Social Science Research 114 (2023) 102915

Contents lists available at ScienceDirect

Social Science Research

journal homepage: www.elsevier.com/locate/ssresearch

Earlier smartphone acquisition negatively impacts language proficiency, but only for heavy media users. Results from a longitudinal quasi-experimental study

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ARTICLE INFO

Keywords:
Age of smartphone acquisition
Learning outcomes
Digital divide
Constructivism
Time displacement
Uses & gratification
Problematic smartphone use
Quasi-experimental design
Weighted difference-in-difference
Standardized test scores

ABSTRACT

There is a growing debate about the proper age at which teens should be given permission to own a personal smartphone. While experts in different disciplines provide parents and educators with conflicting guidelines, the age of first smartphone acquisition is constantly decreasing and there is still limited evidence on the impact of anticipating the age of access on learning outcomes. Drawing on two-wave longitudinal data collected on a sample of 1672 students in 2013 (at grade 5) and 2016 (at grade 8), this study evaluates whether obtaining the first personal smartphone at 10 or 11 years old, during the transition to lower secondary school (early owning), affected their language proficiency trends compared to receiving it from the age of 12 onwards (late owning). Results indicate an overall null effect of smartphone early owning on adolescents' language proficiency trajectories, while a negative effect is found on those who were already heavy screen media users before receiving the device.

Funding sources

This work was supported by the University of Milano-Bicocca [grant number 2016-CONV-0051].

1. Introduction

More and more youths become owners of a smartphone when they are still in their early adolescence (Rideout and Robb, 2019). The Covid-19 pandemic has further anticipated the moment when they get their own mobile device (Adachi et al., 2022). Currently, figures in Europe and the United States identify the average age at which early adolescents receive a first smartphone at 10–11 years old, when they typically enter lower secondary school (Moreno et al., 2019; Gui et al., 2020). This transitional phase is a challenging moment in the life of children (Spernes, 2020; Topping, 2011), where individuals' self-regulatory skills increase their relevance as a key factor for academic success (Rudolph et al., 2001; Topping, 2011).

A heated debate has developed around the question if anticipating the age of access to the smartphone, especially in this stage of development, is a good or a bad thing. Parents and educators seem disoriented: on the one hand they fear the dangers of an early access

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https://doi.org/10.1016/j.ssresearch.2023.102915
Received 16 August 2022; Received in revised form 14 March 2023; Accepted 24 July 2023
Available online 5 August 2023

to mobile screen media, but on the other hand they hope that it will provide additional opportunities for their children (Livingstone and Blum-Ross, 2020). Also, they feel reassured by the control that the smartphone allows them to keep over their children as they start to go out alone (Vaterlaus and Tarabochia, 2021). Mirroring these conflicting needs, opposite positions have characterized the debate. For example, the "Wait until 8th" campaign, started by a parent in Texas, argues that minors should not receive a personal smartphone until the end of middle school. The campaign has received extensive media attention and thousands of pledges from across the US. On the opposite side, a book by Jordan Shapiro (2019) has been a reference for those who think that the early arrival of technologies is inevitable: the author argues that children can be more in control of their digital life if this is introduced and guided from an early age (7 or 8 years old).

The pedagogical and media education literature has mainly focused on the cognitive and relational opportunities favored by smartphones and their use by adolescents (Pachler et al., 2009; Bachmair and Pachler, 2015). In fact, some studies have shown that mobile connection, when used as a learning support and with clear objectives, can be a valuable aid for learning and teaching a variety of school subjects (Hwang et al., 2013; Haβler et al., 2016; Sung et al., 2016). However, research in sociology, psychology and health sciences has highlighted that smartphones are potential distractors and sources of time displacement while studying (David et al., 2015; Ward et al., 2017; Glass and Kang, 2019). Moreover, a negative association emerges in many studies between general smartphone use and learning outcomes (Li et al., 2015; Nayak, 2018; Samaha and Hawi, 2016; Sapci et al., 2021). Despite extant evidence, however, the empirical results obtained so far are often reproached for not being solid from a methodological point of view because they are based on correlational or short-term longitudinal data (Amez and Baert, 2020). The limited available experimental evidence of the effect of banning smartphones in school is mixed: while Beland and Murphy (2016) and Beneito and Vicente-Chirivella (2022) find a positive effect, no effect is found in a recent Swedish study (Kessel et al., 2020). As a result of the lack of robust counterfactual evidence and of mixed results, experts in education and health sciences ended up offering conflicting guidelines to parents and educators (Straker et al., 2018).

Evidence becomes even more limited regarding the specific issue of age of first smartphone acquisition. Research has found that an earlier access to digital technologies by children and adolescents is associated with decreases in sleep and physical activity (Bruni et al., 2015; Edwards et al., 2015; American Academy of Pediatrics, 2016), while few studies exist on the relationship between an early arrival of the smartphone and different kinds of outcomes in the long run. While qualitative research (Vaterlaus et al., 2021) does not identify a significant relationship between the age of smartphone acquisition and later well-being (Vaterlaus et al., 2021), quantitative studies paint a less optimistic picture. Jaalouk and Boumosleh (2018) find that age of access to the first smartphone is negatively associated with smartphone addiction among university students in Lebanon. In an extensive longitudinal study, Dempsey et al. (2020) find that girls who receive phones earlier exhibit lower behavioural adjustment and academic self-concept scores at 13 years of age. Coming to the specific relationship between age of smartphone arrival and academic outcomes, the evidence is even more limited. Correlational evidence suggests that an earlier age of acquisition relates to worse learning performance (Gui et al., 2020), while the only two existing studies approaching this research question longitudinally evidenced both a negative and a null impact. The first study looked at reading and math standardized test scores of 8,500 Irish students between 8 and 13 years of age, finding that those who received their device before 9 show a lower academic development (Dempsey et al., 2019). A second study in Northern California examined the relationships between the age at which children first acquire a mobile phone and their adjustment measures, finding no statistically significant associations with school grades, sleep quality and depressive symptoms (Sun et al., 2023). The scarcity and lack of convergence of existing research, combined with the decision-making needs of families and the school system, make for an urgent need for additional evidence. The impact of having access to a smartphone in the delicate phase of early adolescence is understudied, being the transition between primary and lower secondary school a particularly relevant moment for the acquisition of autonomy (Zimmer-Gembeck and Collins, 2003). Moreover, so far research has not analyzed if specific categories of young people characterized by different media and study habits are more affected by an early arrival of a personal smartphone. Within the wide debate involving scholars of different disciplines about the impact of digital media use on young people's functioning (Mitev et al., 2021; Vaterlaus et al., 2021; Odgers and Jensen, 2022, Haidt and Twenge, ongoing), solid evidence regarding the precociousness of smartphone use represents a relevant contribution to clarify our understanding of the full picture.

This paper contributes for the first time to fill this gap by means of a longitudinal quasi-experimental research design that looks at the impact of the age of smarthone access on students' language proficiency and the moderating role played by their previous screen media related habits. We exploit data from an online survey questionnaire administered to all 10th grade students of 18 high schools in northern Italy and administrative information about their performance in a standardized language proficiency test they took at grade 5 and grade 8. Combining retrospective information on respondents' age of smartphone acquisition with trends in their academic performance over time, we estimate the effect of anticipating smartphone access at the age of transition to lower secondary school, on students' language proficiency using a weighted difference-in-difference estimation method.

1.1. Theoretical framework and research hypotheses

In the so-called "first-level digital divide" literature, Internet access was seen as the opening up of a wide array of opportunities for individuals (see Van Dijk, 2020). According to this approach, mobile connection was expected to serve as an additional resource that - by helping to bridge the digital divide - could particularly benefit young users (Brown et al., 2011), also for what regards learning (Kukulska-Hulme and Traxler, 2005). Following this narration, ownership of a personal smartphone has been perceived as potentially beneficial for youths in many respects: education, industry and governments promoted expanded use of digital technology by young children for reasons including enhancing learning, promoting children's digital skill set and ensuring productive workforce membership (Straker et al., 2018). This view has been supported theoretically within educational sciences by constructivism theory

(Jonassen 1994). This theory claims that learning requires an internal "trigger" factor on the part of the learner, which is located in a concrete context and takes place through forms of collaboration between individuals. The introduction of "learning technologies" in schools has found a strong and recognized theoretical justification in constructivism (Gilakjani et al., 2013; Perkins, 2013). The title of Cochrane and Bateman's (2010) paper, "Smartphones give you wings," is emblematic of the role that smartphones could play in this theoretical perspective. Within media and communication studies, a similar perspective has been sometimes referred to as the "stimulation hypothesis" (Valkenburg and Peter, 2007), where online communication stimulates well-being, as opposed to the "displacement hypothesis", where digital media displaces time spent in other activities (see afterwards). Some empirical evidence seems to support this framework. While non-connected phones had already been identified as promoting autonomy from parents (Ling, 2007), some researches highlight that having access to the Internet can make youths closer to one another and that social media can help daily interactions and well-being (Madden et al., 2013; Mitev et al., 2021). In recent retrospective qualitative research conducted on 686 late adolescents (18–25 years old), Vaterlaus et al. (2021) find that smartphones are perceived as key to inclusion and connection in social relationships during adolescence. Regarding school-related activities, we know that adolescents often use their smartphone as an important tool to do their homework, and that unreliable Internet access is sometimes an obstacle to their completion (Anderson and Perrin, 2018). Indeed, the pedagogical and media education literature have reflected on the cognitive and relational opportunities favored by smartphones and their school-related use (Pachler et al., 2009). Many studies have shown empirically that mobile connections can potentially be used to support learning in different school subjects (Haβler et al., 2016; Talan, 2020). Vaterlaus et al. (2021) find that adolescents perceive their smartphones as important tools to help them be successful in their schoolwork, while not granting access to a smartphone may hinder their success with technology in the future.

Considering the greater school-related responsibilities and self-directed learning students experience in middle school (Ferguson and Fraser, 1998; Zeedyk et al., 2003; Trotman et al., 2015; Bru et al., 2010), those who get their first smartphone early, since the beginning of lower secondary school, could therefore take advantage of its accessibility, multifunctionality and connectivity before others and therefore increase their human capital over time. In line with this first interpretation, we should expect that:

H1. Receiving a first personal smartphone at the age of transition to lower secondary school positively affects students' language proficiency over time compared to receiving it later.

However, the "second-level digital divide" literature has shown that the differences related to the use of digital media go far beyond the binary distinction between haves and have-nots (Hargittai, 2002; DiMaggio et al., 2004). Users differ in skills, usage types, strategies of use (Hargittai, 2010; Van Deursen and Van Dijk, 2014) and these resources grant them different tangible benefits (Helsper et al., 2015). When it comes to smartphones, in particular, we know that these devices can serve a lot of different purposes for adolescents: leisure, maintenance of relationships, information and learning, to name the major ones (Chayko, 2020). We also know that early adolescents are not passive in their use of the smartphone; rather, they have power over this device and assume an active role in interpreting its contents and integrating them into their own lives (Jenkins and Ito, 2015; Chan et al., 2015). According to the Uses and gratifications theory (Katz et al., 1973), there is evidence that adolescents use their smartphones in line with different needs that they seek to satisfy (Ahad and Anshari, 2017; Camerini et al., 2021). To become beneficial for learning, smartphones should be used to satisfy predetermined "capital enhancing" needs (Chan et al., 2015). Indeed, Lin et al. (2021) have analyzed the relationship between different types of smartphone use and academic performance among college students, finding that using mobile learning and news applications positively impacts learning outcomes, while playing mobile games, using social media, music and video is detrimental to them. For all these reasons, it would be not surprising if the overall effect of anticipating access to a personal smartphone could therefore hide different impacts for specific sub-populations that are less or more capable of - and motivated to - exploiting its learning potentials. Therefore, we should expect that:

H2. Receiving a first personal smartphone at the age of transition to lower secondary school positively affects language proficiency only for adolescents who show habits that are beneficial for school learning since before entering lower secondary school.

On the other hand, there are also reasons - and converging evidence - to think that receiving a personal smartphone during early adolescence can be detrimental for learning. According to the "displacement hypothesis" (Valkenburg and Peter, 2007), screen time can affect individuals' productivity and well-being by replacing other relevant activities of their daily life (Romer et al., 2013; Neuman, 1988). In particular, smartphones can negatively impact academic achievement primarily by reducing the time students spend doing capital enhancing activities, such as studying or reading (e.g., Sunday et al., 2021), and those that are essential for well-functioning, such as resting and sleeping (e.g., Rosen et al., 2016). Similar mechanisms have been found among adolescents that are heavy users of TV and video games (Tremblay et al., 2011; Ferguson, 2015). Mobile media, due to their accessibility, multifunctionality, connectivity and ease of use, are even stronger distractors compared to traditional screen media (Kushlev and Leitao, 2020). Users' attentive processes are challenged by smartphones even when they are not replacing other activities (Kushlev et al., 2019). That is, mobile phones can fragment attention even when they are not actively used by supplying a series of hooking stimuli based on instant feedback, notifications and immediate rewards that are hard to resist (Seaver, 2019; Jeong et al., 2016).

Empirical research has confirmed the relevance of these mechanisms in learning processes, highlighting that screens, especially mobile ones, are potential distractors and occasions for time displacement while studying (Glass and Kang 2019). There is also evidence that smartphone overuse among students is associated with reduced sleep duration and quality (Grover et al., 2016) and lower general well-being (Twenge and Campbell, 2019). Such negative associations also regard the impact of the age of first smartphone acquisition, which research has found to be associated with decreases in sleep and physical activity (Hill et al., 2016).

A negative association emerges in many studies between general smartphone use and learning outcomes, confirmed by a first meta-analysis (see Amez and Baert, 2020). In the Italian case, a research report has found a negative relationship between age at first smartphone usage and standardized academic performance (Gui et al., 2020). A study in England and one in Spain have found a positive effect of a smartphone school ban on learning achievements (Beland and Murphy, 2016; Beneito and Vicente-Chirivella, 2022), although its replication in a different context did not lead to the same result (Kessel et al., 2020).

Considering the rapid growth of autonomy deriving from entering middle school (Ferguson and Fraser, 1998; Zeedyk et al., 2003; Trotman et al., 2015; Bru et al., 2010) and the reduced abilities of pre-adolescents to procrastinate and delay gratifications (Wulfert et al., 2002), early owners should perform worse than late owners in standardized reading test overtime due to their longer and untimely exposure to the distracting features of the smartphone. Following the time displacement and interference hypotheses, we should then expect that:

H3. Receiving a first personal smartphone at the age of transition to lower secondary school negatively affects students' language proficiency over time compared to receiving it later.

However, there are reasons to think that the potential damages of early smartphone ownership are unequally distributed as much as the potential benefits, based on individuals' preferences and purposes. Research has increasingly shown that the negative effects of digital media use are distributed unequally across society (Scheerder et al., 2019; Gui and Büchi, 2021). Furthermore, converging evidence suggests that individuals with poorer self-control are more susceptible to problematic smartphone use (Fischer-Grote et al., 2019; West et al., 2021). Odgers (2018) synthesizes recent literature in social science and psychology, concluding that young people from different socio-economic backgrounds have vastly different online experiences. Regarding smartphones, those who struggle offline usually experience greater negative effects from their use. Therefore, individual differences in disposition could lead to the development of particular needs for gratification, which could in turn influence their choices in consuming media (e.g. Camerini et al., 2021; Elhai and Contractor, 2018; Wang et al., 2012).

Under this perspective, therefore, also the tangible damages in terms of learning that students could suffer from an early smartphone access should be distributed unequally, based on their predetermined desires and motivation to do well in school. In particular, the acquisition of a smartphone in a time of growth of autonomy in personal choices could be detrimental in terms of learning outcomes only for those who show a preference for activities that offer immediate gratifications over capital enhancing ones. We therefore formulate the following hypothesis:

H4. Receiving a first personal smartphone at the age of transition to lower secondary school negatively affects language proficiency only for those students who already showed habits that are not beneficial for school learning since before entering lower secondary school.

As we have shown, in the absence of solid empirical evidence, it is still possible to formulate different and partly conflicting hypotheses on the impact of smartphone early ownership on learning outcomes. The impact of the age of smartphone access on learning outcomes is almost completely unknown so far, although it constitutes an extremely urgent question for families and educators (Moreno et al., 2019; Vaterlaus et al., 2021). In the next paragraph we will show our empirical strategy to test the above-mentioned hypotheses.

2. Materials and methods

2.1. Data and sample

This contribution takes advantage of the linkage between data collected in the Digital Well-Being - Schools project (in Italian *Benessere Digitale - Scuole* and hereinafter DWB-S) on a sample of 3659 upper-secondary school students and administrative information retrieved on the same students over time by the *Italian National Institute for Evaluation of the Education System* (INVALSI).

The DWB-S project was aimed at evaluating the impact of a media education programme targeting high school teachers and their 10th grade students by means of a randomized controlled trial (Gui et al., 2023). The invitation to take part in the project was sent to all 42 high schools in three administrative districts in the North of Italy (Lombardy region). We planned for the allocation of about 80 teachers (2 teachers per class) to the intervention, for a total coverage of about 41 classes and around 820 students. Results of a preliminary power analysis suggested the involvement of around 130 comparison classes in the trial (around 2600 students), in order to detect the desired effects on primary outcomes. We then recruited all the 10th grade classes of the first 18 schools that signed our cooperation agreement, respecting the distribution of the different school types located in the districts being studied, for a total of 171 classes and 3659 enrolled students. Specifically, the 42 schools were clustered by school type (lycée, technical and vocational course paths) and then invited to participate. Since some of the schools offered more than one course path, we clustered them based on their 82 course paths: 45 lycée (54.8%), 26 technical (31.7%) and 11 vocational (13.4%). We accepted schools based on their expressions of interest in order of accession, respecting the aforementioned school path proportions. A total of 18 schools representing 37 course paths were selected to take part in the project, including 20 lycée (54.0%), 11 technical (29.8%) and 6 vocational (16.2%) courses.

Students from all 10th grade classes in the 18 participating schools were requested to fill in an online questionnaire twice, at the beginning and the end of the 2017–2018 school year (November 2017 and May 2018, respectively). In both occasions, the survey was administered in the school's computer labs, during class time and under the supervision of external observers. Questionnaires covered several ICTs-related topics, such as attitudes toward digital devices, daily usage habits and possession, including self-reported retrospective information on the age of access to their first personal smartphone. At the end of the entire data collection process, a total of 3635 students completed at least one of the two surveys, allowing to get the self-reported age of smartphone acquisition for more than the 99.3% of the initial sample. Whereas this small number of missing respondents consisted of students randomly absent on both the dates of the survey for health or personal reasons, we can confirm that the sample is representative of the 10th grade students' population in the considered districts by school type.

Data on students' language proficiency, past time management habits and family background were instead retrieved from INVALSI, which is the reference institution in Italy for the assessment of students' achievement since 2007. During its year-end survey activities, all students at various levels of education[1] are requested to perform standardized tests, while schools are in charge of collecting their socio-demographic information (e.g., gender, month and year of birth, migratory background, parental education and occupation). Students at grade 5 are also invited to fill a questionnaire focused on their time management outside school, home possession and other family characteristics. This additional information is linked to the tests via the INVALSI unique identifier, which is assigned to each student inscribed in the National Students Register of the Ministry of Education. The stability of this unique identifier over time also makes standardized test scores of the same student linkable across grades, thus allowing for the construction of longitudinal datasets on their academic performances from primary to upper-secondary school.

For the purposes of our study, we linked students' age of smartphone acquisition – as measured in the DWB-S project – to the large set of data collected by INVALSI at the individual level. To do so, we first asked principals of the enrolled schools to inform parents of the initiative and sign an agreement that allowed us to get hold of data collected by INVALSI, in accordance with current data protection rules. We then received from the INVALSI statistical office the students' unique identifiers and the following set of information on the entire student population: standardized test scores and data extracted from both student questionnaires and school registers at grade 5 (May 2013); standardized test score of the same students at grade 8 (May 2016). The merging procedure, which involved only DWB-S respondents with a regular course of study from grade 5 to grade 10, resulted in a 58% coverage rate (n = 2111). Finally, we considered part of the analytical sample only students who surely accessed a smartphone after finishing primary school. We excluded those who received their first smartphone before the INVALSI test at the end of the 5th grade. The excluded students comprehend those who received it at the age of 9 or less and those who got it at 10 and reached that age before June 2016, i.e. before the end of the school year in Italy and, more importantly, before being tested by INVALSI. That is, they were primarily excluded from further analyses to avoid the baseline values of the outcome being in any way influenced by the treatment. The resulting longitudinal dataset (n = 1672) represents a unique resource for the analysis of the consequences of smartphone age of access on students' language proficiency over time. Detailed sample characteristics at each stage of the data preparation process, including those of the entire student population, are reported in Table 1.

2.2. Analytical strategy

This study employs a weighted difference-in-difference method (PSM-DID) to estimate the relative change in language proficiency between early and late smartphone owners over the entire course of middle school, looking also at the moderating role played by students' habits at the baseline. DID is one of the most popular approaches for evaluating the effect of a treatment in a quasi-experimental scenario. A DID analysis can be conducted any time an outcome is measured at least twice on a sample made up of units that have been exposed to a stimulus (the treatment group) and units not exposed or differentially exposed to it (the control group), one before and one after the stimulus occurred. A graphical representation of the quasi-experimental design we adopted in our study is offered in Fig. 1.

Our treatment condition was defined asking DWB-S respondents to self-report the age in years they received their first smartphone from "up to 9" to "14 or more". As mentioned, those who obtained it before the end of primary school were excluded from the analysis to avoid the baseline values of the outcome being in any way influenced by the treatment. The rest of the sample was instead allocated in two groups: early owners (treated group) and late owners (control group). Early owners accessed their first smartphone at 10 or 11 years old, just before or in the first year after the transition to lower secondary school. Late owners, on the other hand, receive it only from the age of 12 onwards, in the post-transition years. Regardless of being in the early or the late owners' group, students' proficiency in Italian language was measured two times (at grade 5 and grade 8). Language proficiency was standardized separately by year and school grade using the Rasch latent trait modeling approach. The estimates were also corrected by a cheating propensity indicator that accounts for homogeneity in the pattern of responses and non-responses to single items and for the mean-variability ratio in students' scores at the class level (Quintano et al., 2009). The resulting measure was then highly reliable and directly comparable across individuals and groups over time, obviating the issues of subjectivity in teachers' judgements (Meissel et al., 2017) and measurement errors in students' self-reported grade point average (Kuncel et al., 2005). Variations in students' scores over time can be interpreted as changes in individual distances from the national average expressed in standard deviations. Positive values indicate an increase in language proficiency compared to the mean of the entire student population.

According to the DID approach, the average effect of early access to a smartphone on students' language proficiency over time can be estimated with a regression model specified as follows:

$$Y_{ijt} = \beta_0 + \beta_1 early_j + \beta_2 post_t + \beta_3 \left(early_j * \ post_t\right) + \varepsilon_{ijt},$$

where i, j and t respectively denote units, groups and time, *early* identifies early owners as opposed to late owners (i.e. late owners serves as the counterfactual for early owners), *post* is an indicator of the second measurement occasion (at grade 8), and ε represents the

[1] Participation in the survey is compulsory for all the students at various levels of education, including grade 2 and grade 5 for primary schools, grade 8 for lower-secondary schools and grade 10 and, more recently, grade 13 for upper-secondary schools.

Table 1
Descriptive statistics of students' population and samples at each stage of the data preparation process. Data collected at grade 5.

	Students' population (N = 478,146)		DWB-S & INVALSI (N = 2111)		Analytic sample (N = 1672)	
	N	%	N	%	N	%
Gender						
Female	237,705	49.7	1166	55.2	915	54.7
Male	240,441	50.3	945	44.8	757	45.3
missing	–	–	–	–	–	–
Home possessions						
A desk in a quiet place to study at						
no	111,089	23.0	456	21.6	355	21.2
yes	352,432	72.8	1655	78.4	1317	78.8
missing	20,400	4.2	–	–	–	–
A computer connected to the Internet for schoolwork						
no	130,843	27.0	530	25.1	448	26.8
yes	332,404	68.7	1581	74.9	1224	73.2
missing	20,674	4.3	–	–	–	–
Digital or paper encyclopedias						
no	150,433	31.1	613	29.0	471	28.2
yes	313,224	64.7	1498	71.0	1201	71.8
missing	20,264	4.2	–	–	–	–
Number of books at home						
up to 25	186,552	39.0	618	29.3	477	28.5
26-100	143,654	30.0	800	37.9	631	37.7
101-200	68,596	14.4	403	19.1	316	18.9
more than 200	53,833	11.3	290	13.7	248	14.8
missing	25,511	5.3	–	–	–	–
Family background						
Language spoken at home						
Italian	427,438	88.3	1979	93.7	1569	93.8
other language	33,030	6.8	132	6.3	103	6.2
missing	23,036	4.9	–	–	–	–
Parents highest educational level[a]						
up to lower secondary	135,301	28.3	382 (363)	18.1 (17.2)	277 (276)	16.6 (15.5)
upper secondary	160,978	33.7	1011 (772)	47.9 (36.6)	796 (631)	47.6 (35.4)
tertiary or more	86,666	18.1	718 (447)	34.0 (22.6)	599 (423)	35.8 (23.7)
missing	95,201	19.9	-(499)	-(23.6)	-(452)	-(25.4)
Time management						
Screen media: TV and video games						
less than 2 h a day	347,197	72.6	1756	83.2	1416	84.7
more than 2 h a day	112,199	23.5	355	16.8	256	15.3
missing	18,750	3.9	–	–	–	–
Reading books or magazines						
no	109,245	22.9	408	19.3	311	18.6
yes	350,962	72.4	1703	80.7	1361	81.4
missing	17,939	3.7	–	–	–	–
Doing homework's						
Up to 2 times a week	93,039	19.5	710	33.6	560	33.5
3 times a week or more	363,592	76.0	1401	66.4	1112	66.5
missing	21,515	4.5	–	–	–	–
Language proficiency test score at grade 5[b]	0.0	1.0	0.3	0.9	0.4	0.9
missing	–	–	–	–	–	–
Smartphone acquisition by age						
up to 9	–	–	167	7.9	–	–
10	–	–	272	12.9	1	0.1
11	–	–	707	33.5	707	42.3
12	–	–	635	30.1	634	37.9
13	–	–	239	11.3	239	14.3
14 or more	–	–	91	4.3	91	5.4
missing	–	–	–	–	–	–

[a] Distribution of parents' education level without missing replacement in parentheses.
[b] Continuous variable: mean and standard deviation.

random error term. Consequently, the DID estimate of the average treatment effect (ATT) on early owners is defined as

$$ATT = \left(\overline{Y}_{early,post} - \overline{Y}_{early,pre}\right) - \left(\overline{Y}_{late,post} - \overline{Y}_{late,pre}\right),$$

where time changes in average test scores within the two groups are used to estimate the effect of early access to a smartphone on language proficiency trends.

On this ground, heterogeneity of the effect of an early smartphone access across groups of respondents can be explored simply

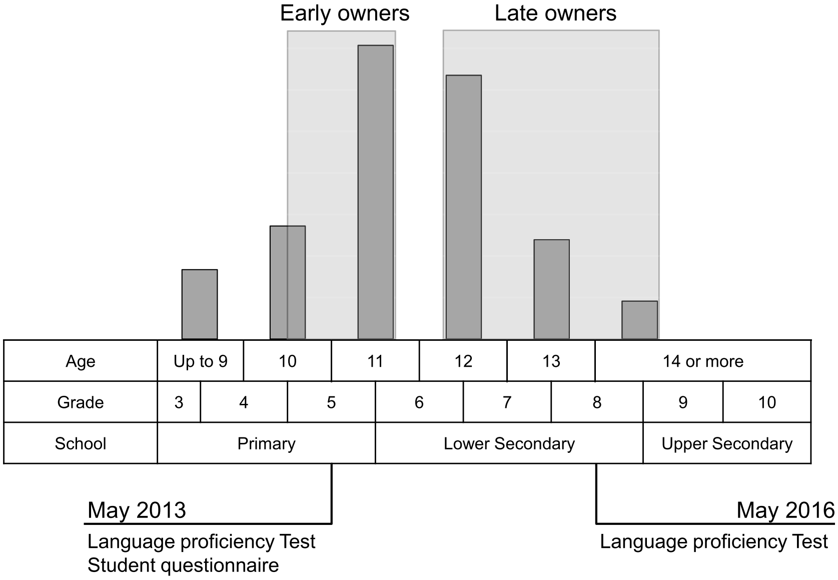

Fig. 1. Graphical representation of the quasi-experimental design.

adding an interaction term to the previous equation, resulting in the following specification:

$$\overline{Y}_{ijt} = \beta_0 + \beta_1 early_j + \beta_2 groupA_i + \beta_3 post_t + \beta_4\left(early_j * \ groupA_i\right) + \beta_5\left(early_j * \ post_t\right) + \beta_6\left(groupA_i * \ post_t\right) + \beta_7\left(early_j * groupA_i * \ post_t\right) + \varepsilon_{ijt},$$

were *groupA* distinguishes the A respondents from the rest of the sample (*groupB*) as measured at grade 5. In this case, the difference in average treatment effects of early access to the smartphone conditional to being in the groupA at the baseline (CATT) can be estimated as

$$CATT = \left[\left(\overline{Y}_{early,groupA,post} - \overline{Y}_{early,groupA,pre}\right) - \left(\overline{Y}_{late,groupA,post} - \overline{Y}_{late,groupA,pre}\right)\right] - \left[\left(\overline{Y}_{early,groupB,post} - \overline{Y}_{early,groupB,pre}\right) - \left(\overline{Y}_{late,groupB,post} - \overline{Y}_{late,groupB,pre}\right)\right].$$

At this point, it is important to underline that DID approaches allow to produce unbiased estimates of the treatment effect only if early and late owners have parallel outcome trends over time except for the variations introduced by the age of smartphone access (e.g., Lechner, 2011). This is also equivalent to assuming the absence of unobserved heterogeneity across the two groups in the distribution of confounding variables related with both treatment assignment and expectations for changes in the outcome over time (e.g., Daw and Hatfield, 2018).

To make the parallel trends assumption more plausible, we adopted the propensity score matching (PSM) method before applying DID, to equate early and late owners on a set of potential confounders of the average effect of early access to smartphones. Compared to controlling linearly for explanatory variables in a DID regression, PSM have the main advantage of not imposing a predefined functional form on their relationship with the outcome (Rosenbaum and Rubin, 1983). Thus, it guarantees a more appropriate weighting of covariates by avoiding the risk of extrapolating twins beyond the region of common support (i.e., including early owners without suitable late owners twins in the analysis).

The PSM procedure requires the identification of a set of confounders expected to influence language proficiency trends. All variables were measured at grade 5, in order to avoid the issue of endogeneity (Table 1). First, we focused on students' gender (0 = "male" and 1 = "female") and home possessions that proved to predict verbal abilities and school success during childhood and adolescence (e.g., Conte et al., 2020; Conte et al., 2023; OECD, 2016; Sammons, 1995; Sikora et al., 2019). More specifically, we accounted for reading resources with a single-item question asking respondents to report the number of books in their household on a pictorial response scale recoded in 4 categories (from 0 = "Up to 25" to 3 = "more than 200"). Moreover, we included a set of dummy variables (0 = "No" and 1 = "Yes") checking for the availability of the following objects of educational significance at home: a desk in a quiet place to study at, a computer with a link to the Internet for schoolwork, digital or paper encyclopedias.

Turning to family background, schools were requested to collect information on the highest level of education achieved by both parents. This proxy of social origins represents a robust predictor of individual differences in students' verbal abilities and educational outcomes (e.g., Hackman and Farah, 2009; Bukodi and Goldthorpe, 2013). However, the administrative data collected by Invalsi resulted in a relatively high percentage of non-responses to this question (Table 1). Therefore, we assumed the stability of parents' educational level over time and replaced missing values with the same information collected in the DWB-S project directly from students. Following a dominance criterion, we then accounted for the highest qualification registered among both parents, distinguishing three reference levels (0 = "up to lower secondary"; 1 = "upper secondary"; 2 "tertiary") in accordance with the International Standard Classification of Education (ISCED; UNESCO Institute for Statistics, 2012). We also accounted for potential differences in reading and language comprehension across first- and second-language students (e.g., Melby-Lervåg and Lervåg, 2014), including a dummy variable distinguishing those who mainly spoke Italian (0) and a foreign language (1) at home at the time of the interview.

Different ways of managing time that might have affected students' language proficiency trends were captured by examining their daily use of screen media for leisure purposes, as well as their reading habits and weekly study commitment. In line with previous research, watching TV and playing video games for 2 h per day or more (0 = "No" and 1 = "Yes") was considered a threat to the improvement of academic achievement (e.g. Ferguson 2015; Tremblay et al., 2011), while students who reported to read books or magazines (0 = "No" and 1 = "Yes") and doing homework on a regular basis for at least half of the week (0 "up to 2 times", 1 "3 times or more") were expected to foster them over time (e.g. Cooper et al., 2006; Romer et al., 2013).

Based on the average difference emerged in pre-period levels of the outcome among early and late owners and the associations we found between pre-period levels and the pre-post outcome changes in both groups (see the results section), we finally opted to account also for students' scores in language proficiency tests performed at grade 5. That is, previous research has shown that matching treatment and comparison groups on the baseline level of the outcome when substantial pre-period difference and serial correlation are found can greatly reduce bias (e.g., Daw and Hatfield, 2018; Ryan et al., 2015).

Given the complete list of observed confounders, we estimated propensity scores with the following logistic model that calculates students' probability of early receiving a smartphone:

$$P_i = P(Z_{it}),$$

were $S = \{T, C\}$ represents all students, including both early and late owners, while Z_{it} summarizes the confounders that can influence the probability of a student being included in the early owners group. Early and late owners were then matched exploiting alternative weighting algorithms, searching for the optimal trade-off between bias and efficiency (e.g., Bryson et al., 2002; Caliendo and Kopeinig, 2008). We compared several algorithms (nearest neighbor with and without replacement; 2-nearest neighbors with replacement; radius and caliper matching) and identified radius matching with $r = 0.02$ as the best performing solution in balancing the properties of control variables.

In the last stage of analysis, we estimated the average effect of students' early access to the smartphone by fitting an OLS regression model with PSM weights and robust standard errors at the individual level to account for autocorrelation within students over time (Bertrand et al., 2004). Three additional models were also estimated, interacting the treatment condition with the amount of time respondents spent on screen media, their leisure reading habits and regularity in doing homework as measured at grade 5. As mentioned above, these model specifications were aimed at evaluating the heterogeneity of the effect of an early access to the smartphone across students with different time management habits. The PSM-DID analyses were entirely conducted with the STATA 17.0 statistical software.

3. Results

A descriptive analysis of language proficiency trends was first conducted to inspect changes in test scores over time among early and late smartphone owners and, within the two groups, by students' daily amount of screen media use, leisure reading habits, and regularity in doing homework at grade 5. On average, early owners get better results in the language proficiency test at the end of primary school (before receiving a smartphone). They show a statistically significant baseline difference of 0.090 points ($p = .039$) compared to late owners, suggesting that selection contributes to the pre-period association between early access to the smartphone and students' performances. Moreover, we examined the relationship between pre-period levels and the pre-post changes in the outcome, finding significant associations for both groups (early owners: $\beta = -.366, p < .001$; late owners: $\beta = -0.385, p < .001$). Taken together, these results highlight the need to accommodate selection bias by implementing a longitudinal research design that accounts for relevant covariates and language proficiency levels at grade 5.

Turning to the analysis of students' performance over time, a first visual inspection to our graphical representation reveals relatively small changes for both groups (Fig. 2). Although early owners reported a slightly lower increase compared to late owners, variation in their trajectories do not seem sufficient to confirm a substantial effect of early smartphone acquisition on language proficiency.

However, signs of heterogeneity in its effect emerged across groups of students reporting different levels of exposure to screen media at the baseline. On the one hand, light screen media users show similar trajectories regardless of being in the early or late owners' group. Their average change in the outcome level over time is also in line with that of the entire late owners' group (overall sample), meaning that light screen media users who received their smartphone at the age of transition to middle school are expected to improve their performance as much as all respondents who receive it at a later age. On the other hand, early owners of the heavy screen media users subsample - upon visual inspection - reported a noticeable reduction in their test score over time against the growth recorded once again by late owners.

This further result confirms that there might be a substantial negative effect of early smartphone acquisition on heavy screen media users. A less evident and probably negligible decline is instead observed for early owners not doing homework regularly at grade 5, while their classmates who did not read for leisureshowed an almost null increase in reading performance over time.

To evaluate the consistency of these descriptive results, we performed a DID-PSM analysis by first balancing early and late owners

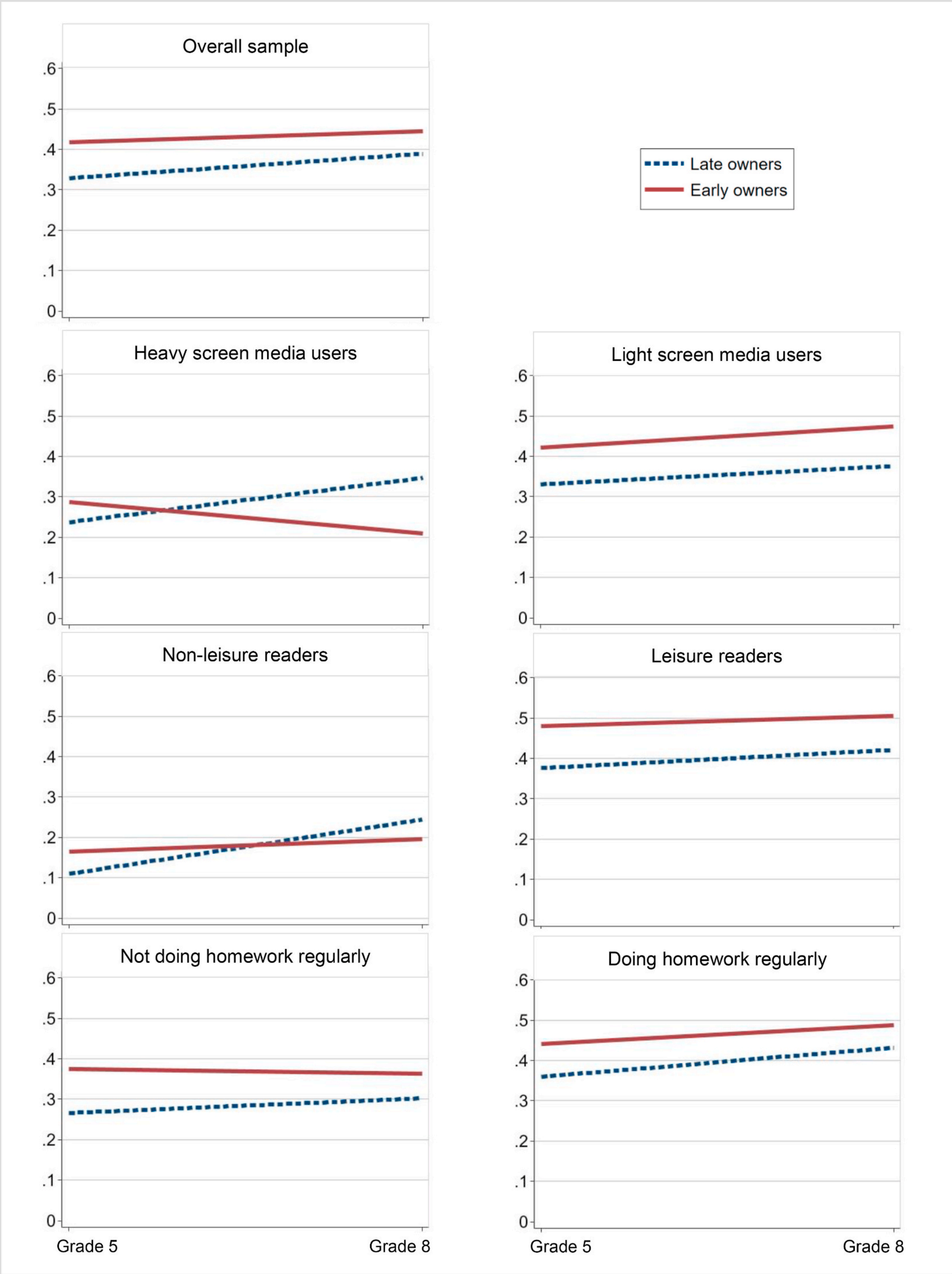

Fig. 2. Unadjusted language proficiency trajectories of early and late owners' groups.

on the list of relevant covariates. Table 2 focuses on the balance of early and late owners on the selected list of confounders before and after PSM, showing that matching significantly contributed to a reduction of the standardized bias below the 5% threshold for all of them and maintained a cross-group variance ratio of the outcome around 1 (Caliendo and Kopeinig, 2008; Zhang et al., 2019). Only 5 treatment observations did not meet the common support condition, with a negligible loss of information on early owners in the matched sample. Based on this result we can confirm that PSM succeeds in balancing the covariates, thus making the common trend assumption more plausible without significantly altering estimates consistency outside the common support.

Table 3 summarizes the results from the four regression models we estimated to evaluate the effects of smartphone early access on

Table 2
Covariate balancing: mean differences, standardized percentage bias and variance ratio before and after matching.

	Before matching				After matching			
	Early owners	Late owners	% Bias	V(early)/V(late)	Early owners	Late owners	% Bias	V(early)/V(late)
Gender (ref.: male)								
Female	0.568	0.532	7.2	–	0.568	0.567	0.2	–
Home possessions								
A desk in a quiet place to study at (ref.: no)								
yes	0.801	0.778	5.6	–	0.799	0.801	−0.3	–
A computer connected to the Internet for schoolwork (ref.: no)								
Yes	0.763	0.710	12.1	–	0.764	0.763	0.2	–
Digital or paper encyclopedias (ref.: no)								
Yes	0.713	0.722	−1.9	–	0.717	0.716	0.2	–
Number of books at home (ref.: up to 25)								
26-100	0.398	0.362	7.5	–	0.398	0.401	−0.6	–
101-200	0.172	0.201	−7.4	–	0.171	0.173	−0.6	–
more than 200	0.150	0.147	0.7	–	0.151	0.150	0.3	–
Family background								
Language spoken at home (ref.: Italian)								
ther language	0.055	0.066	−4.7	–	0.054	0.055	−0.2	–
Parents highest educational level (ref.: up to lower secondary)								
upper secondary	0.499	0.460	7.8	–	0.498	0.494	0.9	–
tertiary or more	0.355	0.361	−1.4	–	0.357	0.360	−0.7	–
Time management								
TV and videogames (ref.: less than 2 h)								
more than 2 h a day	0.155	0.152	1.1	–	0.155	0.154	0.3	–
Reading books or magazines (ref.: no)								
Yes	0.804	0.822	−4.6	–	0.804	0.806	−0.7	–
Doing homework's (ref.: up to 2 times a week)								
3 times a week or more	0.657	0.671	−3.0	–	0.657	0.659	−0.4	–
Language proficiency test score	0.419	0.329	10.2	1.16	0.415	0.410	0.5	1.16

Notes: All covariates are measured at the baseline (grade 5).

language proficiency trajectories over the entire course of middle school. As shown in the first row of the table, the weighted OLS model carried out on the entire analytical sample of respondents with a common support confirmed that early access to smartphones does not significantly affect students' performances in the language proficiency test overtime. Given that, we reject both H1 and H3.

The subsequent model tests whether the amount of daily time spent using TV or video games before entering middle school significantly moderates the effect of an early access to the smartphone on students' language proficiency trajectories. Our results show that light screen media users' performance over time seems to be not affected by the age of smartphone access, while heavy screen media users who got their first smartphone at the age of transition to middle school reported a significant decrease in their language proficiency trajectory compared to late owners ($\beta = -0.222$, $p < .020$). Once directly compared across the two groups, the estimate of students' average change in language proficiency resulted in a significant differential effect of early smartphone access to the detriment of heavy screen media users ($\beta = -0.246$, $p < .016$). As such, we reject H2, but confirm our expectations around H4 at least for respondents who were spending more than 2 h per day watching TV or playing videogames since before entering upper secondary school.

Table 3
Early access to the smartphone and learning proficiency: overall effect and heterogeneity by time management habits at grade 5.

	N_t/N_c	ATT	S.E.	CATT	S.E.
Overall sample	703/964	−0.013	0.037	–	–
Time management					
TV and videogames					
Less than 2 h per day	594/818	0.025	0.041	−0.246*	0.103
More than 2 h per day	109/146	−0.222*	0.095		
Reading books or magazines					
No	138/172	−0.102	0.084	0.109	0.094
Yes	565/792	0.008	0.042		
Doing homework					
Up to 2 times a week	241/317	−0.042	0.066	0.043	0.080
More than 2 times a week	462/647	0.002	0.045		

*pvalue<0.05; **pvalue<0.01; ***pvalue<0.001.
Standard error of the estimates clustered at the individual data in brackets.

4. Discussion and conclusion

This study sought to evaluate whether and how receiving the first personal smartphone at the age of transition to lower secondary schools affects students' language proficiency trends over time. To do so, self-reported retrospective information on students' age of access were linked to their standardized test scores collected at the end of both primary and lower secondary school, allowing for the analysis of their language proficiency trajectories over three years. A PSM-DID approach was adopted to estimate average changes in the outcome for those who obtained their first smartphone at the age of transition (early owners), net of those who received it at a later age (late owners), with the two groups made homogeneous for a wide range of covariates measured at grade 5.

Our results suggest that, overall, early access to a smartphone does not significantly affect students' performance in language proficiency overtime. That is, we found a null effect of receiving a smartphone at 10 or 11 years old compared to getting it from the age of 12 onwards. On the one hand, the absence of a positive effect should be discussed as it contrasts with a great amount of literature that sees smartphones as a resource for learning, even at young ages (Pachler et al., 2009; Bachmair and Pachler, 2015; Hwang et al., 2013; Haβler et al., 2016; Sung et al., 2016). This research disavows the idea that giving a personal device connected to the Internet to a pre-adolescent can contribute to their cognitive development. It challenges a series of theoretical approaches suggesting that Internet use could naturally translate into cognitive and social benefits, even at an early age. Various theoretical approaches have contributed to this general idea, including education theories such as constructivism (Gilakjani et al., 2013; Perkins, 2013), media and communication theories like the 'stimulation hypothesis' (Valkenburg and Peter, 2007), and implicitly, socio-economic theories such as the digital divide (Kukulska-Hulme and Traxler, 2005; Brown et al., 2011). The absence of a negative effect, on the other, is consistent with research that criticizes moral claims of large and general damages brought by digital media (Mitev et al., 2021; Odgers, 2018). In general, this first result is in line with the empirical literature that finds null or negligible impacts of digital media use on learning performance (Biagi and Loi, 2013; Gui et al., 2018).

Things change looking at the heterogeneity of the effects for screen media usage habits at grade 5. Early owners who spent at least 2 hours a day using TV or videogames resulted in a significant decrease in their language proficiency overtime compared to their late owner counterparts, meaning that smartphone early owning negatively influences the school performance of heavy screen media users. This further result supports the literature highlighting that the negative consequences of smartphone use on learning performance are not traceable on all users (Baert et al., 2020). In particular, it corroborates the argument of Odgers (2018) that the side effects of permanent connection only regard specific subpopulations of young people that manifest different kinds of vulnerability. In line with this interpretation, students showing intensive media use before middle school could be more prone to smartphone intensive use as well; in turn, we know that smartphone pervasiveness and addiction are negatively related to learning outcomes (e.g., Gerosa et al., 2022; Sunday et al., 2021). Then, we can confirm the existence of a negative effect of early smartphone possession on language proficiency trends for intensive screen media users. Therefore, not only have the theories expecting a positive effect of free smartphone use in minors not been confirmed, but the only evidence of the impact that has emerged shows the opposite effect, albeit only for a specific segment of the sample. We confirm the emerging evidence that the side effects of smartphone use during adolescence concentrate on young people already showing specific behavioral, psychological, and social vulnerabilities (Odgers, 2018; Gui and Gerosa, 2021). Future research will need to investigate whether and how extensive screen time during childhood is associated with other indicators of socio-economic and psychological disadvantage.

Turning to the analysis of other factors of heterogeneity, there are null effects for students reporting habits that could best predict a capital-enhancing use of the smartphone. In other words, we did not find any "tangible benefits" (Helsper et al., 2015) of early smartphone ownership at the age of transition to lower secondary school, even for the most learning- and reading-oriented students. Moreover, this is also a relevant result as it rejects the hypothesis – limited to the time period of the study – that early possession of a personal smartphone can have a beneficial effect on learning outcomes for the most promising students. Finally, this is consistent with existing literature in this particular field, which has only demonstrated null or negative impacts of early smartphone usage on academic performance (Dempsey et al., 2019; Sun et al., 2023).

Before concluding, some general limitations of the sampling procedure and methodological approach adopted in this study need to be acknowledged. A first threat to the external validity of our results concerns the selected nature of the analytical sample we employed in the analyses. That is, students' selection took place at least at three different stages of our study, questioning the validity of inferences about whether the causal relationship we identified is maintained over variations in person and settings (Shadish et al., 2002). First, we involved only 18 upper secondary schools participating in the DWB-S project. These schools were all self-selected and located in a relatively strict area of the country, thus generating imbalances on many personal and socio-demographic characteristics compared to the rest of the Italian population of students at grade 10 (see Table 1). Second, we focused only on regular students with a linear education path in order to be able to link them correctly to the INVALSI longitudinal dataset. Despite being a marginal phenomenon at lower secondary school, students who fail at this educational stage certainly represent a subgroup of great interest for the analysis of smartphone effect on school performance. Third, we included in the analyses only students who obtained their first smartphone after the end of primary school (grade 5), based on the need to prevent one of the treatment conditions from affecting the baseline values of the outcome. Future research will have to devote more attention to the diminishing age at first smartphone ownership (8% of our sample received it before entering lower secondary school), both to understand the dynamics that push families to anticipate the entrance of children into permanent connection and the social and psychological developmental impact of such an anticipation.

Finally, from a methodological standpoint, it should be mentioned that our data did not allow us to test the equivalence of linear trends between early and late owners prior to the intervention due to lack of information on students' academic performance before grade 5. To fill this gap, future research should invest in the collection of longitudinal data on students' learning outcomes at multiple times before the advent of their first smartphone. With multiple pre-intervention periods, the parallel trends assumption could be indeed effectively examined by testing whether pre-intervention trends are statistically different between early and late owners (e.g., Ryan et al., 2015).

Besides these limitations, our study adds new evidence to the body of previous literature on the age of smartphone access by combining the availability of administrative data on students' academic performance over time with a two-group longitudinal counterfactual research design. Assuming that change in outcome performance over time would have been equal in the absence of smartphones and that events or factors other than obtaining this device did not differentially affect outcome trends across the two groups, we can argue that early access has no overall effect on language proficiency. It is detrimental only for participants who already showed signs of intensive media use since before entering lower secondary school.

Based on these findings, policy makers should inform families of the potential risks of intensive media use during primary school and of early possession of a personal smartphones for those children who, for individual or contextual reasons, are already heavy users of screen media. Policies should focus on those households where parents are not able to limit screen time during primary school. Educational institutions and families could instead act in two different ways: they should 1) give young people the skills to avoid the distracting effect of screen media since elementary school; 2) provide young people with a smartphone only when they demonstrate they can manage their time with other screen media without displacement. It is crucial for researchers to continue studying the effects of smartphones on children's development, also taking into consideration earlier ages than those considered in the present study. The arrival of smartphones before lower secondary school is becoming more and more frequent and could impact children more profoundly. Future research will need to investigate whether and how the pandemic, along with the distance learning experiences that accompanied it, affected the relationship between children, preteens, and smartphones, and how this alters the context of the current study. This additional evidence will provide policy makers and educators with a deeper understanding of both the advantages and disadvantages of the use of this device across childhood and preadolescence and enable the development of more focused guidelines and policies.

Funding statement

This work was supported by the University of Milano-Bicocca [grant number 2016-CONV-0051]. Open access funding was provided by SUPSI - University of Applied Sciences and Arts of Southern Switzerland.

Aknowledgements

We wish to thank INVALSI and the participating schools for their collaboration.

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