition). Analyses are based on the Longitudinal Study of Australian Children (LSAC), which provides comparable, self-reported 24-hour time use diaries at two time points (at ages 10/11, and 12/13).

The first main advantage of this design is that it eliminates confounding resulting from time-constant characteristics, the main threat to causal identification in correlational studies. Second, by using mobile phone acquisition as a proxy for a subsequent increase in mobile phone use, the design comes closer to an experimental design. Although the timing of initial phone acquisition is not random, it is largely determined by adolescents' parents and should hardly be influenced by adolescents' current time use. This diminishes reverse causality problems which often hamper studies of media effects relying on longitudinal survey data. Finally, as opposed to experiments which create an artificial scenario for a limited period, the results have high external validity, as first mobile phone acquisition is an observed real-world event that is regarded as an important developmental milestone in families across many countries (Perowne & Gutman, 2023).

Background and research questions

This section reviews previous literature on time displacement effects in childhood and adolescence and develops the research questions to be addressed in the empirical part of the paper. It starts by reviewing the empirical literature on how adolescents' allocation of time relates to developmental outcomes, identifying the most relevant types of activities. It then discusses previous empirical findings on time displacement effects of media and technology use, before outlining theoretical principles from media displacement research. Based on this theoretical and empirical background, three research questions are derived to examine whether mobile phone use displaces developmentally beneficial time use among early adolescents.

Developmentally beneficial time use in adolescence

The allocation of adolescents' time outside of school has long been known to affect their cognitive skills and academic performance (e.g., Caetano et al., 2019; Del Boca et al., 2017; Jürges & Khanam, 2021), health and wellbeing (e.g., Chaput et al., 2016; Stiglic & Viner, 2019) and, ultimately, their future educational and occupational success (Hernæs et al., 2019). Three types of time use have particularly well-documented links to developmental outcomes: Enrichment activities, physical activity, and sleep. Enrichment activities are activities adolescents can perform in their free time, which are intended to foster their cognitive or noncognitive skills (Caetano et al., 2020). This includes activities like reading, homework, extracurricular lessons, and cultural activities like making music or arts or going to a museum. Several studies have reported positive effects of enrichment time on adolescents' cognitive skills (e.g., Cabane et al., 2016; Covay & Carbonaro, 2010; Jürges & Khanam, 2021). Physical activity is generally considered to benefit mental and physical health, but also cognitive development and academic performance (World Health Organization, 2020), although studies mostly report rather small effects regarding the latter (Barbosa et al., 2020). Finally, a lack of sleep has detrimental effects on academic performance (Curcio et al., 2006) and different health indicators (Chaput et al., 2016).

Previous empirical findings

Since the advent of the television era, researchers have extensively studied the question of which activities are displaced by the introduction of new media (e.g., Putnam, 2000).

A particularly large strand of research has investigated the displacement effects of television on children's and adolescents' reading time (Koolstra & van der Voort, 1996; Neuman, 1995). Other studies have investigated the displacement of homework by television viewing (Vandewater et al., 2006). Most previous studies investigating time displacement effects of children's and adolescents' technology engagement in general (screen time) have focused on physical activity (e.g., Gebremariam et al., 2013; Lizandra et al., 2019) and on sleep (Fomby et al., 2021; Hale & Guan, 2015; Przybylski, 2019). These studies tend to report moderate negative correlations between screen time and physical activity or sleep. However, most studies rely on associational designs. It is therefore unclear whether time displacement effects have caused the reported negative correlations or whether the latter result from unobserved differences between heavier and less heavy screen users or from reversed causality.

The very few studies that specifically focus on displacement effects of mobile phones have mostly investigated the displacement of sleep, because the portability of mobile phones facilitates their use in bed, which in turn might affect sleep patterns and sleep quality (Grover et al., 2016; Lemola et al., 2015; Schweizer et al., 2017). For enrichment activities, available evidence is limited to studies investigating mobile phone use in the classroom, which can negatively affect students' learning (Sunday et al., 2021). For physical activity, some studies report negative correlations between mobile phone use and physical activity levels (Lepp et al., 2013). Again, studies with longitudinal or experimental designs are still lacking, questioning whether mobile phones actually displace developmentally beneficial activities.

Principles of time displacement

Why should mobile phone use affect the time adolescents spend on enrichment, physical activity, or sleep? Among others, media displacement research has developed two general principles: the principal of marginal fringe activities and the principle of functional similarity (Bryant & Fondren, 2009). The principle of marginal fringe activities postulates that new media tend to displace less structured activities or unstructured free time, over which individuals tend to have more control. Hence, new media are likely to displace less structured leisure activities like leisure reading or unstructured physical activity, leaving highly structured activities like structured sports practice unaffected.

The idea of functional similarity is that new media displaces activities that previously served the same function for the consumers but yielded comparatively lower satisfaction (e.g., radio as a source of evening entertainment before the introduction of television in the 1950s). Applying this theoretical principle can be difficult particularly when a medium is used for multiple purposes (Koolstra & van der Voort, 1996). Finally, some studies on the effects of television on children's reading habits have discussed other theoretical mechanisms explaining negative effects. Koolstra and van der Voort (1996) found that television watching affected children's attitudes towards reading negatively and it also had detrimental effects on their ability to concentrate on reading.

Research questions

In sum, the review of the displacement literature suggests that mobile phones should be more likely to displace leisure reading, unstructured physical activity, and sleep rather than time spent on highly structured activities such as sports practice or extracurricular lessons. Similar mechanisms like the one described by Koolstra and van der Voort (1996) could induce negative effects of mobile phone use on reading and doing homework, which require high degrees of concentration and self-regulation (Kushlev & Leitao, 2020). The distraction potential of the mobile phone regarding homework and studying has been demonstrated in a range of studies (David et al., 2015; Mrazek et al., 2021; Ward et al., 2017). Whether distraction and interference lead to permanently lower net time spent on reading, homework, or other high-focus activities, has hardly been investigated empirically. It nevertheless seems plausible, especially for activities over which adolescents possess much control (e.g., leisure reading, unstructured physical activity).

The case of mobile phones is also special in another regard: They can be used in parallel to many other activities. Since the introduction of smartphones and tablet computers, children's use of screens as a secondary activity has increased (Goode et al., 2020). It may therefore be expected that mobile phones do not necessarily displace any time spent on enrichment, physical activity, or sleep, but rather increase the amount of "divided" time that is spent simultaneously on multiple activities. However, because use times among adolescents accumulate to multiple hours a day (Radesky et al., 2023), it is very likely that some displacement occurs when mobile phones enter early adolescents' lives. This leads to the first, largely explorative research question:

> **RQ1:** Does mobile phone use negatively affect the time adolescents spend on enrichment activities, physical activity, and sleep?

Displacement effects may differ by sociodemographic groups, because mobile phones can be used for different purposes, and with varying intensity. Given the effects of enrichment activities on educational outcomes, the social stratification of enrichment activities (Covay & Carbonaro, 2010), and their symbolic status function (Choi, 2017), it could be expected that displacement processes of mobile phone acquisition differ between adolescents with different socioeconomic backgrounds. The parenting style literature suggests that socioeconomically more advantaged parents are both more invested in fostering their children's talents by structuring their leisure activities (Lareau, 2011) and in actively mediating their ICT use, e.g., by enforcing technology bans in bedrooms (Koch et al., 2024). This would make it less likely for socioeconomically more advantaged adolescents to displace enrichment, physical activity, or sleep time. Such an effect would be in line with the "third-level digital divide" (van Deursen & Helsper, 2015), which states that socioeconomically advantaged adolescents can derive more desirable outcomes from their ICT use due to their higher possession of certain resources such as digital competencies or parental support (Bohnert & Gracia, 2023). However, regarding displacement, it may also be the other way around: Because more advantaged adolescents spend on average more time on enrichment activities, these adolescents have "more to lose" in terms of absolute enrichment or physical activity time. Hence, the second research question states:

> **RQ2:** Does the effect of mobile phone use on the time adolescents spend on enrichment, physical activity, and sleep differ by adolescents' socioeconomic background?

Applying the principle of functional similarity is difficult for a multi-purpose medium like the modern mobile phone. However, one may still argue that other recreational screen activities (watching television or videos, electronic games) are more functionally similar to mobile phone use than enrichment activities and should therefore rather be displaced instead. In line with pediatric guidelines (e.g., World Health Organization, 2019), parents frequently impose limits on children's and young adolescents' overall screen time (Mollborn et al., 2022). Such restrictions may necessitate trade-offs between early adolescents' screen activities, potentially leading to displacement effects regarding other electronic media activities. This yields the final research question:

> **RQ3:** Does mobile phone use negatively affect the time adolescents spend on other electronic media activities?

Method

This study uses a quasi-experimental design to study the effects of adolescents' mobile phone use on the time spent on developmentally beneficial activities.[10] The core idea of this design is to use adolescents' first mobile phone acquisition as a proxy variable for an increase in mobile phone use over time. The effects of this quasi-experimental treatment are then evaluated using a weighted difference-in-differences design, which controls for the time trend among those adolescents who do not own a mobile phone across the observation period. This research design is based on two core assumptions. First, mobile phone acquisition is assumed to be a robust proxy for an increase in early adolescents' daily mobile phone use time during the period of observation (up to two years after the initial acquisition). Second, the relationship between mobile phone acquisition and the outcome variables is

[10]A similar design has been used before on a sample of Italian adolescents in a study investigating effects of earlier smartphone acquisition on language proficiency (Gerosa & Gui, 2023).

assumed to be much less affected by unobserved confounding variables (third variables affecting both the independent and the dependent variables) and reversed causality than the relationship between the time spent using the mobile phone and the outcome variables. At which point in time adolescents acquire their first mobile phone is mostly decided by their parents, and parental criteria on the right timing should depend on factors largely unrelated to adolescents' current time allocation (Perowne & Gutman, 2023). Under these assumptions, analyzing the effects of mobile phone acquisition comes much closer to a natural experiment than directly analyzing the effects of changes in time spent using a mobile phone. The first assumption can be tested empirically using the present data (see below), while the second assumption cannot. Potential violations of these assumptions are discussed in the final section of this article.

Data

Analyses are based on two panel waves from the Longitudinal Study of Australian Children (LSAC; Department of Social Services et al., 2021). The LSAC is a nationally representative, biennial study of two Australian birth cohorts. The LSAC is one of the very few large-scale survey datasets worldwide that includes repeated measures of adolescents' time use based on 24h-diaries, the current gold standard in time use research. For this study, data is used only from the younger "Birth Cohort", covering infants born between March 2003 and February 2004. The data analyzed in this study stems from wave 6 (surveyed in 2014) and wave 7 (surveyed in 2016), when participants were 10-11 years and 12-13 years old, respectively. Time use diaries were filled out by the early adolescents themselves under the in-person supervision of an interviewer. The remaining variables including phone ownership stem from parent interviews. 3,257 adolescents participated in both waves. After removing adolescents with missing time use information ($n = 442$), incomplete or implausible diaries ($n = 304$) in one of the waves, and adolescents with missing values in one of the control variables ($n = 305$), an initial analysis sample with 2,206 adolescents remained. All results presented in the following account for the sampling design, selective nonresponse in the first wave, and for selective panel attrition by applying a longitudinal survey weight and by calculating cluster-robust standard errors.[11]

[11]Listwise deletion results in a slight overrepresentation of adolescents with higher family SEP in the analysis sample compared to the original sample. The application of a self-calculated inverse probability weight to account for this additional selection has a negligible effect on the results.

Measures

Treatment

Mobile phone acquisition is measured based on the following question in the parent questionnaire: "Does [your] child own or use a mobile phone? Exclude mobile phones that are only used for playing games or do not contain a SIM card". Response categories are "0 No"; "1 Yes, [the child] has [its] own phone"; "2 Yes, [the child] uses someone else's phone"; "3 Yes, [the child] has [its] own phone and uses someone else's phone". For this study, acquisition is defined as adolescents receiving their own phone, which includes categories 1 and 3. Adolescents who exclusively use someone else's phone are treated as not owning their own phone.

Figure 3.1 shows the distribution of the phone ownership variable in the initial analysis sample. A large share of early adolescents received their first mobile phone between the panel waves at age 10/11 and age 12/13 (1,319 individuals). This "treated" group represents 58.8% of the cohort.[12] At the same time, 25.4% of early adolescents (538 individuals) did not acquire their own mobile phone up to the second measurement (age 12/13). This group serves as the control group ("untreated") in the following analyses.[13] The 15.8% of early adolescents who already had their own mobile phone at age 10/11 are removed from the analysis sample because they do not represent a meaningful comparison group in the analytical framework of this study. The resulting final sample consists of 1,857 early adolescents (50.6% male).

Dependent variables

The detailed records of adolescents' time use diaries provided by the LSAC include information on one random day of the week (24h) for each adolescent, with standardized codes indicating the start and end time of one main activity and up to three parallel secondary activities. For the main analyses, daily time spent on an activity is calculated by summing up the duration of all intervals in which the activity was performed, including primary and up to three secondary activities. For some variables, several codes are combined. This calculation acknowledges the fact that mobile devices may facilitate multitasking. Other studies analyzing the same time use dataset have used a different calculation, dividing the duration of time intervals by the number of parallel activities (Cano & Gracia, 2022). Results from a robustness test using this alternative calculation are presented at the end of the results section. In general, data based on 24h recall diaries is considered the current

[12] Minor inconsistencies between the percentages and the number of cases result from the application of survey weights.

[13] In principle, the same analysis could be conducted for the change from age 12/13 to the next panel wave (age 14/15), because the same variables are available in the LSAC for this wave. However, because approximately 95% of early adolescents in the dataset acquired a mobile phone up to age 14/15, this analysis would have to rely on a very small control group, yielding insufficient statistical power.

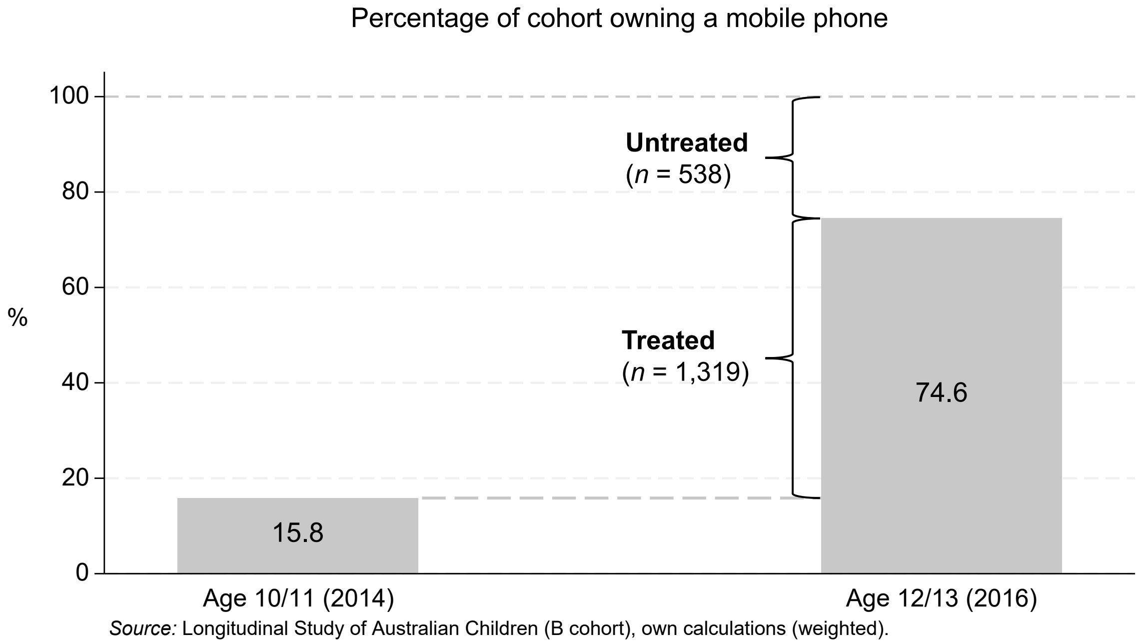

Figure 3.1: Mobile phone ownership status by panel wave ($N = 2{,}206$)

gold standard in time use research because it is more accurate than retrospective survey questions, and such data has been used in many other studies on adolescents' time use before (e.g., Cano & Gracia, 2022; Fomby et al., 2021).

Enrichment activities are measured separately, using three different types of enrichment: "Reading for pleasure", "homework"[14], and "cultural activities and other enrichment". The latter category includes a diverse range of activities, from creative activities like playing musical instruments, over structured after-school activities such as going to clubs or tutoring, to highbrow cultural activities like going to the museum. Physical activity is measured distinguishing between "structured sports" (e.g., soccer practice) and "unstructured physical activity", which includes unstructured sports, walking, running, and other active play. Sleep is measured focusing on nighttime sleep, calculated as the difference between the wake-up time and the time adolescents went to bed on the day the diary was filled out. "Watching TV, movies, or videos" and "playing games on an electronic device" indicate the two most common electronic media activities that are available as pre-coded categories in the data. Table 3.A1 (Appendix) presents the original codes used to generate the dependent variables. Table 3.1 presents summary statistics of the dependent variables. For nighttime sleep, the reported averages of 9:49 hours (age 10/11) and 9:29 hours (age 12/13) are in line with benchmark values from other studies (e.g., Price et al., 2014), demonstrating the validity of the time-use measures.

[14]The "homework" variable analyzed in this study includes both homework via electronic devices and homework not via electronic devices (see Table 3.A1 in the Appendix). Excluding homework via electronic devices from this variable does not lead to substantially different results.

Control variables

In addition, certain time-varying variables are included as controls. As a developmental milestone which is often associated with changes in commute distance and longer school hours, the change to secondary school may also motivate parents to purchase their child a mobile phone (Perowne & Gutman, 2023). The variable indicating early adolescents' current school type differentiates between primary, secondary, combined, and special schools. Parent-reported household income is included as a control variable because children's time allocation can be affected by periods of financial hardship (Arnup et al., 2022). Changes in household income may also affect the purchase of a mobile phone. Parental separation can affect children's time allocation (Cano & Gracia, 2022), and it may also affect mobile phone acquisition because of the increased coordination required in families after parental separation. The number of parents living in the household is measured using a binary variable indicating the presence of either one or two parents in the household.

Statistical modeling

Difference-in-differences

This study applies a weighted difference-in-differences (DID) method, which is a very popular econometric method to study treatment effects in observational settings. DID compares the change in the outcome between treated and untreated units across measurements. The resulting coefficients can be interpreted as an average treatment effect on the treated (ATT) under the assumption of parallel trends (de Chaisemartin & D'Haultfœuille, 2023). The parallel trends assumption states that in the hypothetical case of an absence of the treatment (here: mobile phone acquisition), the treated individuals (here: early adolescents who acquired their first mobile phone between the two measurements) would have had the same trend in the outcome variable as the untreated individuals (here: early adolescents who did not acquire their first mobile phone during the same period). A main advantage of the DID design is that unobserved time-constant differences between treated and untreated units do not affect the estimate as long as they are unrelated to future trends in the outcome (their association with the outcome is assumed to be constant over time). This assumption is much weaker than the exogeneity assumption typically made in studies reporting cross-sectional correlations.

For this study, the DID is estimated using a two-way fixed effects regression model (TWFE), which allows controlling for time-varying confounders. The latter are events which affect both the timing of mobile phone acquisition and time spent on enrichment, physical activity, sleep, or electronic activities subsection on control variables). The applied statistical model can be noted as follows:

$$y_{ijt} = \beta_j x_{it} + \mu_{jt} + \alpha_{ij} + \varepsilon_{ijt} \tag{1}$$

where y_{ijt} is the time spent by adolescent i on an activity j at timepoint t and x_{it} is the vector of time-varying predictors including the phone ownership status and the control variables. β_j stands for the vector of regression coefficients. μ_{jt} denotes period dummies for both time points. α_{ij} denotes the unit-fixed effects, and ε_{ijt} the idiosyncratic error term.

Table 3.1: Summary statistics, by panel wave (age)

	Age 10/11	Age 12/13
Enrichment activities (daily minutes)		
Reading for pleasure	21.9 (45.9)	19.6 (48.5)
Homework	14.3 (34.5)	28.2 (58.0)
Cultural activities and other enrichment	27.5 (56.6)	17.2 (47.3)
Physical activity (daily minutes)		
Structured sports	26.3 (54.8)	28.3 (58.8)
Unstructured physical activity	50.9 (72.8)	30.9 (61.0)
Sleep (daily minutes)		
Nighttime sleep	589.3 (69.7)	569.1 (81.0)
Electronic media activities (daily minutes)		
TV, movies, or videos	143.4 (123.3)	142.2 (125.4)
Electronic games	71.8 (106.6)	64.7 (105.9)
Type of school (%)		
Primary	83.3	8.4
Secondary	0.2	62.9
Combined / special	16.5	28.7
Number of parents living in the household (%)		
One	11.9	13.4
Two	88.1	86.6
Household income (in 1,000 Australian Dollars, imputed)	2.4 (1.6)	2.6 (1.8)
N (adolescents)	1,857	1,857

Note. Standard deviation in parentheses for continuous variables.

Matching procedure

In addition, matching on pre-treatment covariates is combined with the DID approach. This technique can effectively reduce bias in DID analyses resulting from violations of the parallel trends assumption (Ham & Miratrix, 2022). Adolescents who receive a mobile phone earlier may differ systematically from those who do later, e.g., regarding their sex (Gerosa & Gui, 2023). Such differences can affect not only the levels, but also the trends in the outcome variables. For instance, as girls and boys at this age develop specific interests, sex differences in time use are likely to become larger over time. To account for such violations of the parallel trends assumption of the DID, multivariate distance matching (MDM) based on an Epanechnikov Kernel matching algorithm with automatic bandwidth selection is applied prior to the DID analysis (using the package “kmatch” in Stata 18.0: Jann, 2017).

MDM is performed based on the following variables suspected to be related to both mobile phone acquisition and time trends in the outcome variables: sex, family socioeconomic position (SEP), parental perception of school performance at age 10/11, and remoteness of place of residence. Family SEP is measured using a composite measure provided by the LSAC (Baker et al., 2017). The original variable is divided into quartiles for the matching to achieve a good balance across the whole spectrum of family SEP. Adolescents’ school performance may affect their time allocation, and their parents may consider school performance in their assessment of the child’s readiness to possess a mobile phone (Perowne & Gutman, 2023). The parental perception of the child’s current school achievement in comparison to classmates at age 10/11 is measured based on a four-point scale from “[well] below average” to “excellent”. Table 3.2 displays the covariate balance before and after performing MDM. For variables like remoteness of place of residence or sex, the matching minimizes a previously large imbalance (indicated by the standardized mean difference [SMD]) between treated and untreated early adolescents. Overall, MDM achieves almost perfect covariate balance between both groups.

Model validation

To validate the design, independent variable, and the statistical model employed in this study, a preliminary analysis examines the effect of mobile phone acquisition on the time spent using a mobile phone. This analysis aims to ensure the data and research design are capable of capturing displacement effects of mobile phone use on the outcome activities in the first place. To this end, an additional variable is created which captures all time intervals explicitly spent using a mobile phone. Table 3.A2 (Appendix) presents the categories and detailed labels of the time use intervals which are used to code this variable. Only intervals which unambiguously refer to mobile phones are included. The resulting variable captures only a subset of the relevant time intervals because many of the detailed activity labels are still too generic in nature (e.g., “video (watch)”) and can therefore not be related to a

Table 3.2: Covariate balancing before and after MDM

	Before matching			After matching		
	Treated	Untreated	SMD	Treated	Untreated	SMD
Family SEP quartile (%)						
First (low SEP)	27.2	28.8	−.04	27.2	27.2	.00
Second	26.2	25.9	.01	26.2	26.2	.00
Third	23.7	25.4	−.04	23.7	23.7	.00
Fourth (high SEP)	22.9	19.9	.07	22.9	22.9	.00
Sex (%)						
Male	47.6	59.0	−.23	47.6	47.6	.00
Remoteness of place of residence (%)						
Major city	68.1	49.4	.39	68.1	68.1	.00
Inner regional Australia	22.0	32.6	−.24	22.0	22.0	.00
Outer regional / remote Australia	10.0	18.0	−.23	10.0	10.0	.00
Parental perception of school performance (scale 1-4)	2.7	2.7	.02	2.7	2.7	−.01
N (adolescents)	1,319	538		1,319	538	

certain device. In addition, secondary activities cannot be included (except "talking on a mobile phone") because detailed labels for these activities are unavailable. It is generally difficult to capture time spent using mobile devices based on time use diaries (Barr et al., 2020; grosse Deters & Schoedel, 2023). For these reasons, the resulting variable most likely underestimates adolescents' actual phone use (mean = 2.3 minutes at age 10/11; 15.0 minutes at age 12/13), but it is sufficient to conduct the intended test.

The test based on the model as specified in Eq. 1 (with MDM) shows a 16.7 minute increase ($p < .01$) in daily mobile phone time associated with early adolescents' first mobile phone acquisition between age 10/11 and age 12/13 (see Figure 3.A2, Appendix). Hence, changes in adolescents' time allocation caused by mobile phone acquisition can in principle be captured by the data and research design of this study. The results also demonstrate the validity of the mobile phone ownership variable. While adolescents who, according to their parents, receive a mobile phone between both time points, strongly increase the self-reported time spent using a mobile phone, there is no change in mobile phone use time in the control group. A visualization of the (unadjusted) trends in all outcome variables by treatment status is provided in Figure 3.A1 in the Appendix.

Results

Effects on enrichment, physical activity, and sleep

Figure 3.2 presents the main results from six weighted DID models ($N = 1{,}857$). Addressing RQ1, the coefficients refer to the change in the time spent on enrichment activities (reading for pleasure, homework, and cultural activities and other enrichment), physical activity (structured sports and unstructured physical activity), and sleep associated with early adolescents' first acquisition of a mobile phone (net of the trend in the control group and the time-varying controls). The marker (dot) indicates the estimated change in adolescents' daily minutes spent on each activity between age 10/11 and age 12/13. According to Figure 3.2, there are no displacement effects of mobile phone acquisition on early adolescents' daily time spent regarding any of the outcome activities. While the coefficients are negative for reading, cultural activities and other enrichment, and nighttime sleep, none of these coefficients are significantly different from zero ($p > .05$).

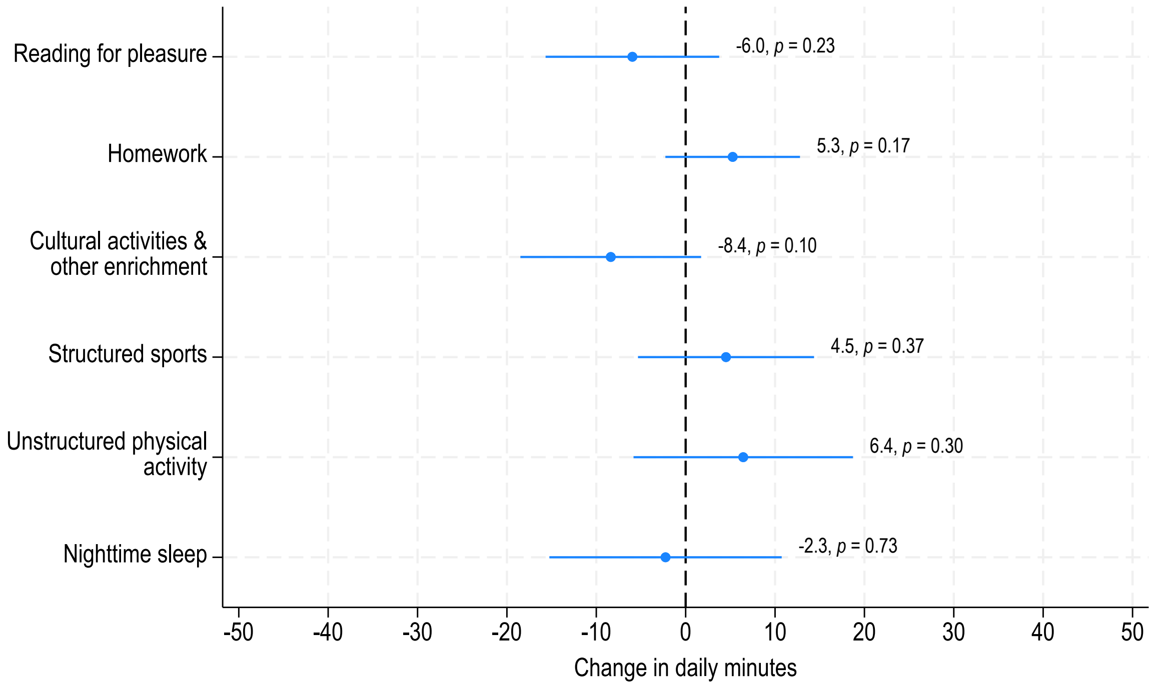

Figure 3.2: Displacement effects on enrichment, physical activity, and sleep

Note. $N = 1{,}857$. Changes in early adolescents' enrichment, physical activity, and sleep time after first mobile phone acquisition (coefficients with 95%-confidence intervals).

Moderation by family socioeconomic position

Does the effect of mobile phone acquisition on enrichment, physical activity, and sleep differ by family SEP (RQ2)? Figure 3.3 displays average marginal effects of first mobile phone acquisition separately for early adolescents with higher and lower family SEP (based on the same statistical model as Figure 3.2, extended by a moderation term). None of the differences between the coefficients by family SEP are significant at the 5%-level. There are no statistically significant negative coefficients for both subgroups, either. Hence, there is no evidence for displacement effects among the subgroups of early adolescents with either higher or lower SEP. For early adolescents with higher family SEP, there are positive coefficients regarding the time spent on structured sports (+13.9 daily minutes) and unstructured physical activity (+11.9 daily minutes), which are however not statistically significant. For early adolescents with lower family SEP, both coefficients are close to zero.

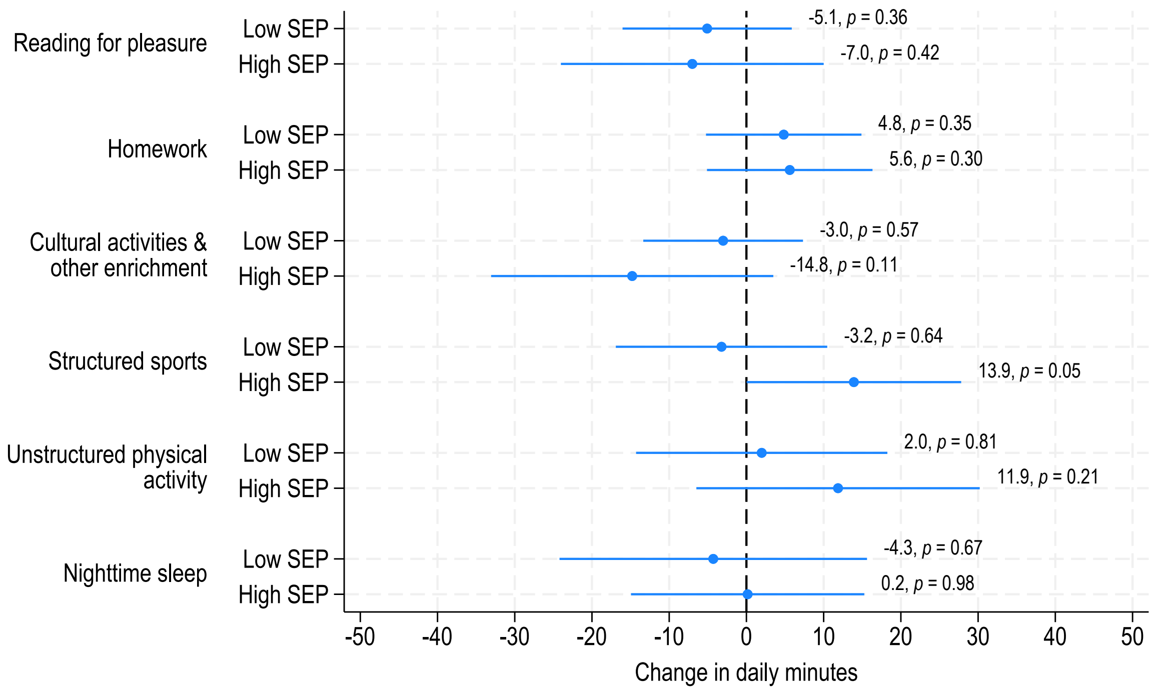

Figure 3.3: Displacement effects by family SEP

Note. $N = 1{,}857$. Changes in early adolescents' daily minutes spent on enrichment, physical activity, and sleep after first mobile phone acquisition, by family SEP. Average marginal effects with 95%-confidence intervals derived from TWFE regression models.

Effects on electronic media activities

Figure 3.4 reports the effects of mobile phone acquisition on the time early adolescents spend on TV, movies, or videos, and on electronic games (RQ3). Adolescents' first mobile phone acquisition between age 10/11 to age 12/13 is associated with a decrease of −27.6

minutes per day of watching TV, movies, or videos ($p < .05$). For electronic games, the coefficient is also negative, but not statistically significant ($p > .10$). This result implies a considerable displacement effect of mobile phone acquisition on early adolescents' screen-related activities with regard to watching TV, movies, or videos.[15] The average daily time early adolescents aged 10/11 spend on watching TV, movies, or videos is 143.4 minutes, according to Table 3.1. Hence, the reported effect corresponds to a 19.2% decrease.

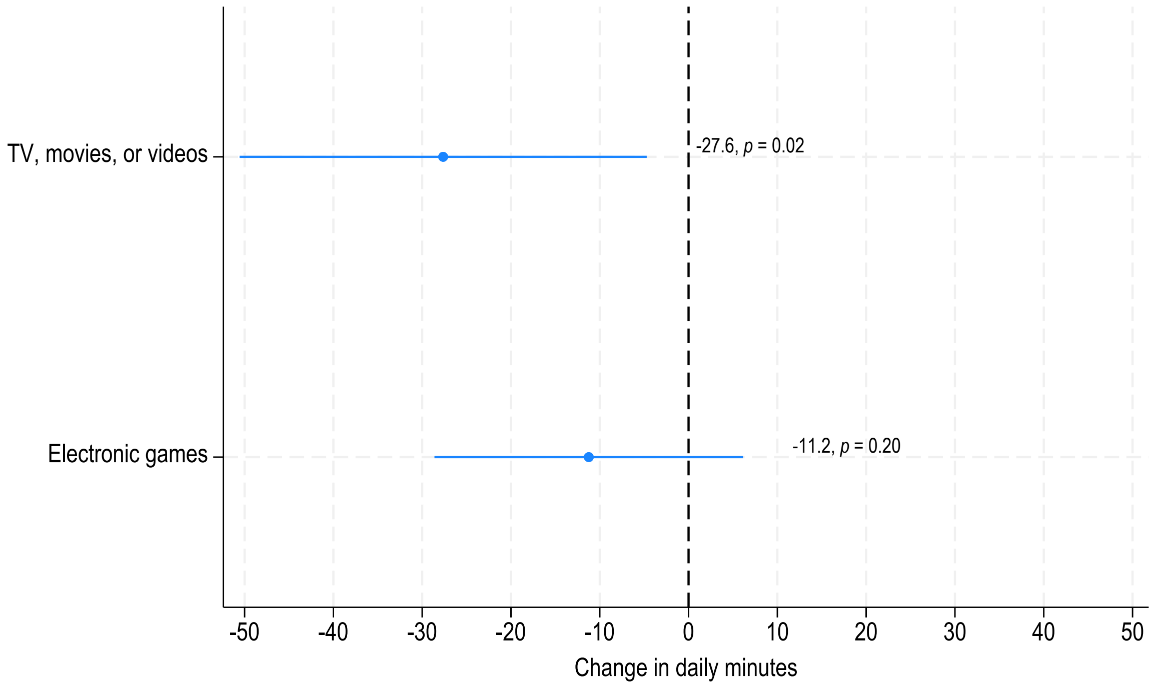

Figure 3.4: Displacement effects on electronic media activities

Note. $N = 1{,}857$. Changes in early adolescents' daily minutes spent on electronic activities after first mobile phone acquisition (coefficients with 95%-confidence intervals).

Robustness tests

For the main analyses presented in this study, the dependent variables are calculated as the sum of all daily time intervals, irrespective of whether they refer to the primary or to (up to three) secondary activities. An alternative way of dealing with secondary activities is dividing the time spent on each of the parallel activities by the number of parallel activities (e.g., as in Cano & Gracia, 2022), so the total of daily activities sums up to exactly 24 hours. Repeating the main analysis from Figure 3.2 with dependent variables based on this alternative calculation (except nighttime sleep because no parallel secondary activities are

[15]An additional analysis (not reported) based on detailed activity labels shows that the identified decrease in "Watching TV, movies or videos" associated with mobile phone acquisition is mostly based on a decrease in watching television programs, and, to a lesser extent, on a decrease in watching movies. Daily minutes of watching videos (e.g., YouTube), are not significantly reduced.

recorded during sleep) yields the same substantial conclusions (see Figure 3.A3, Appendix). In addition, Figure 3.A4 (Appendix) displays estimates from a DID model without prior matching on pre-treatment covariates (MDM). While the negative effect on cultural activities and other enrichment is similar in magnitude to the result with MDM, it is statistically significant in the model without matching. The remaining coefficients are largely similar, except the effect on “TV, movies, or videos”, which is still negative, but only marginally significant (−19.9 daily minutes; $p = .07$) in the DID model without matching.

Discussion

Mobile phones are being discussed as one of the driving forces behind the decline in adolescents’ cognitive skills across many countries (Thompson, 2023) and worrying trends regarding mental health, particularly in Anglo-Saxon countries (Haidt, 2024). According to the time-displacement hypothesis, their extensive mobile phone use displaces time adolescents would have spent on developmentally more beneficial activities, thereby harming their cognitive skill development, wellbeing and health. Both empirical studies and public debates often refer to this hypothesis to argue why mobile phone use can have negative effects on adolescent development (Gerosa & Gui, 2023). However, whether adolescents’ mobile phone use really displaces developmentally beneficial activities has hardly been tested before using robust empirical designs. This study has performed such a test based on a large sample of Australian early adolescents (ages 10-13), using high-quality longitudinal time use data and a weighted difference-in-differences design. The quasi-experimental study setup overcomes several limitations of previous empirical studies related to unobserved confounding, reversed causality, or threats to external validity. Specifically, it was examined whether the acquisition of their first own mobile phone causes changes in early adolescents’ time spent on different enrichment activities (including reading, homework, and cultural and other enrichment), physical activity (structured sports and unstructured physical activity), and sleep, activities which are generally assumed to be beneficial for adolescents’ development.

The results showed no evidence for time displacement effects of adolescents’ mobile phone acquisition on the daily time invested in developmentally beneficial activities. Changes in time use were not significantly different from zero for all activities under study, and these null effects remained stable across multiple robustness checks. Moreover, there were no significant displacement effects for adolescents with higher or lower family SEP, and the model coefficients did not differ significantly between these two groups. However, the results showed a large displacement effect of first mobile phone acquisition between the ages of 10/11 and 12/13 on the time spent watching television, movies, or videos.

Overall, these results challenge the time-displacement hypothesis regarding mobile phones, that is, the notion that the extensive daily mobile phone use of contemporary adolescents (Radesky et al., 2023) displaces time the adolescents would have spent on activities which are beneficial for their development (Gerosa & Gui, 2023). This finding advances current debates on the developmental effects of adolescents' mobile phone use in multiple ways. It helps explain why studies on the direct effects of adolescents' mobile phone use on educational and health outcomes tend to find only small or null effects when applying more rigorous causal inference designs (e.g., Gerosa & Gui, 2023; Odgers, 2018): One of the mostly used theoretical explanations for negative media effects on children and adolescents, the time-displacement hypothesis, may in fact be unfounded in relation to mobile phones. Instead, the results of this study are more in line with the principle of functional similarity (Bryant & Fondren, 2009), indicating that although mobile phones are extremely versatile and can generally be used for very different purposes, their use in early adolescence seems to compete mainly with other screen-related activities, like watching television, movies or videos. Instead of displacing developmentally beneficial activities, the increase in mobile phone use among adolescents may instead be part of "ongoing changes in media and device preference" (Hall & Liu, 2022, p. 3).

Overall, this study has not only provided robust empirical evidence against the time-displacement hypothesis in early adolescence but also advanced theoretical knowledge around the effects of mobile phone use on early adolescents' out-of-school activities. While the results were in line with the principle of functional similarity, they showed no support for the marginal fringe principle, according to which less structured activities like reading or unstructured physical activity, over which adolescents possess more control than structured activities like sports practice, should rather be displaced when new media are introduced (Bryant & Fondren, 2009). Given the flexibility and mobility of mobile phones and their ability to be used simultaneously to other activities (Fomby et al., 2021), it was plausible to assume that this central principle of the time displacement literature would apply to mobile phones, but the findings did not support this theoretical argument.

Mobile phone use habits in Western societies have changed since the collection of the studied data in 2014 and 2016. More capable devices, faster internet connections, and new social media trends, such as the rise of TikTok, have made phone use much more pervasive. Does this mean the findings of this study are time-bound and less relevant for today's debates? Looking at the study population of Australian 10-13-year-olds, mobile phone use habits have changed gradually rather than fundamentally between the data collection and the publication of this study. In Australia, ownership rates among 10-13-year-olds rose from 45% in the LSAC in 2014-2016 (own calculation), to 55% in 2023 (Office of the Australian Information Commissioner, 2023). The percentage of adolescents using mobile phones for different activities increased moderately between 2015 and 2020 (Australian Communications and Media Authority, 2020), but the trends are quite similar for different activities like gaming, texting, taking photos/videos, app use, indicating little compositional change in what mobile phones are used for in this age group.

In addition to the only moderate increase in ownership rates, another major reason for the relatively gradual changes in this age group over the last ten years is that social media use still has a different meaning for many 10-13-years olds compared to teenagers or young adults. In 2016 as well as in 2024, the video platform YouTube was the most popular social media app among 8- to 12-year-olds in Australia. TikTok, which had not been available in 2016, emerged as the second most popular social media app in this age group in 2024, but still only a minority of 31% used it (Office of the eSafety Commissioner, 2016, 2025). Hence, there certainly was an increase in mobile phone use intensity among 10-13-year-olds since 2014-2016, but usage habits are not fundamentally different today. Admittedly, the trend towards algorithmic-driven content recommendations may affect use patterns and lead to displacement effects among those who have their own device and use social media, as platforms make it harder for users to close apps when they want to (Virós-Martín et al., 2024).

The geographical context of this study is specific to some extent. Compared to other countries such as the UK, where the proportion of mobile phone owners at age 11 in 2021 was 91% (Ofcom, 2021), phone ownership rates among Australian early adolescents are significantly lower. Australia is also among the first countries to discuss and implement federal legislation banning social media use for under 16-year-olds (Archer, 2025). Moreover, the relatively high daily time that early adolescents in the study sample spend on television, movies, or videos (more than two daily hours) may be lower in other countries, potentially leading to differing results regarding time displacement. While the design of the present study is generally transferable to other contexts, replication approaches would have to take into account the possibly lower age of first mobile phone acquisition. Although children acquire their first phones earlier in some societies, this does not necessarily lead to greater time displacement effects, as younger children's phone use remains less intensive, and younger children are less prone to extensive social media use, which is at the center of concerns about negative effects of mobile phone use, including time displacement.

Nevertheless, as children grow and their phone use becomes more extensive, time displacement effects may occur and could also extend to other activities. Despite its advantages for causal identification, the research design of this study is unable to capture such displacement effects occurring more than two years after initial acquisition. Delayed effects are also made more likely by the fact that parental mediation becomes less strict with increasing age of adolescents (Suárez-Álvarez et al., 2022). Other research designs are needed to investigate displacement effects in later adolescence, when nearly all adolescents have their own device. As an additional limitation, the variable used in this study to identify mobile phone acquisition did not distinguish between phones of different types (e.g., smartphones vs. flip phones or phones with limited capabilities). Because fully functioning smartphones have a much broader range of possible applications than other types of mobile phones, their acquisition is likely to lead to a stronger increase in use times than, e.g., a flip phone acquired mainly to facilitate communication with other family members. This means that the effects of acquisition may differ for the subgroup of smartphone owners, with potentially larger (negative) effects than reported in this study. Future studies with more detailed information are needed to study whether different device types or modes of access in early adolescence have different effects on relevant outcomes (Gerosa et al., 2024).

Next, the reported effects in this study represent only a population average. Studies on media effects often report negative effects only for particular subgroups of the population (Gerosa & Gui, 2023; Odgers, 2018). While the moderation analysis of family SEP aims to capture heterogeneity of this type, it may be that other subgroups display significant displacement effects. Finally, although DID is one of the most powerful methods for causal identification based on observational data, the interpretation of the model coefficients as causal effects still relies on assumptions. The determinants of earlier or later mobile phone acquisition are not well understood (Gerosa et al., 2024). Other relevant unobserved factors, which were not considered in the presented analysis (e.g., changes regarding the behavior of important peers), could violate the parallel trends assumption.

Despite these limitations, the results of this study have practical relevance because the acquisition of the first own mobile phone is considered an important developmental milestone in many societies (Moreno et al., 2019) and its use by adolescents is an important source of tension and conflict in families (Matthes et al., 2021). Parents differ in their decision when to grant their children the permission to acquire their first mobile phone and have different concerns regarding the potential consequences of this milestone (Moreno et al., 2019; Perowne & Gutman, 2023; Vaterlaus et al., 2021). Many parents around the globe therefore ask for scientific evidence regarding the effects of mobile phones on their children and discussions on appropriate age recommendations for first mobile phone acquisition are often controversial (Gerosa & Gui, 2023). The findings of this study offer no further evidence supporting recommendations for restricting mobile phone access in early adolescence, at least not on the societal level. In addition to being functionally similar, e.g., when early adolescents use their mobile phones to watch videos, the link between mobile phone ownership and reduced television or movie watching may be due to parental restrictions on adolescents' screen time, enforcing trade-offs in early adolescents' time allocation. Hence, the absence of displacement effects also suggests that parental mediation in this age group may overall be successful in protecting the time early adolescents spend on developmentally beneficial activities (Mascheroni, 2014).

Most of the time early adolescents spend on mobile phones may be used in ways that are not particularly "enriching" for their cognitive skill development or beneficial for their health (Radesky et al., 2023). Still, the presented results suggest that adolescents most likely would not have spent a significant amount of this time on developmentally beneficial activities anyway (Jorge et al., 2022). This conclusion is in line with recent experimental research showing that displacement effects of social media use are largely limited to activities which have no positive effect on affective well-being either (Hall et al., 2019). However, the question where adolescents take all that time to use their mobile phones remains partly unresolved. Recent advances in collecting accurate data on mobile technology use in the family context (e.g., Barr et al., 2020) might help to shed more light on this question in the future.

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Appendix

Table 3.A1: Coding of dependent variables

Activity	LSAC-provided codes aggregated for the analyses
Reading for pleasure	"Reading for pleasure"
Homework	"Doing homework (not via electronic devices)", "Doing homework (electronic device)"
Cultural activities and other enrichment	"Arts" (e.g., drawing), "Attend courses (excluding school /university)", "Attendance at concert/theatre", "Attendance at museum / exhibition / art gallery", "Attendance at zoo / animal park / botanic garden", "Clubs", "Going out not further specified" (e.g., going to the library), "Handwork crafts (excl. clothes making)", "Hobbies, collections", "Playing musical instruments or singing for leisure" and "Private music lessons/practice, academic tutoring"
Structured sports (team and individual sports activities)	"Archery / Shooting sports", "Athletics / Gymnastics", "Fitness / Gym / Exercise", "Ball Sports", "Martial arts / Dancing", "Motor Sports / Roller Sports / Cycling", "Water/Ice/Snow Sports", and "Organized team sports and training other"
Unstructured physical activity	"Archery / Shooting sports (unstructured)", "Athletics / Gymnastics (unstructured)", "Fitness / Gym / Exercise (unstructured)", "Ball Sports (unstructured)", "Martial arts / Dancing (unstructured)", "Motor Sports / Roller Sports / Cycling (unstructured)", "Water/Ice/Snow Sports (unstructured)", "Unstructured active play Other"
Nighttime sleep	[Difference between wake-up time and bedtime]
TV, movies, or videos	"Watching TV programs or movies/videos"
Electronic games	"Playing games (electronic device)", "Playing games (electronic device) not further defined"

Table 3.A2: Detailed labels used to code mobile phone time

Main activity code	Detailed activity label
Playing games (electronic device)	Smart phone (gaming)
	iphone (gaming)
	Mobile (gaming)
Watching TV programs or movies/videos	Phone (smart watch movie/tv)
	iphone (watch movie/tv)
	Mobile (watch movie/tv)
General application use	Phone (read)
	iphone (read)
	Mobile (read)
Texting/emailing	Texting
	Messaging
	SMS
	iMessage
Online chatting / Instant messaging	Messenger
Listening to music	iphone (listen music)
Talking on a mobile phone	[all labels, both main and secondary activities]

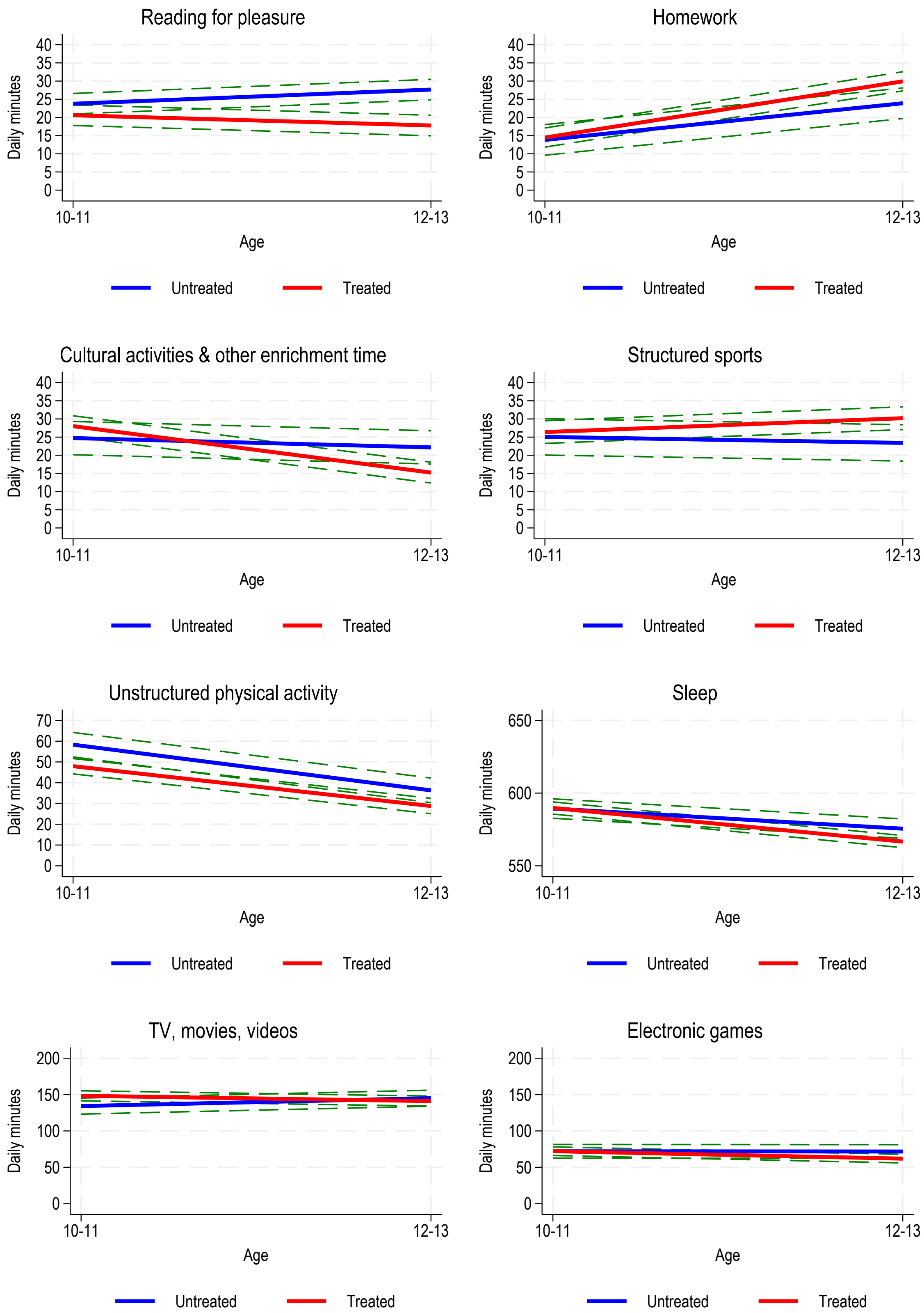

Figure 3.A1: Time use trends across treated and untreated adolescents

Note. $N = 1{,}857$. Development of adolescents' daily time spent with enrichment, physical activity, sleep, and electronic media activities between panel waves, by treatment group. Linear growth curves obtained from random-effects regression models (weighted, no matching or control variable adjustment).

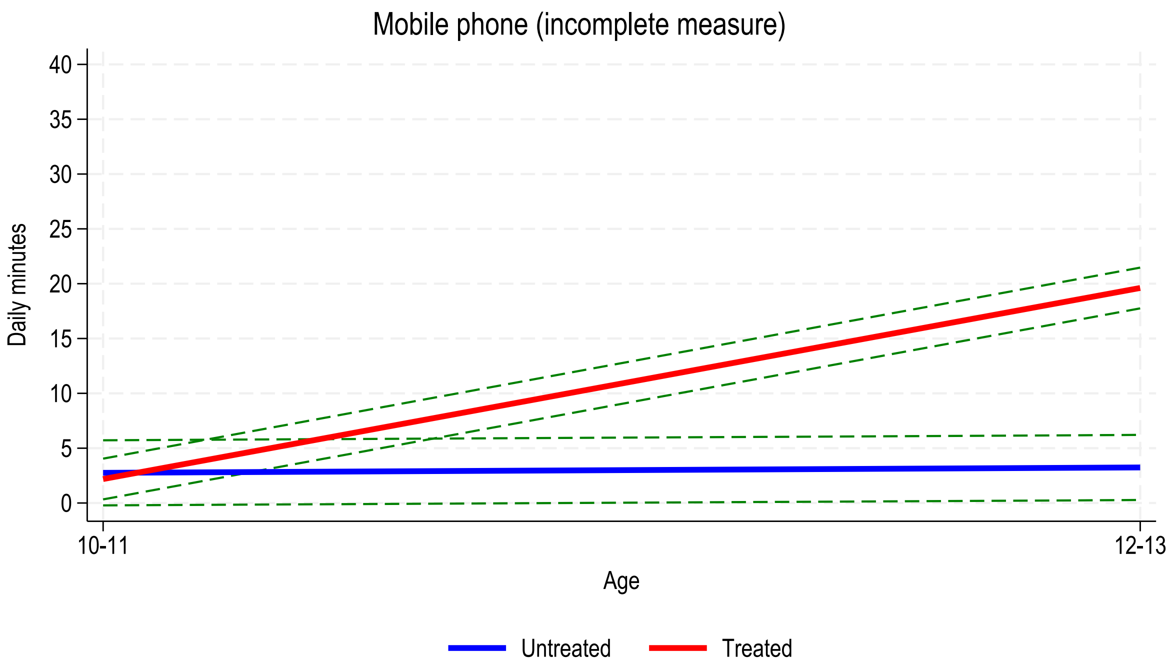

Figure 3.A2: Mobile phone use time trend across treated and untreated adolescents)

Note. N = 1,857. Development of adolescents' daily time spent with using a mobile phone between panel waves, by treatment group. Estimates from linear growth curve models obtained from random-effects models (weighted, no matching or control variable adjustment).

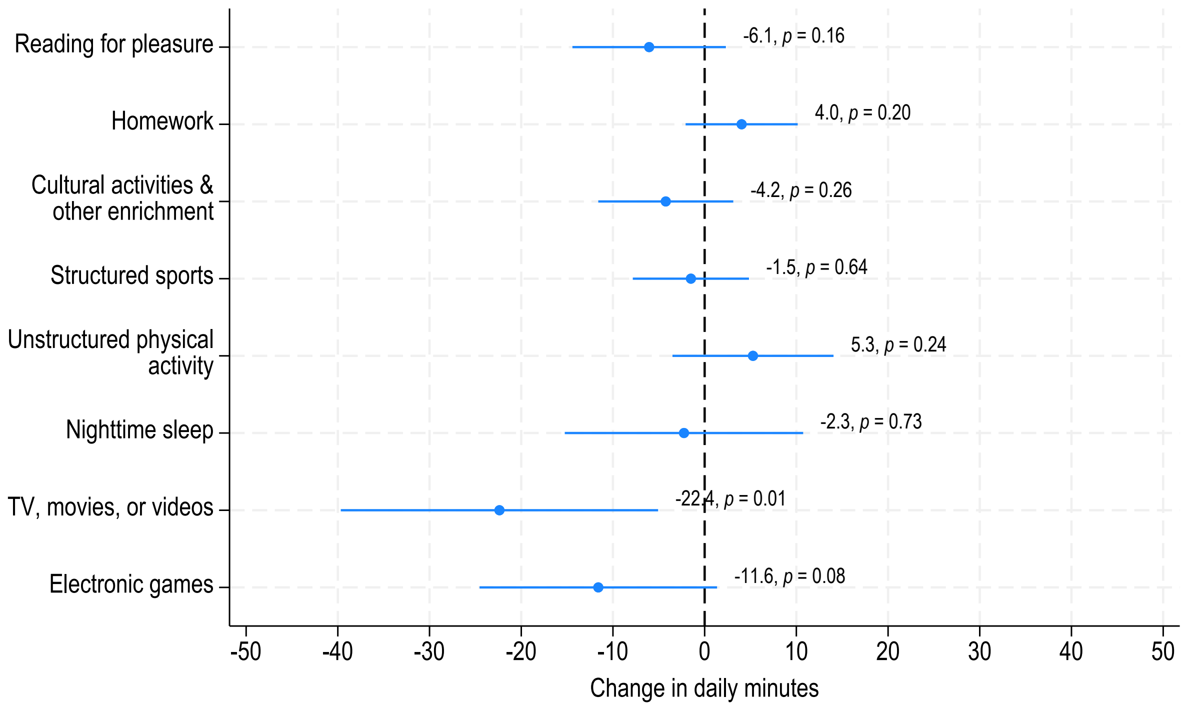

Figure 3.A3: Robustness test: Alternative calculation of time use

Note. $N = 1{,}857$. Estimated changes in adolescents' daily enrichment, physical activity, and electronic activity time after children acquire their first mobile phone. Based on an alternative calculation of the dependent variables with time intervals divided by the number of parallel activities (with matching).

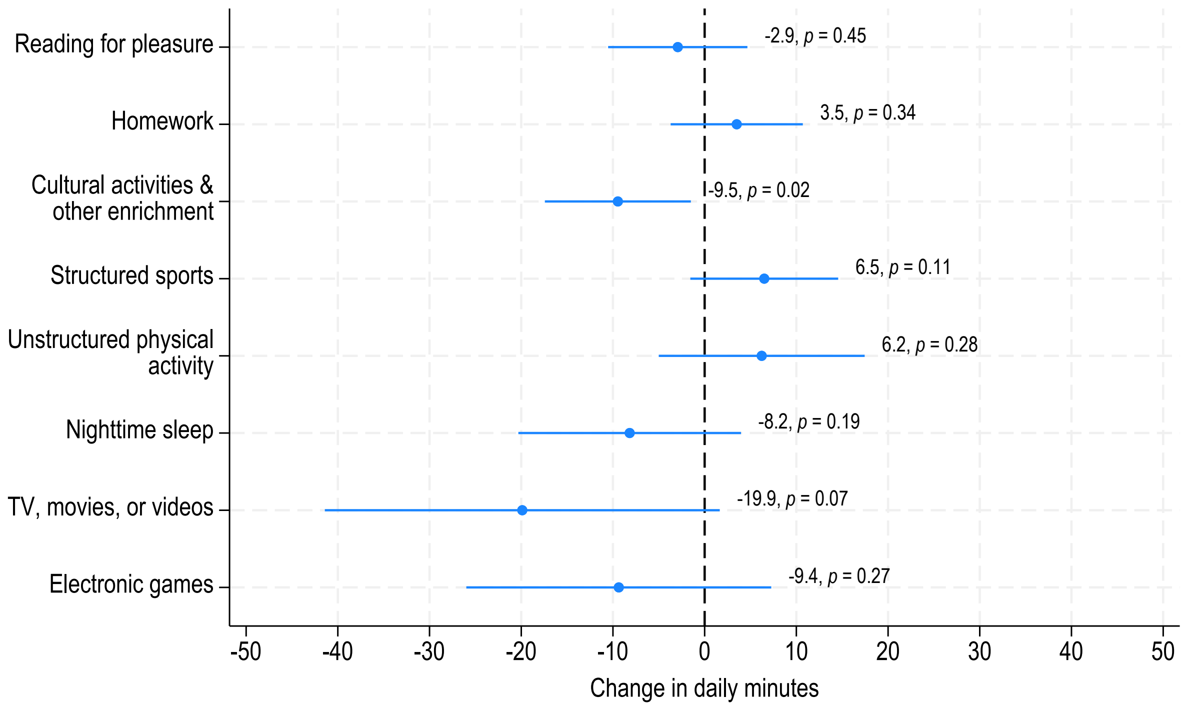

Figure 3.A4: Robustness test: Estimation without MDM

Note. $N = 1{,}857$. Estimated changes in adolescents' daily enrichment, physical activity, and electronic activity time after children acquire their first mobile phone. Based on a DID analysis without matching on pre-treatment covariates (MDM).

Study 4:

ICT interest and self-concept as determinants of Swiss adolescents' vocational choices

Abstract. This study examines whether adolescents' interest in and self-concept regarding information and communication technologies (ICT) influence their subsequent career paths through the selection into different vocational education and training (VET) programs. Drawing on Eccles' situated expectancy value theory, we argue that ICT interest and self-concepts shape vocational choices, possibly contributing to occupational gender segregation regarding ICT. We use longitudinal data from the Swiss TREE (Transitions into Education and Employment) study, comprising 1,964 adolescents transitioning into firm-based VET, which we link to a novel database of ICT use intensity across occupations. Results show that higher ICT interest predicts both basic ICT (e.g., email, word processing) and advanced ICT use intensity (e.g., programming, specialized software) in adolescents' future occupations, while a more positive ICT self-concept only predicts advanced ICT use intensity. Notably, girls' lower average ICT interest and less positive self-concepts jointly account for nearly half of the gender gap in advanced ICT use. Strongly gender-specific patterns emerge: For girls, we find significant associations with occupational task content only regarding their ICT interest, while for boys, significant associations are limited to their ICT self-concept. These findings reveal how gendered dispositions towards ICT shape early vocational choices and perpetuate occupational segregation.

This study is co-authored by Jessica M. E. Herzing, Andrés Gomensoro, and Dominique Krebs-Oesch. An alternative version of this study has been published in *Empirical Research in Vocational Education and Training*, 17, 24. DOI: 10.1186/s40461-025-00199-z.

Introduction

Interests and self-concepts regarding domains like mathematics, reading, or science are well-established as important determinants of vocational choices in adolescence (Volodina & Nagy, 2016). Consequently, gender differences in interests and self-concepts regarding mathematics and science are a central and longstanding explanation for the continuing female underrepresentation in certain STEM professions (Science, Technology, Engineering, and Mathematics; Kang et al., 2021; Kriesi & Imdorf, 2019; Su et al., 2009). In this study, we focus on a particular domain which has received limited attention in the vocational choice literature to date despite its great and ever-growing importance in modern labor markets: information- and communication technologies (ICT).

Over time, the use of ICT has become an integral part of the task profiles of many occupations across sectors (Fernández-Macías et al., 2023). The use of computers in general, but also specialized, highly technical activities like programming, are widespread in and outside the ICT sector. A robust economic literature finds that ICT-related skills are in high demand and associated with high wage premia (e.g., Atasoy et al., 2021; Falck et al., 2021). Graduates from vocational education and training (VET) programs that include ICT skills in their curricula are more likely to find a job (Kiener et al., 2022). Despite the importance of ICT in contemporary labor markets, there is relatively little empirical research from a vocational choice perspective yet. In particular, the psychosocial processes leading adolescents to choose careers with differing levels of ICT use are not fully understood. Previous empirical research is largely restricted to studies investigating the effects of interests and self-concepts in predicting the choice of or the aspiration to select computer science as a subject in secondary or tertiary education (e.g., Sáinz & Eccles, 2012). Much less is known about the role of ICT interests and self-concepts in the selection of occupations, particularly in the context of VET.

Building on established theories of vocational choices like the (situated) expectancy-value theory of achievement motivation (Eccles et al., 1983), we argue that the increased use of ICT at work in recent decades may have led ICT interest and ICT self-concept to being important determinants of vocational choices in adolescence. Similar to other domains like mathematics or science, individuals faced with the need to choose between occupational alternatives may consider the anticipated role of ICT in these occupations. We expect that this applies to occupations both within and outside the ICT sector. Next, we examine how these choice processes relate to gender. The pronounced female underrepresentation in occupations that involve a high level of advanced ICT use is a problem both from an equity perspective and from a human capital perspective (Beyer, 2014), because these occupations tend to pay high wages, and there is a shortage of skilled workers in most countries (European Institute for Gender Equality, 2018). We therefore investigate to what extent girls' (expected) lower average interests and self-perceived abilities regarding ICT explain their (expected) lower likelihood to select occupations requiring a more extensive use of advanced ICT. This analysis is highly relevant for policy and practice, because it is informative about the extent to which fostering girls' ICT interest and self-concept could potentially be able to mitigate the gender gap in ICT-intensive occupations. Finally, we explore whether ICT self-concepts and interests affect vocational choices differently depending on gender, as suggested by previous research.

For our empirical analyses, we draw on a sample of Swiss compulsory school leavers transitioning to dual VET, a consequential first career choice for a majority of Swiss adolescents. We link this information on adolescents' vocational choices to a novel taxonomy that quantifies the intensity of ICT use across different occupations and industries in Europe (Fernández-Macías & Bisello, 2022). Our findings are relevant to both research and educational policy, as they enhance understanding of the underexplored processes around (gendered) choices of occupations with regard to the ICT domain, which may work differently compared to other domains such as mathematics or science.

Background

Vocational choice and the importance of person-environment alignment

It is well-established that when choosing an occupation, individuals generally strive for a good subjective fit between their personality and the features of their future work environment (Caplan, 1987; Holland, 1959). The Person-Environment (P-E) fit concept has been central to vocational psychology, particularly in vocational choice theories (for an overview see: Brown & Lent, 2005). This concept suggests that alignment between individual characteristics and the occupational environment is associated with greater occupational satisfaction and success (Wilkins & Tracey, 2014) and improved emotional well-being and general life satisfaction beyond the occupational context (Gander et al., 2020; Nägele & Neuenschwander, 2015). Within this P-E fit tradition of career choice research, both interests (Gottfredson, 2005; Holland, 1959, 1997; Lent & Brown, 2013) and self-concepts (Betz, 1994; Eccles & Wigfield, 2020; Eccles et al., 1983; Lent & Brown, 2013) are considered important predictors of the fit between individuals and work environments (Brown & Lent, 2013; Volodina & Nagy, 2016).

Morgan et al. (2019) provide a comprehensive definition of interest from a psychological perspective. They describe interest as an outwardly directed preference that influences an individual's attention and engagement with a particular activity or subject area. When individuals are interested in the content of their work, they report higher satisfaction, better performance, and greater perseverance at work (Dawis, 2005; Nye et al., 2021). Vocational interests in particular domains have thus long been a foundational pillar of career counselling (Morgan et al., 2019) and career-focused research (Dawis, 2005).

The term self-concept on the other hand, refers broadly to an individual's perception of themselves. As a mental model, it encompasses all self-related evaluations, including assessments of abilities, traits, and values. Self-concepts can be differentiated into ability self-concepts, self-efficacy, and expectancy of success (Mohr, 2021). Due to their conceptual similarity, these constructs are often difficult to distinguish empirically (see Marsh et al., 2019, for details).

The development of interests and self-concepts is shaped by socialization processes, which reinforce or limit career possibilities (Watt, 2006). Social influences shape subjective perceptions of different occupations, contributing to a limited range of career options that individuals seriously consider (Gottfredson, 2002, 2005). Consequently, domain-specific interests and self-concepts significantly mediate the impact of achievement and gender on career-related choices. They do so by shaping how individuals perceive their own abilities and which value they place on different career paths (Eccles & Wigfield, 2020; Eccles et al., 1983; Lent et al., 1994; Volodina & Nagy, 2016).

Domain-specific interests and self-concepts in Eccles' SEVT

The (situated) expectancy-value theory of achievement motivation (SEVT; Eccles & Wigfield, 2024; Eccles et al., 1983) was originally developed to explain the cultural phenomenon of why girls were less likely to choose STEM courses or careers. It serves as our main theoretical anchor point for the discussion of ICT-related vocational choices in the following sections. The SEVT aims to identify the major categories of social and psychological influences on people's achievement-related behavioral choices as well as task-oriented choices, which includes the choice of occupations (Eccles & Wigfield, 2024).

The SEVT particularly emphasizes two core components: subjective task value and expectancy of success. Subjective task value is a "function of four components: intrinsic value or enjoyment, utility value or usefulness of the task for other goals, attainment value, and perceived cost" (Eccles & Wigfield, 2024, p. 5). Intrinsic value is also called interest value and is conceptually very similar to situational interest, thus is often operationalized with measurements of interest (Eccles & Wigfield, 2020). Simply speaking, intrinsic value in the SEVT refers to the enjoyment someone gets from engaging in a certain activity (Eccles et al., 1983). Expectancy of success, on the other hand, is defined as "individuals' estimates of how well they would do in the near or far future on any specific task or activity" (Eccles & Wigfield, 2024, p. 51). This expectation is influenced by a range of task-related beliefs, including goals, self-perceptions, and perceptions of the demands of tasks. Among the task-related beliefs, self-concepts of abilities are particularly important, and they are often used as a direct measure of expectation of success (Eccles & Wigfield, 2024).

A major strength of the SEVT is its integration of the socio-cultural perspective (Eccles & Wigfield, 2020). According to the SEVT, gender stereotypes and the beliefs and behaviors of significant others, such as parents, peers, and teachers, shape how children and young adults interpret their achievement-related experiences. The interpretation and memory of these experiences ultimately affect children's self-concepts and subjective task values. Depending on socio-cultural influences, similar experiences (e.g., a successfully passed exam) can be attributed very differently by children (e.g., "due to luck", vs. "due to skill"). This attribution process is often used to explain why girls and boys develop different ability beliefs in domains like mathematics, although they tend to perform similarly in standardized tests (Perez-Felkner et al., 2017). In line with the SEVT, mathematical interests and self-concepts have been consistently found to strongly predict STEM career aspirations, and their predictive power tends to outweigh the predictive power of actual skill levels in mathematics (Eccles & Wang, 2016; Sax et al., 2015; Watt et al., 2017).

The most important takeaway from the SEVT is that when adolescents are faced with the need to make a vocational choice, they consider the tasks associated with different vocational options in a certain way: They anticipate whether they will be intrinsically motivated to complete these tasks on a daily basis with reference to their relevant domain-specific interest values, and whether they think they can successfully complete these tasks, referencing their respective domain-specific self-concept. Hence, along with utility values, attainment value, and perceived costs, interest and self-concept regarding a certain domain can directly influence adolescents' choice behavior. Moreover, the SEVT suggests that the effect of self-concepts on choice behavior is partially mediated by interests (Eccles & Wigfield, 2020; Volodina & Nagy, 2016). In the following, we apply this framework to the ICT domain.

ICT as an underexplored domain of vocational choice

One of the most visible consequences of computerization and automatization during the late 20th and early 21st century is the overall increase in the use intensity of ICT across the labor market, a trend still ongoing to date (Fernández-Macías et al., 2023). The use of computing devices (personal computers, but also other devices) and software can be understood as the use of a specific tool to perform some kind of task (Fernández-Macías et al., 2023). On the one hand, this overall increase of ICT use at work can be attributed to changing ways of performing a task within existing occupations, i.e., when a certain task which used to be performed "by hand" is now performed using ICT. On the other hand, technological change has created entirely new sectors, occupations, and tasks necessitating the use of ICT, often connected to a strong specialization on programming and software.

With the increasing importance of skilled ICT use at work, it becomes more relevant to understand vocational choice behavior related to the ICT domain. Previous empirical research in the field has mostly focused on the choice of rather specific tertiary- (or secondary-) level study programs such as computer science (e.g., Beyer, 2014; Sáinz & Eccles, 2012). This relatively narrow focus is understandable given the shortage of ICT specialists (e.g., computer scientists and programmers) across developed countries, which can affect economic development on a national scale (Düll, 2020). But it also neglects the fact that the role ICT use will play in an occupation may affect adolescents' vocational choices directly, e.g., when adolescents choose a vocational training program, or a regular occupation after completing secondary or tertiary education. Moreover, computer use per se has been related to lower routine task content and ultimately, objectively higher job quality (Menon et al., 2020) and higher job satisfaction (Minardi et al., 2023). Occupations where computers are used also tend to grow in terms of worker demand (Bessen, 2015). Vocational choices that are related to higher or lower importance of ICT-related tasks may therefore be considered as a societally relevant outcome in themselves.

Research questions

ICT interest and ICT self-concept as determinants of vocational choices

Similarly to other domains like mathematics, reading, or science, individuals develop differing levels of interest and self-concepts towards ICT (Beyer, 2014; Hatlevik et al., 2018; Sáinz & Eccles, 2012). In contrast to the popular notion of "digital natives", a pronounced heterogeneity in terms of ICT interests and self-concepts is also present among adolescents born in the 1990s and later (European Commission, Directorate-General for Education, Youth, Sport and Culture, 2019). Hence, we argue based on the SEVT, that ICT interest and ICT self-concept may also affect adolescents' choice of occupations in terms of the intensity and difficulty (or specificity) of ICT use associated with occupational alternatives. If adolescents enjoy using computing devices (intrinsic value, as part of the subjective task value), they should be more likely to choose an occupational pathway leading to higher intensity of ICT use. Similarly, if adolescents perceive themselves as competent users of ICT (self-concept of ability as a determinant of the expectation of success) regardless of their "true" abilities, they should be more likely to choose occupations requiring a more intensive, and possibly more advanced, use of ICT.

In line with our general argument, ICT interest is often cited by computer science students as a main reason for choosing this subject (Beyer, 2014; Kori et al., 2015). Differences in ICT self-concept are related to the intention to pursue ICT-related studies (Beyer, 2014; Sáinz & Eccles, 2012). Higher technical abilities with regard to ICT (objectively measured) are also associated with the intention to study or work in the ICT sector in the future

(Kaarakainen, 2019). Average ICT competence levels differ systematically between different VET professions, suggesting that selection into different VET programs is influenced by individuals' affinity to ICT (Findeisen & Wild, 2022). Finally, recent research describes the specific transitioning process from early interests and ICT-related hobbies into occupational plans (the "hobby-to-career-reckoning"; Peterson et al., 2024). Otherwise, there is hardly any empirical evidence yet to demonstrate that ICT interest and ICT self-concept indeed predict occupational pathways. In particular, we are unaware of any studies which conceptualize ICT use at work more broadly and consider the use of ICT both in and outside of ICT-specialist occupations.

Compared to other domains like mathematics and science, the role of the ICT domain in today's world of work is conceptually special in at least two respects. First, ICT-related tasks at work can involve tasks across a broad range of difficulty, from rather basic applications which are part of everyday life in affluent countries today (e.g., office applications, email, internet use to find information) to very technical and advanced applications (e.g., programming, use of specialized software; European Commission, Directorate-General for Education, Youth, Sport and Culture, 2019). The difficulty of mastering the tasks may differ between basic and advanced ICT use. Consequently, empirical studies on ICT use in the workplace and the associated skill demands often distinguish between basic and advanced levels of ICT use and skills (Falck et al., 2021; Fernández-Macías & Bisello, 2022). Second, the use of both basic and advanced ICT at work permeates occupations across almost all sectors. The use of advanced ICT at work such as using specialized software or programming computer code has become part of occupations that are not typical "ICT specialists", such as jobs in accounting, (online) marketing, care, and many more. Particularly the growing importance of data in many sectors (e.g., healthcare or business) requires the skilled use of specialized software also for workers who are not ICT specialists.

Given these arguments, the association between ICT interests and self-concepts on the one hand and the intensity of ICT use in the chosen occupation on the other hand may differ, depending on the specific type of ICT use required in a certain occupation. It seems likely that due to its close relationship with abilities, ICT self-concepts should be more relevant for selecting an occupation regarding the use of more advanced ICT (e.g., programming), while intrinsic motivation to use computers (interest) may be similarly important in affecting the intensity of basic and of advanced ICT use in a future occupation. These considerations lead to our first research question:

> **RQ1:** Do adolescents' ICT interest and ICT self-concept predict the intensity of basic ICT use and advanced ICT use in their future occupations?

Gendered vocational choices regarding ICT

Women continue to be strongly underrepresented in occupations in the ICT sector (e.g., software engineers) and in related postsecondary education programs (Düll, 2020). According to empirical research, female underrepresentation in computer sciences is largely unrelated to ability (Beyer, 2014). Instead, most studies attribute female aversion to ICT-related careers to stereotypes that are incompatible with most women's gender identities (Beyer, 2014; Gottfredson, 2002), to women's lower interest in working with things as opposed to people (Su et al., 2009), and to women's typically lower self-perceived abilities regarding certain aspects of ICT use (Borokhovski et al., 2018). At the same time however, women are generally more likely to use computers at work than men (Kristal et al., 2024). Hence, women are not generally more reluctant to select occupations involving ICT use than men. It is specifically those occupations that involve a high intensity of tasks related to the more technical aspects of ICT like software or system engineers, that many women appear to avoid (Combet, 2024).

In addition to the stereotype of software engineers as male geeks that emerged with the rise of the home computer (Abbate, 2012), women's lower self-perceived abilities regarding ICT are an important explanation for their lower likelihood to select careers that involve technically advanced use of ICT (Beyer, 2014). In the logic of the SEVT, women's less positive average ICT self-concept will make them less likely to believe they can successfully complete the tasks requiring advanced ICT use. In line with the differentiation between basic and advanced ICT we are making, young women tend to display significantly lower self-perceived abilities mainly regarding the use of advanced ICT (referring to more technical ICT tasks) compared to young men (European Commission, Directorate-General for Education, Youth, Sport and Culture, 2019).

Gender differences in ICT self-concepts may be related to the specific way in which these self-concepts develop (Gnambs, 2021). In contrast to other domains which are traditionally featured in schools (e.g., mathematics, science), ICT-related ability beliefs emerge largely independently of schools, e.g., through ICT use at home or in peer contexts (Juhanák et al., 2019). Hence, compared to mathematics, self-concepts of ability regarding ICT likely have a stronger relationship to ICT-related leisure behaviors. Boys and girls show marked differences in the ways they use ICT during leisure time. Boys tend to play more video games, while girls use ICT more for social media and communication purposes (Leonhardt & Overå, 2021).

Through the lens of the SEVT, boys' and girls' differing experiences with ICT may lead to different ability perceptions and interests regarding ICT. This may contribute to boys perceiving they have higher technical ICT skills, as gaming is more strongly related to performance feedback regarding technological aspects than social media use, even if displayed skills are largely limited to gaming environments, and not necessarily of much value for most future careers. Because ability signals from teachers are much weaker regarding ICT-related abilities compared to school subjects for which students regularly receive grades, children's experiences regarding their ICT use leave much scope for individual (mis-)perceptions of ICT-related abilities shaped by stereotypes.

Gendered parenting may also play an important role: Parental mediation of ICT use in childhood and adolescence often differs by children's gender. Parents are more worried about harmful experiences online for girls than for boys, resulting in more controlling mediation of girls' digital activities (Steinberg et al., 2024). Applied to the SEVT, parents may display different values of ICT to girls and boys or attribute their experiences with ICT in different ways, ultimately resulting in gendered interests and self-concepts regarding ICT. Finally, similar to the relationship between verbal and mathematical self-concept, so-called internal frame of references-effects (Marsh & Hau, 2004) may also apply to the ICT domain: Because many girls perceive themselves as relatively more competent regarding languages than ICT, they may develop a lower confidence regarding their ICT-related abilities than boys.

Finally, empirical research demonstrates that women's higher interest in working with people and men's higher interest in working with things are powerful explanations for occupational gender segregation (Kuhn & Wolter, 2022; Su et al., 2009). Although ICT have become an important means of social communication, their core is arguably still fundamentally technical. Hence, the more technical aspects of ICT are likely to raise more intrinsic interest among young men. In sum, we can assume female adolescents to be less likely to choose occupations requiring a high intensity of advanced ICT use due to their lower interest and less positive self-concept regarding ICT. However, we are unaware of previous empirical studies explicitly testing to what extent female underrepresentation in occupations requiring more intensive advanced ICT use can be attributed to gender differences in ICT interest and self-concept.

> **RQ2:** To what extent do the (expected) gender differences in adolescents' ICT interest and ICT self-concept explain the (expected) gender gap regarding the intensity of advanced ICT use in their future occupations?

The effects of domain-specific interests and self-concepts on vocational choice behavior may differ between genders. Considering many initiatives targeted explicitly at either girls or boys' choices of ICT-related careers (European Institute for Gender Equality, 2018), heterogeneous effects by gender would be of high practical relevance (Kang et al., 2021, p. 529). Nevertheless, we are unaware of previous empirical research exploring such effect heterogeneity by gender specifically for the ICT domain.

In general, empirical studies on vocational choice often find that women's career choices are more strongly aligned with their interests (intrinsic values) than men's (Beyer, 2014, p. 172). For example, female students in STEM subjects in higher education tend to report a greater fit between their interests and the content of their program than male students (Schelfhout et al., 2021). Science interest has also been found to be a stronger predictor of science aspirations for women than for men (Kang et al., 2021). The reasons for this pattern are not entirely clear. It may be related to the male breadwinner model and related gender stereotypes (Davis & Greenstein, 2009), according to which men must more strongly prioritize material aspects when choosing careers than women (Combet, 2024), possibly leaving more room for women to choose careers in line with their interests. Based on these considerations and the state of research, we expect ICT interest to have stronger predictive effects for girls than for boys.

For ICT self-concept, it is less clear whether to expect effect heterogeneity by gender. Given that occupations involving high intensity of advanced ICT use are stereotyped as male, one could argue that most girls will only choose ICT-intensive careers if they have a strong expectancy of success (indicated by a positive ICT self-concept), while boys are more likely to choose such careers not because of a positive ICT self-concept, but simply because these careers align well with their gender identity. Hence, we would expect a stronger predictive effect of ICT self-concept for girls than for boys, particularly regarding advanced ICT use in future occupations.

> **RQ3:** Does gender moderate the relationship between adolescents' ICT interest, ICT self-concept, and the intensity of basic and advanced ICT use in their future occupations?

Methods

Context of the present study

The context for our empirical analyses is Switzerland, a country with a strong tradition of VET. In Switzerland, VET gives access to over 240 different occupations, from low-skilled ones such as hairdresser, bricklayer or waiter, to highly skilled ones such as commercial clerk, electrician or web and multimedia developers. Approximately two thirds of compulsory school leavers in Switzerland enter the vocational track typically lasting for three or four years (Gomensoro & Meyer, 2021). Most compulsory school leavers enter firm-based vocational training programs which combines in-firm training (in general for three days of the week) and training at a vocational school (for the rest of the week). The participation of employers in the system aims to ensure that the skills taught align with employers' own needs, allowing for a smooth transition into the general labor market (Bonoli & Wilson, 2019).

To start a firm-based vocational training program, the apprentice must find an apprenticeship position with a training company, with which the apprentice signs an apprenticeship contract. Unlike fully school-based education (whether general or vocational), where access conditions are clearly defined, the allocation of firm-based apprenticeship positions is scarcely regulated by the state. The companies select apprentices on a competitive basis that is similar to hiring employees in the general labor market. The selection process accounts for various characteristics of applicants, such as their educational outcomes (school grades, level of requirement of the attended lower secondary track, etc.), and individual characteristics such as motivation, interest in the occupation and relative tasks, personality, soft skills, age, etc., to assess their suitability for the job (Duc & Lamamra, 2022). As a result, the matching between candidates and apprenticeship positions is influenced by the hiring companies, particularly when there are more applicants than positions available (Imdorf, 2018).

After obtaining a VET certification, some graduates enter tertiary education. Nevertheless, the Swiss labor market is marked by a strong link between VET and future occupations (Hupka-Brunner & Meyer, 2023). Hence, in the Swiss context, the transition from compulsory school to vocational training is particularly consequential for adolescents' future careers. Because occupations are strongly linked to certain VET programs, gendered choices of VET are hardly attenuated over the life course. The high share of each cohort entering a firm-based training coupled with the tight link between entered VETs and future careers in the strongly segmented Swiss labor market makes this a well-suited case for investigating our research questions. We therefore use the occupations for which school leavers are preparing in their VET programs as proxies for their most likely future occupation. The employer selection to some extent attenuates the empirical leeway for interests and self-concepts to influence selection into firm-based VET, as not all applicants will be granted access to their preferred occupation.

Data

The individual-level data stems from the second cohort of TREE (Transitions from Education to Employment), a representative panel survey following up post-compulsory school leavers from Switzerland (Hupka-Brunner et al., 2023). The baseline survey with 8,429 participating respondents was conducted in 2016, when participants were in 9th grade, the final year of compulsory schooling in Switzerland. The participants were subsequently interviewed annually. At the time of the data analysis for this study, data was available for the first three years after the baseline survey (data release version 2.0.0: TREE, 2023).

In the baseline survey of TREE2, 4,261 respondents were assigned to the questionnaire version covering the questions on ICT interest and self-concepts (random sample split). In total, 2,207 of these respondents reported having entered a firm-based vocational training program within the first three years after the baseline survey and therefore qualify for our analysis sample. In case of interruption or change of VET during the observation period, we consider the first firm-based VET undertaken (this applies only to a few cases). After performing listwise deletion of respondents with missing information in one of the variables used for the analysis, 1,964 respondents remain in our final analysis sample. All variables except those referring to the firm-based VET are measured at the baseline wave. Sample characteristics for the analysis sample are presented in Table 4.1.

In each wave, the respondents reported both the occupation their current training program is leading to, and the industry branch of their current training firm. We use these occupation-industry combinations to construct the dependent variable on ICT use by merging external data: The external data stems from a novel database, the European database of task indices for socio-economic research (Bisello et al., 2021; Fernández-Macías & Bisello, 2022). This database contains a large set of indicators which describe the intensity of both work tasks and the tools used at work, across occupation-industry combinations. The database classifies occupations according to the International Standard Classification of Occupations (ISCO-08, two digits) and industry branches according to the European classification system NACE Rev. 2.

For their calculation of the task indices, Bisello et al. (2021) used three different datasets: PIAAC (OECD Survey of Adult Skills), EWCS (European Working Conditions Survey), and ICP (Italian Indagine Camionara sulle Professioni). For each occupation-industry combination, the database provides a continuous 0–1 indicator on the estimated intensity of certain task content and use of methods and tools of work. Simply speaking, the indicators describe to what extent workers do something (do a task, use a tool) on a regular basis. We assume that the indicators from this European database should be applicable in the Swiss context.

Measures

Dependent variables

We measure the intensity of basic ICT use (first dependent variable) by linking each occupation-industry combination of respondents' firm-based VET to the respective indicator from the European database of task indices. The basic ICT use indicator in the database is based on four individual items which were surveyed in the PIAAC study. The four items refer to the frequency of using email, spreadsheet software, word processors, and the Internet, the latter to "better understand issues related to your work" as part of the respondents' current jobs (Bisello et al., 2021). The intensity of advanced ICT use (second dependent variable) is measured following the same logic, linking respondents' firm-based VET to the respective indicator from the European task database. The advanced ICT use indicator is based on several items surveyed in the PIAAC study and in the ICP. These items cover the frequency of using a programming language to write computer code, respondents' knowledge of different aspects of the technical aspects of computer hardware and software, the use of computers "to program, write software, adjust functions, enter data, or process information" and the writing of computer programs "for various purposes" (Bisello et al., 2021, p. 38). The correlation between the basic ICT use and the advanced ICT use intensity variables in our analysis sample is $r = .59$ (Pearson correlation coefficient). Summary statistics of the dependent variables and all other measures are presented in Table 4.1.

Independent variables

We measure adolescents' ICT self-concept using a scale which is based on the three items "I have always been good at working with computers", "I know more about computers than most people of my age", and "I am able to give advice when others have problems with computers" (agreement on a four-point scale). ICT interest is measured as a scale based on the three items "Using computers is fun", "I am interested in technology", and "I like learning with computers" (agreement on a four-point scale). The individual items originate from the International Computer and Information Literacy Study (ICILS) 2013. The correlation between ICT interest and ICT self-concept in our analysis is $r = .69$, suggesting that the concepts are overlapping, but are sufficiently differentiated to be analyzed separately.

Control variables

We include verbal and mathematical self-concepts measured at the baseline survey as control variables, because subject-specific self-concepts have been shown to be interdependent and may therefore be correlated with ICT self-concept (Marsh & Hau, 2004). Moreover, we include mathematics performance measured in a standardized test (weighted likelihood estimates [WLE]) at the end of the final (9th) school year, self-reported school marks in science, and self-reported school marks in mathematics, and first and second language (averaged). The importance of family values (scale) is controlled in the model because it may affect vocational choices directly, given that ICT specialists enjoy relatively favorable opportunities for part-time or remote work (European Commission, Directorate-General for Education, Youth, Sport and Culture, 2019). Family values may also be correlated with subjective task values, as part of a larger set of value orientations. We also include the self-reported level of extraversion as a control variable, because it has been found to be inversely related to programming skills, in line with the common stereotype (Gnambs, 2015).

Table 4.1: Descriptive statistics

	Mean (SD) or %
Dependent variables:	
Intensity of ICT use in future occupation (scale 0-1)	
Basic ICT	0.56 (0.19)

Table 1 (continued)

	Mean (SD) or %
Advanced ICT	0.17 (0.16)
Independent variables:	
ICT interest	0.05 (0.91)
ICT self-concept	0.09 (0.92)
Control variables:	
Verbal self-concept	−0.07 (0.90)
Mathematical self-concept	−0.03 (1.00)
Mathematics performance at school year nine (WLE)	−0.41 (1.20)
School mark in science (1-6)[a]	4.67 (0.66)
GPA (1-6)[a]	4.64 (0.43)
Importance of family values (scale 1-4)	3.20 (0.75)
Big Five: Extraversion (scale 1-5)	3.37 (0.83)
Highest parental HISEI-08 (socioeconomic status)	51.50 (20.32)
At least one parent is ICT specialist	
No	95.7%
Yes	4.3%
Gender	
Female	45.5%
Male	54.5%
Highest parental educational attainment	
Compulsory schooling	16.3%
Upper secondary education	55.1%
Tertiary education	28.6%
Language region	
German	84.5%
French	13.3%
Italian	2.2%
School requirement at lower secondary level	
Basic / Low	42.5%
Advanced	50.9%
High	6.6%
N	1,964

Note. SD = Standard deviation. Weighted statistics. [a] GPA = grade point average across three subjects: mathematics, first and second language. 6 = best possible mark, 1 = worst possible mark.

Parents working as ICT specialists may serve as role models and may therefore be particularly effective in fostering their child's ICT interest and ICT-related careers (Adya &

Kaiser, 2005), which is why we control for this case based on a classification developed by the OECD (Grundke et al., 2017). Furthermore, demographic variables like parental socio-economic status (highest ISEI-08 value), respondents' gender, highest parental educational attainment, and language region are included as control variables. Finally, the level of school requirements is an important determinant of occupational pathways in Switzerland, as it is used by employers as a signal for applicants' academic performance. Similarly, it may also affect adolescents' self-concept of abilities, as the SEVT would suggest, so we include it as our final control variable.

Analytical strategy

We apply multivariate ordinary least squares (OLS) regression models to estimate the relation between ICT interest and ICT self-concept and both outcome variables, the occupational task content indicators (Research questions 1 and 3). To assess the robustness of the results to the bounded nature of the dependent variable, we estimate fractional logit models (Papke & Wooldridge, 1996). Fractional logit is specifically designed for dependent variables that lie within the unit interval [0,1] and include boundary values. It uses a quasi-likelihood approach based on the Bernoulli distribution with a logit link. We stick to OLS regression for our main models because the results are easier to interpret than fractional logit. Results from fractional logit models are presented as part of the Appendix and discussed in the results section of this paper. The results we obtain from fractional logit models are substantively similar to those from OLS, suggesting that our main findings are not sensitive to model specification.

For RQ2, we apply a twofold linear Oaxaca-Blinder decomposition model (Blinder, 1973; Oaxaca, 1973). This model estimates how much of the observed difference in an outcome variable between two groups (e.g., mean wage of women vs. men) can be statistically "explained" by a group difference in one or more predictor variables (Jann, 2008). Essentially, the decomposition model compares the observed mean difference in the outcome to the mean difference in the counterfactual scenario that the predictor variable(s) were equal in both groups. All analyses are survey weighted to correct for the disproportionate sampling design. In addition, the applied survey weight corrects for selective panel attrition (Hupka-Brunner et al., 2021). Strata and clustered sampling are considered in the calculation of statistical inference.

Results

Description of dependent variables

Table 4.2 presents descriptive statistics of both dependent variables (basic and advanced ICT use intensity in future occupations) by gender. On average, girls in our sample selected into occupations with a slightly lower intensity of basic ICT use, but the mean difference is not statistically significant on the 95%-level. The median is also larger for boys than for girls. As expected, we find a significant gender difference regarding the intensity of advanced ICT use, with boys selecting into occupations requiring significantly more intensive use.

Table 4.2: Descriptive statistics of dependent variables, by gender

	Girls		Boys		Difference Boys - Girls	
	Mean (SD)	Median	Mean (SD)	Median	Mean Diff.	p-value[b]
Intensity of basic ICT use	0.54 (0.19)	0.45	0.57 (0.19)	0.52	0.03	.08
Intensity of advanced ICT use	0.13 (0.10)	0.13	0.20 (0.19)	0.15	0.07	< .001

Note. $N = 1{,}964$. Weighted. SD = Standard deviation. Diff. = Difference. [b] p-value obtained from a weighted bivariate OLS regression model.

Figure 4.1 visualizes the distribution of both dependent variables by gender, using histograms. The left panel illustrates that most occupations require some amount of basic ICT use. The large spike among girls between 0.4 and 0.5 in the left panel can mainly be attributed to occupations in the care sector (e.g., nursing professionals, medical and dental assistants), which typically require a moderate intensity of basic ICT use and are also strongly female-dominated. The second largest spike for both boys and girls (around 0.8) is related to the large group of office clerks in the sample.

For intensity of advanced ICT use (right panel), the distribution is right-skewed. Most adolescents in the sample selected into occupations requiring only limited use of advanced ICT. The spike between 0.1 and 0.2 for girls is mainly related to occupations in the care sector, which can require a limited amount of sector-specific software use. The spike above 0.2 for boys and girls is mainly due to office clerks, an occupation which typically requires some advanced ICT use, like the use of business or banking software. Three occupations (according to ISCO-08) are mainly responsible for values exceeding 0.5 on the advanced ICT use scale: systems administrators, web and multimedia developers, and applications programmers. All are strongly male-dominated in our sample, as apparent in the densities between 0.5 and 1.

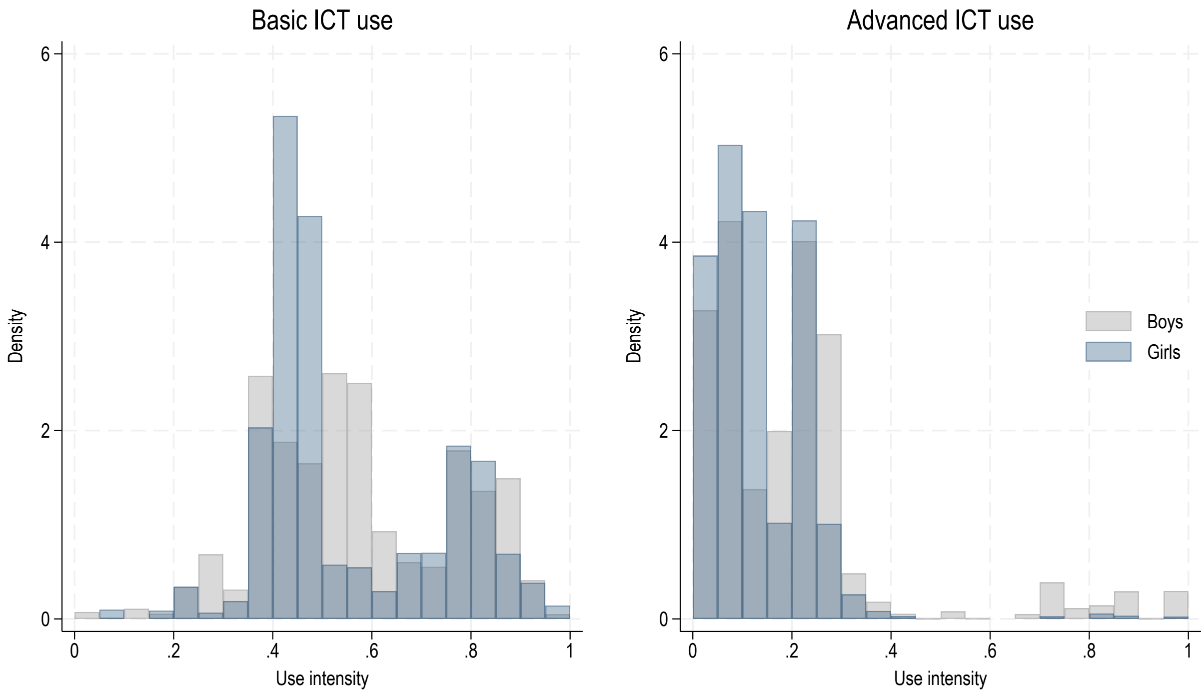

Figure 4.1: Histograms of the dependent variables by gender

Note. $N = 1{,}964$. Weighted.

ICT interest and self-concept as predictors of ICT use in adolescents' future occupations (RQ1)

The analysis of ICT interest and ICT self-concept as predictors of ICT use in future occupations of adolescents on the vocational track reveals several key findings. The results displayed in Figure 4.2 show that in the bivariate specification without control variables, there is a statistically significant positive association between ICT interest and the intensity of both basic and advanced ICT use in adolescents' future occupations (upper coefficient in both panels; $p < .05$). Adding the full set of control variables, including self-concepts for mathematics and reading, attenuates the coefficients for ICT interest only slightly, and they remain statistically significant on conventional levels for both outcome variables ($p < .05$). These positive associations are in line with our theoretical expectations, although relatively small in magnitude.

For ICT self-concept, we find a significantly positive association only with the intensity of advanced, but not with the intensity of basic ICT use. This finding also aligns with our theoretical expectation that ICT self-concept should be more relevant for the choice of occupations in terms of the intensity of advanced as opposed to basic ICT use. Repeating the analysis using fractional logit instead of OLS regression models yields substantively similar results (see Figure 4.A1, Appendix).

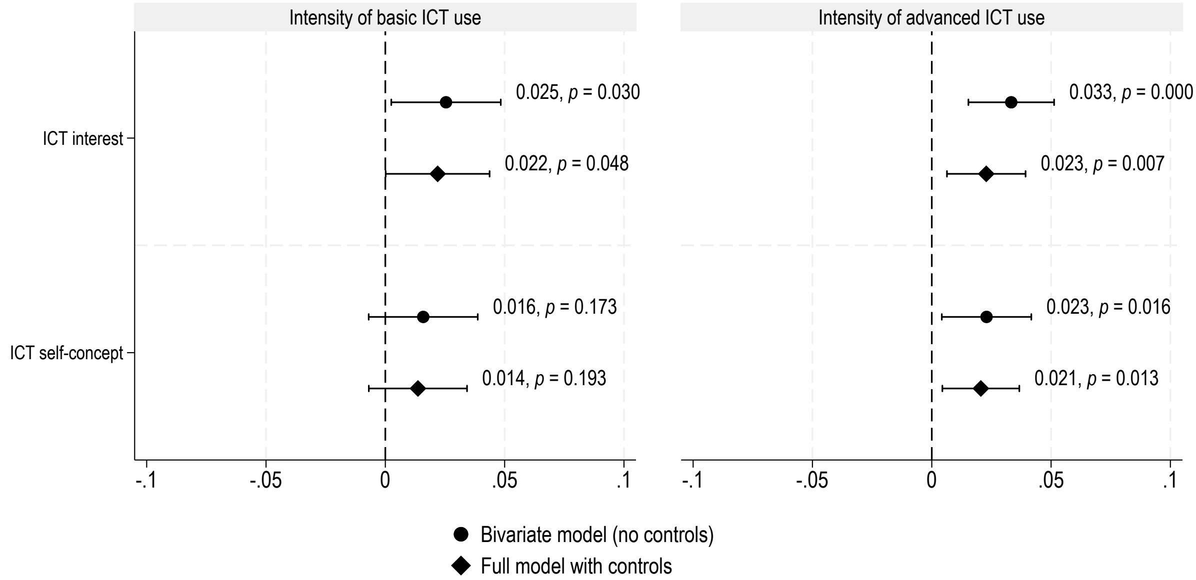

Figure 4.2: OLS regression coefficients of ICT interest and ICT self-concept

Note. $N = 1{,}964$. OLS regression coefficients of ICT interest and ICT self-concept predicting the intensity of basic and advanced ICT use in future occupations, with 95%-confidence intervals. Full model coefficients presented in Table 4.A1 (Appendix). Models included all control variables listed in Table 4.1. Interpretation: A marginal increase in ICT interest or self-concept is associated with an estimated increase in the dependent variable by X scale points.

ICT interest and self-concept as mediators of gendered vocational choices (RQ2)

If girls exhibit lower ICT interest and a less positive ICT self-concept compared to boys, these factors could help explain the gender disparity in the extent of advanced ICT use in future occupations, as reported in Table 4.2. As expected, girls in our sample show, on average, both lower ICT interest and a less positive ICT self-concept than boys. Specifically, the mean ICT interest score for girls is −0.35, compared to 0.38 for boys. For ICT self-concept, the mean is −0.24 for girls and 0.36 for boys. The gender differences in these mean values are statistically significant for both ICT interest and ICT self-concept ($p < .001$).

Table 4.3 presents the results from the twofold Oaxaca-Blinder decomposition model, which directly addresses RQ2. According to the pooled model, gender differences in ICT interest and self-concept jointly explain 39.4% of the total gender gap in the intensity of advanced ICT use in the chosen occupation (equivalent to 0.026 scale points). The individual contribution of ICT interest is slightly higher (24.7%) than that of ICT self-concept (14.6%). However, the confidence intervals indicate that these estimates are relatively imprecise, primarily due to the small size of the total gender gap. Nevertheless, we can conclude that the combined statistical contribution of these two factors is substantial: the lower bound of the 95%-confidence interval (0.014 scale points) still corresponds to a 23.1% contribution.

The pooled decomposition model is useful for understanding the overall extent to which ICT interest and self-concepts contribute to the gender gap in advanced ICT use. However, it reflects a counterfactual scenario in which girls' and boys' ICT interest and self-concept levels are equalized through averaging. From a practical perspective, it may be more relevant to consider how the gender gap would change if girls' levels of ICT interest and self-concept were increased to match those of boys, without altering boys' levels. To explore this, we present additional decomposition results using either girls or boys as the reference group.

Table 4.3 reveals pronounced asymmetries depending on the chosen reference group. If girls' ICT interest and ICT self-concept were equal to the levels observed for boys, the gender gap would be reduced by 26.9% (equivalent to 0.018 scale points). When looking at the individual components, we find that only ICT interest contributes to the total gender gap. This implies that, mathematically, equalizing girls' ICT self-concept to that of boys would not affect the gender gap in advanced ICT use, whereas increasing their ICT interest would lead to a partial reduction. Conversely, using boys as the reference group (right column in Table 4.3)—although this counterfactual scenario may be less socially desirable—suggests that adjusting boys' ICT interest and self-concept down to the levels observed for girls would reduce the gender gap by 43.7% (0.028 scale points). Interestingly, ICT self-concept makes a strong contribution in this case, despite not contributing to the gap when girls are the reference group (middle column). We discuss this asymmetry further in the following section.

Table 4.3: Decomposition of gender gap in advanced ICT use

	Pooled model	Ref.: Girls	Ref.: Boys
Total gap (Boys − Girls)	.065 (.043, .087)	.065 (.043, .087)	.065 (.043, .087)
Explained gap[c]	.026 (.014, .037)	.018 (.009, .026)	.028 (.012, .045)
Explained components:			
ICT interest	.016 (.005, .027)	.019 (.007, .031)	.008 (−.008, .025)
ICT self-concept	.010 (.001, .018)	−.001 (−.009, .006)	.020 (.006, .034)

Note. $N = 1{,}964$. Contributions of ICT interest and self-concept to the gender gap in the intensity of advanced ICT use. Results from twofold linear Oaxaca-Blinder decomposition models with control variables (full control variable set, as presented in Table 4.1). 95%-confidence intervals in parentheses.
[c] Endowment (excluding control variables).

Gender as a moderator of ICT interest and self-concept (RQ3)

Figure 4.3 displays the gender-specific associations of ICT interest and ICT self-concept with both outcome variables (intensity of basic and advanced ICT use) as AMEs (average marginal effects). Except for the moderation term, the results in Figure 4.3 are obtained using the same model specification used to generate Figure 4.2. Results remain stable when applying fractional logit regression (see Figure 4.A2 in the Appendix).

Overall, the patterns for basic and advanced ICT use look quite similar. We find that higher ICT interest significantly predicts higher intensity of both basic and advanced ICT use only for girls, not for boys. For ICT self-concept, the pattern is reversed. For boys, but not for girls, a more positive ICT self-concept is related to a significantly higher use intensity regarding both types of ICT. The gender difference in the estimates is statistically significant for all predictors ($p < .05$), except ICT interest in the model predicting advanced ICT use intensity (see Figure 4.3, right panel; $p = .346$). These results help explain the asymmetrical results of the decomposition analysis in Table 4.3. For example, because their ICT self-concept is unrelated to girls' selection into occupations in terms of ICT use intensity, adjusting girls' self-concept mathematically does not affect the size of the gender gap. However, because boys' ICT self-concepts are strongly related to the outcome variables, we find that adjusting their ICT self-concepts indeed affects the gender gap. The opposite holds for ICT interest.

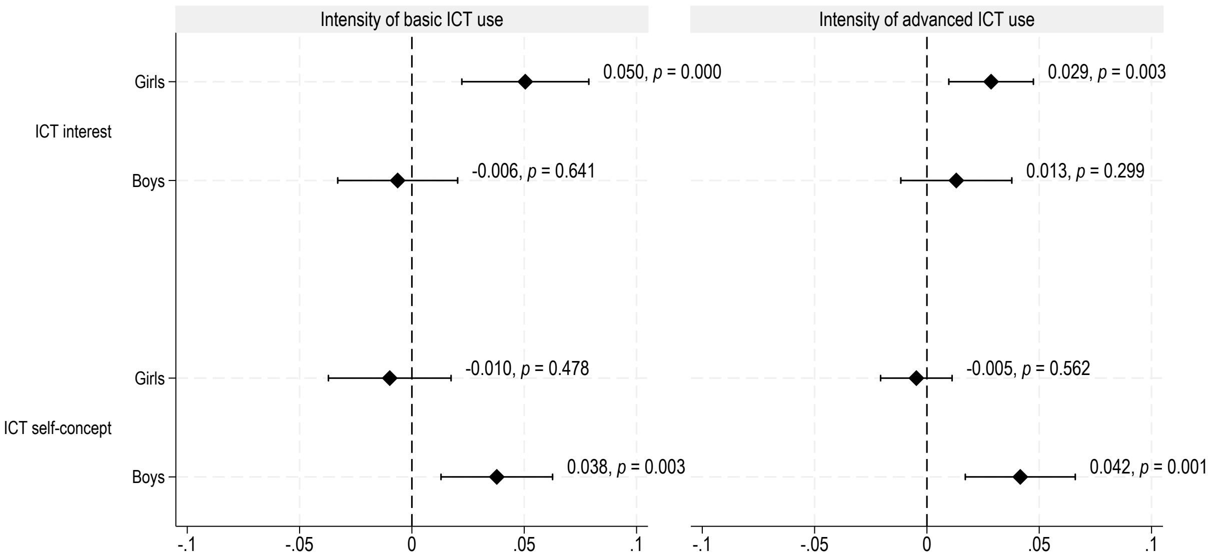

Figure 4.3: Gender-specific AMEs of ICT interest and self-concept

Note. $N = 1{,}964$. Group-specific AMEs obtained from OLS regression models. Models included all control variables listed in Table 4.1. Full model coefficients presented in Table 4.A2 (Appendix). Interpretation: A marginal increase in ICT interest or self-concept is associated with an estimated increase in the dependent variable by X scale points for girls (boys).

In-depth analyses of ICT specialists

Finally, we conduct an additional analysis to account for the highly right-skewed distribution of the advanced ICT use variable (see Figure 4.1, right panel). Occupational choice processes may differ for roles within the ICT specialist domain, particularly due to the (gender) stereotypes associated with these careers. As highlighted in prominent theories (e.g., Gottfredson, 2005), many girls do not seriously consider ICT specialist careers because of prevailing gender stereotypes. These dynamics may differ for occupations that involve advanced ICT use but are not explicitly associated with the ICT sector. Additionally, ICT self-concepts may play a more salient role in the selection of such occupations, given the perceived difficulty and technical demands typically associated with ICT specialist roles. To explore this, we construct a binary variable that distinguishes between the small subset of ICT-specialist occupations characterized by very high intensity of advanced ICT use (> 0.5 on the scale, $n = 80$) and all other occupations ($n = 1{,}884$). Occupations classified as ICT specialists include systems administrators, applications programmers, web and multimedia developers, and a few other highly ICT-oriented occupations. We then perform logistic regression analysis to predict the selection into an ICT-specialist career path, with AMEs presented in Figure 4.4.

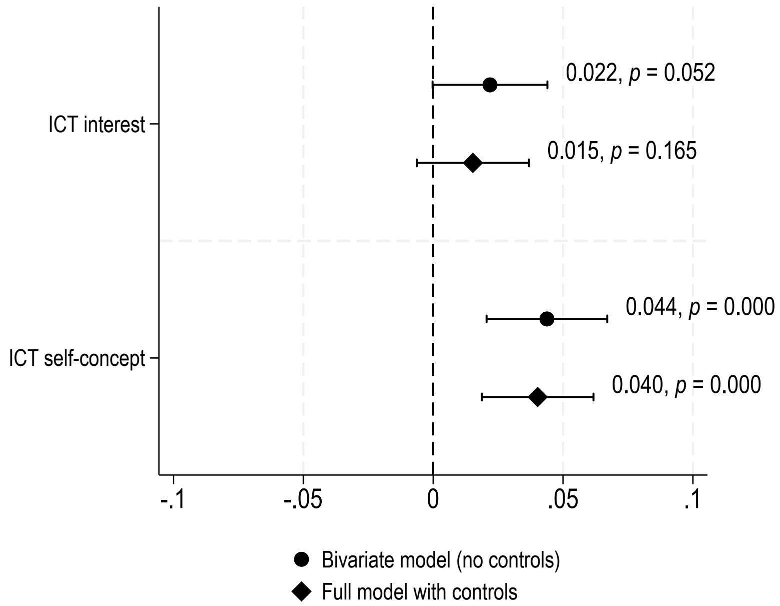

Figure 4.4: AMEs on the probability to become an ICT specialist

Note. $N = 1{,}964$. AMEs on the probability to select into an occupation with a very high intensity of advanced ICT use (> 0.5), obtained from a logistic regression model. Full model coefficients presented in Table 4.A3 (Appendix). Interpretation: A marginal increase in ICT interest or ICT self-concept is associated with an increase in the probability of entering an occupation with very high intensity of advanced ICT use by X percentage points.

Our analysis shows that higher interest in ICT is not significantly associated with a higher probability of entering an ICT specialist occupation. This finding stands in contrast to the earlier results shown in Figure 4.2, where ICT interest was significantly and positively associated with the overall intensity of advanced ICT use. However, consistent with the general results from the linear model (see Figure 4.2, right panel), we find that ICT self-concept is significantly and positively associated with the probability of selecting into an ICT-specialist occupation. The AME from the full model indicates that a marginal increase in ICT self-concept (approximately equivalent to one standard deviation) is associated with a four-percentage-point increase in the probability of selecting an ICT specialist career. Unfortunately, we are unable to estimate gender-specific effects from this logistic model due to the very small number of girls in our sample who selected an ICT-specialist occupation (n = 12). As a result, any gender-specific coefficient for girls would be statistically unreliable.

Discussion

Using a novel database of ICT use intensity across occupations and individual-level panel data on school-to-VET transitions in Switzerland, this study examined the role of ICT interest and ICT self-concept in vocational choice processes in adolescence and the implications for occupational gender segregation. In line with theoretical expectations derived from Eccles' Situated Expectancy-Value Theory (SEVT), we found that adolescents' ICT interest and self-concept at the end of compulsory schooling significantly predicted the intensity of both basic and advanced ICT use in their future occupation, as reflected by their chosen VET program and the industry branch of their training firm.

Our findings contribute to an improved theoretical understanding of the role of psychological dispositions towards ICT in vocational choice processes, a topic that has received limited empirical attention. A first key insight is that adolescents with higher ICT interest tend to select into occupations that involve greater basic and advanced ICT use. However, they are not more likely to enter ICT-specialist occupations. This suggests that aspects of ICT use at work that are less technical, such as information processing or desk work, may at least partially explain the observed relationship with ICT interest. A second important insight is that adolescents with a more positive ICT self-concept—indicating greater confidence in their ability to solve ICT-related tasks—are more likely to enter occupations with high levels of advanced ICT use and to choose ICT-specialist careers, but not occupations with higher basic ICT use. These findings indicate that ICT interest and ICT self-concept affect adolescents' occupational pathways in distinct ways, and that these effects depend on how the role of ICT in an occupation is conceptualized and measured.

Our study also provides interesting insights into the relationship between gender and ICT in vocational choice processes. What was previously known is that although women tend to be more likely to use ICT at work in general than men (Kristal et al., 2024), they remain severely underrepresented in ICT-specialist roles, such as software engineering (Beyer, 2014). This underrepresentation is problematic from multiple perspectives: ICT specialist jobs tend to offer favorable conditions regarding work-life balance, facilitate childcare arrangements, and the wages paid in these jobs are particularly high, so increasing the share of women working in this sector could help diminish the gender pay gap (European Institute for Gender Equality, 2018). Additionally, ongoing shortages of (female) ICT specialists can hamper economic development on a national scale (Düll, 2020).

Numerous studies have linked the underrepresentation of women among ICT specialists to the influence of stereotypes of "computer nerds" being incompatible with female gender identity and associated fears of a work environment marked by lack of empathy and communication, or even, misogyny (Wiener, 2020). Our study provides additional insights to more recent debates around the contribution of gendered preferences for certain types of occupational tasks, like a higher aversion to systemizing, technical tasks among women, to their underrepresentation in STEM fields (Combet, 2024). Our findings highlight the particular importance of ICT interest in shaping girls' vocational choices. The girls in our sample appeared to evaluate their enjoyment of ICT-related activities in relation to the ICT use intensity linked to different occupational alternatives, while we found no such effect for boys. Other studies also have noted that girls' occupational choice behavior is more strongly related to their domain-specific interests than boys' (Beyer, 2014). Our study is among the first to demonstrate that this pattern extends to the ICT domain.

Contrary to our theoretical expectations, girls' ICT self-concept was unrelated to both basic and advanced ICT use intensity, whereas for boys, ICT self-concept was positively associated with both. A similar gender-specific pattern was reported by Kang et al. (2021) in a study on science aspirations. Still, the reasons why ICT self-concept appears to play a role only for boys remain unclear—particularly in light of the extensive literature emphasizing girls' lower self-concepts as a key explanation for their underrepresentation in STEM (Kriesi & Imdorf, 2019).

In terms of practical implications, our results suggest that fostering girls' interest in ICT could increase female participation in occupations requiring more advanced ICT use. However, we would caution against assuming that simply raising average ICT interest among girls would translate into greater representation in ICT-specialist careers. Instead, our findings point to the potential of strengthening ICT self-concept as a more effective pathway for promoting gender equity in this domain. That said, because this association was primarily driven by the small subgroup of boys who selected into ICT-specialist careers, further research is needed to assess whether the same mechanism holds for girls.

Increasing the share of female ICT specialists remains a complex challenge. Our findings suggest that altering occupational task profiles or rebranding roles may help attract more women to ICT. Stereotypes may be less influential when occupations are not narrowly defined by programming or coding, but instead encompass a broader array of tasks and methodologies. In this regard, we support Combet's (2024, p. 252) suggestion to explicitly advertise the diversity of tasks and skills involved in STEM (and ICT) programs and careers as a strategy to attract more women.

Lastly, the fact that interest in ICT was predictive of occupational pathways only for girls, but not for boys, raises questions about potential mismatches between boys' vocational interests and their realized occupations. Given the well-documented benefits of congruence between vocational interests and job characteristics (Wilkins & Tracey, 2014), it is worth exploring why highly interested boys in our sample did not end up in occupations with higher ICT use. One possible explanation is that boys' comparatively lower school grades—an important selection criterion for training firms in the Swiss VET system—may have constrained their occupational options. Future research should investigate the long-term consequences of such interest-environment mismatches, especially for boys whose interest in ICT is not mirrored in their future occupations.

Limitations and future research

Overall, we see our study as an explorative starting point for a potentially fruitful discussion of the psychosocial processes of vocational choices regarding the ICT domain. In the following, we acknowledge and discuss the study's main limitations, highlighting several unanswered questions that could guide future research.

First, while our main research question concerns the causal effect of interests and self-concepts on career choices, our research design can provide only associational evidence. The association between ICT interest and its use in future occupations may partly reflect adolescents' choice of training programs as suggested by our theoretical reference to the SEVT as well as employers' preferences for interested and motivated candidates, particularly in early-career positions (Duc & Lamamra, 2022). We are essentially unable to disentangle the causal contribution of adolescents and the training firms to the reported associations empirically. Hence, the results represent an important first step, identifying associations that future studies may try to understand in more detail. Second, using school-leavers' VET programs and training firm industries as proxies for future occupations captures career pathways in the Swiss labor market with good accuracy (the long-term probability of staying in the initial training occupation exceeds 50%; Bundesamt für Statistik, 2020). Still, accuracy could be further improved by using data on actual occupations over time, which was not available to us.

Third, our measures could be refined. It is generally complex to empirically measure expectancies, values, and many of the constructs in the SEVT, with measures often being one-sided or simplified (Eccles & Wigfield, 2024). Future studies could benefit from differentiating more finely between basic and advanced, or technical and user-focused dimensions of ICT interests and self-concepts, which may help address potential gender differences with more nuance (European Commission, Directorate-General for Education, Youth, Sport and Culture, 2019). Fourth, the outcome variables are based on European averages rather than Swiss-specific data (Bisello et al., 2021). Incorporating more precise measures could strengthen the findings, although similarities with countries like Germany and Austria and Denmark, which also put high emphasis on dual VET and are included in the underlying database, may reduce the impact of this limitation. Fifth, our results are mainly relevant to vocational choice in the context of VET. The role of ICT in vocational choice processes involving tertiary education (e.g., regarding computer science; Beyer, 2014) may differ because tertiary education programs are less closely connected to specific occupations.

Finally, with the introduction of applications relying on forms of artificial intelligence (AI), the nature of ICT use in professional contexts is currently changing. The benefits of working with AI may depend on prior levels of ability, but also on ability beliefs (Caplin et al., 2024). The role of ability beliefs in determining ICT-related career choices may therefore change in the future, as AI assistants promise to help solve complex tasks. Although we could not address the role of AI in this paper as our data was collected between 2016 and 2019, this represents an interesting starting point for future studies.

Conclusions

While labor market demands for ICT skills have been extensively studied, there is a notable research gap in terms of how the growing importance of ICT use at work (Fernández-Macías et al., 2023) affects vocational choice processes. Given the unresolved shortage of ICT specialists and the underrepresentation of women in this field, this is a highly relevant gap for research and practice (Beyer, 2014; Gorbacheva et al., 2019). Our study is among the first to investigate the psychosocial determinants of ICT-related vocational choices in the context of VET. Our findings highlight how heterogeneity in adolescents' ICT interest and self-concepts is related to subsequent occupational pathways and how it potentially contributes to gendered vocational trajectories. By recognizing the differentiated impacts of these factors on boys and girls that our study revealed, educators and policymakers can develop targeted interventions to support diverse pathways into ICT-related occupations. Future research should continue to explore these gender-specific dynamics and identify additional factors that can help bridge the gender gap and mitigate the general shortage of workers in professions with high levels of advanced ICT use.

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Appendix

Table 4.A1: Full OLS regression model coefficients for Figure 4.2

Dependent variable	(1) Basic ICT use	(2) Basic ICT use	(3) Advanced ICT use	(4) Advanced ICT use
ICT interest	0.025*	0.022*	0.033***	0.023**
	(2.18)	(1.98)	(3.64)	(2.72)
ICT self-concept	0.016	0.014	0.023*	0.021*
	(1.37)	(1.30)	(2.41)	(2.50)
Verbal self-concept		0.016		0.010
		(1.90)		(1.74)
Mathematical self-concept		0.009		0.009
		(0.99)		(0.99)
Mathematics performance test (WLE)		0.016		0.027**
		(1.91)		(3.30)
School mark in science		0.010		0.003
		(0.72)		(0.21)
GPA in math, 1st and 2nd language		0.036		0.005
		(1.35)		(0.15)
Importance of family values		0.008		−0.003
		(0.82)		(−0.32)
Big five: extraversion		0.013		−0.001
		(1.61)		(−0.17)
Parental HISEI-08		0.000		−0.000
		(1.00)		(−0.37)
Parent is ICT specialist (Ref. no)		0.012		0.056
		(0.34)		(1.21)
Gender: Male (Ref. female)		−0.004		0.022*
		(−0.26)		(2.22)
Parent educ.: Upper sec. (Ref. compulsory)		−0.018		−0.009
		(−0.86)		(−0.58)
Parent educ.: Tertiary (Ref. compulsory)		−0.001		0.022
		(−0.04)		(0.87)
Language region: French (Ref. German)		−0.016		−0.019
		(−0.75)		(−1.36)
Language region: Italian (Ref. German)		0.034		0.054
		(0.94)		(1.52)
School req.: Advanced (Ref. basic / low)		0.085***		0.049**
		(4.84)		(3.20)

Table 4.A1 (continued): Full OLS regression model coefficients for Figure 4.2

Dependent variable	(1) Basic ICT use	(2) Basic ICT use	(3) Advanced ICT use	(4) Advanced ICT use
School req.: High (Ref. basic / low)		0.123***		0.070*
		(3.92)		(2.42)
Constant	0.553***	0.220	0.165***	0.116
	(70.21)	(1.70)	(25.82)	(0.87)
Observations	1,964	1,964	1,964	1,964

Note. t-statistics in parentheses.
*$p < .05$, **$p < .01$, ***$p < .001$.

Table 4.A2: Full OLS regression model coefficients for Figure 4.3

Dependent variable	(1) Basic ICT use	(2) Advanced ICT use
ICT interest	0.050***	0.029**
	(3.51)	(2.98)
Gender: Male (Ref. female)	−0.007	0.021*
	(−0.40)	(2.27)
Gender: Male (Ref. female) × ICT interest	−0.057**	−0.015
	(−2.93)	(−0.94)
ICT self-concept	−0.010	−0.005
	(−0.71)	(−0.58)
Gender: Male (Ref. female) × ICT self-concept	0.048*	0.046**
	(2.54)	(3.08)
Verbal self-concept	0.017	0.010
	(1.96)	(1.71)
Mathematical self-concept	0.010	0.009
	(1.01)	(1.00)
Mathematics performance test (WLE)	0.017*	0.028***
	(1.98)	(3.39)
School mark in science	0.011	0.003
	(0.79)	(0.16)
GPA in math, 1st and 2nd language	0.035	0.002
	(1.36)	(0.06)
Importance of family values	0.009	−0.003
	(0.89)	(−0.32)
Big five: extraversion	0.013	−0.001

Table 4.A2 (continued): Full OLS regression model coefficients for Figure 4.3

Dependent variable	(1) Basic ICT use	(2) Advanced ICT use
	(1.64)	(−0.19)
Parental HISEI-08	0.000	−0.000
	(1.03)	(−0.28)
Parent is ICT specialist (Ref. no)	0.014	0.053
	(0.39)	(1.13)
Parent educ.: Upper sec. (Ref. compulsory)	−0.019	−0.009
	(−0.93)	(−0.60)
Parent educ.: Tertiary (Ref. compulsory)	−0.002	0.021
	(−0.08)	(0.82)
Language region: French (Ref. German)	−0.018	−0.018
	(−0.87)	(−1.33)
Language region: Italian (Ref. German)	0.040	0.059
	(1.13)	(1.71)
School req.: Advanced (Ref. basic / low)	0.085***	0.048**
	(4.95)	(3.25)
School req.: High (Ref. basic / low)	0.122***	0.066*
	(4.07)	(2.34)
Constant	0.223	0.129
	(1.78)	(0.96)
Observations	1,964	1,964

Note. t-statistics in parentheses.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 4.A3: Full logistic regression model coefficients for Figure 4.4

Dependent variable	Occupation with high advanced ICT use (> 0.5)	
	Coef.	t-statistic
ICT interest	0.586	(1.29)
ICT self-concept	1.542***	(4.52)
Verbal self-concept	0.475*	(2.16)
Mathematical self-concept	0.193	(0.64)
Mathematics performance test (WLE)	0.844***	(3.53)
School mark in science	0.497	(0.85)
GPA in math, 1st and 2nd language	−1.391	(−1.67)
Parent is ICT specialist (Ref. no)	1.385*	(2.04)
Language region: French (Ref. German)	−1.950*	(−2.42)
Language region: Italian (Ref. German)	0.825	(0.77)
Advanced	−0.217	(−0.32)
Basic / Low	−1.500	(−1.59)
Parental HISEI-08	−0.009	(−0.58)
Parent educ.: Upper sec. (Ref. compulsory)	0.469	(0.42)
Parent educ.: Tertiary (Ref. compulsory)	1.260	(1.04)
Gender: Male (Ref. female)	0.702	(1.00)
Importance of family values	−0.009	(−0.03)
Big five: extraversion	−0.319	(−1.46)
Constant	−0.018	(−0.01)

Note. $N = 1{,}964$. Logit coefficients.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

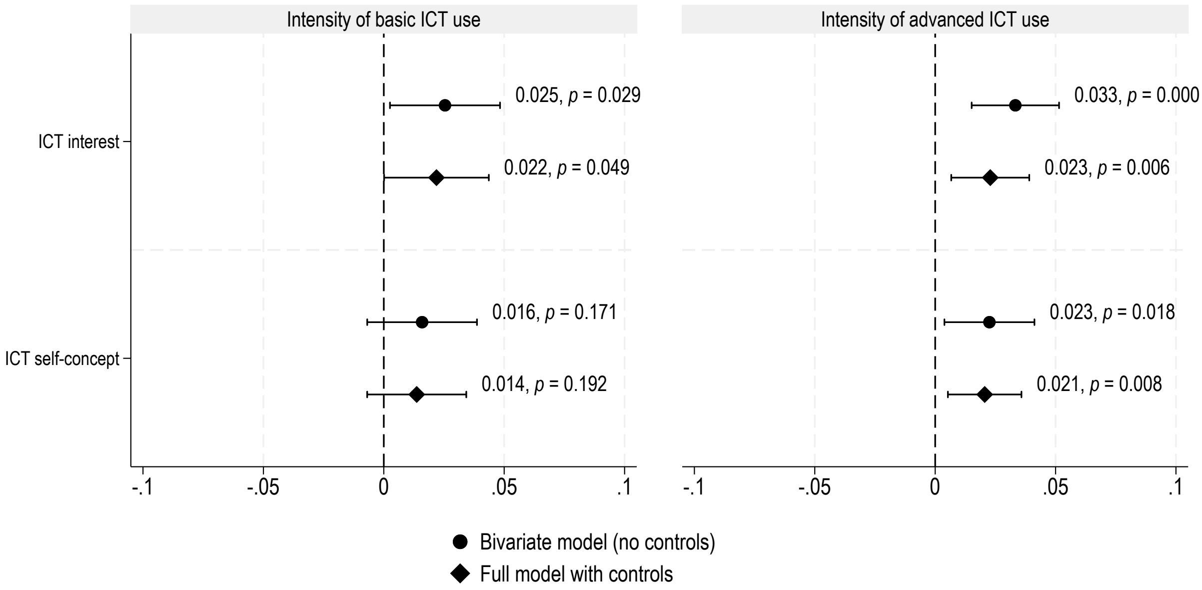

Figure 4.A1: Robustness test: Fractional logit regression results

Note. $N = 1{,}964$. AMEs with 95%-confidence intervals obtained from fractional logit regression models. Full model includes all control variables listed in Table 4.1. Interpretation: A marginal (small) increase in ICT interest or ICT self-concept is associated with an estimated increase in the dependent variable (basic or advanced ICT use intensity with range 0-1) by X scale points. A marginal increase corresponds approximately to a one unit change in both presented predictors.

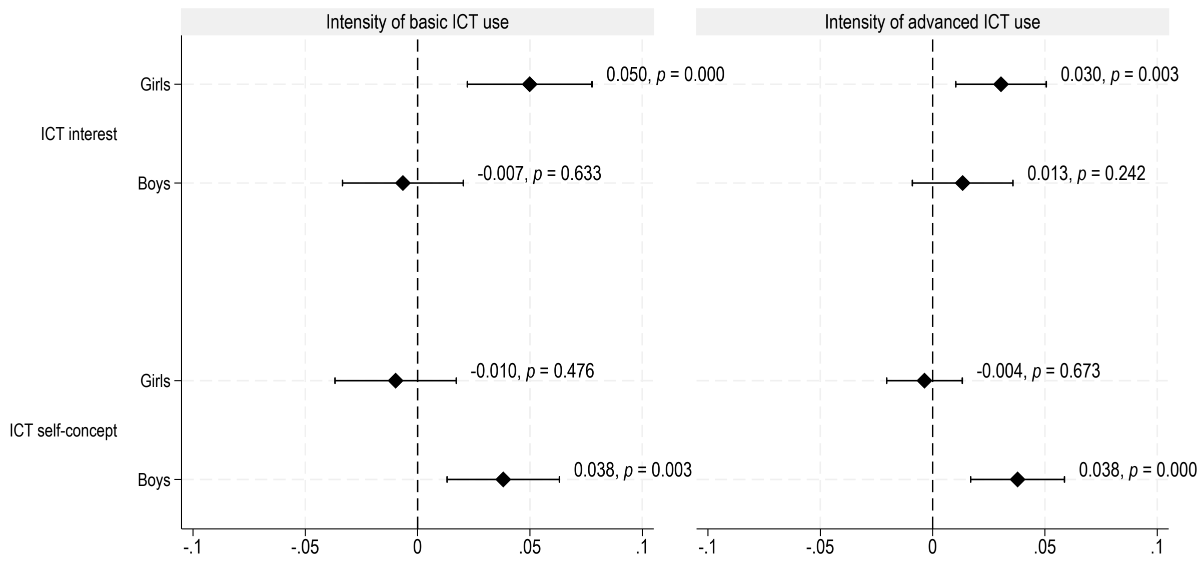

Figure 4.A2: Robustness test: Fractional logit regression, by gender

Note. $N = 1{,}964$. Group-specific AMEs obtained from fractional logit regression models, including two terms interacting gender with ICT interest and ICT self-concept, respectively. Models included all control variables listed in Table 4.1. Interpretation: A marginal increase in ICT interest or ICT self-concept is associated with an estimated increase in the dependent variable (task content indicator with range 0-1) by X scale points for girls (boys). A marginal increase corresponds approximately to a one unit change in in both presented predictors.