Italian Journal of Educational Technology, 32(2), 49-64, 2024
ISSN 2532-4632 (print) – ISSN 2532-7720 (online)
DOI: 10.17471/2499-4324/1360
https://ijet.itd.cnr.it

Italian Journal of Educational Technology

itd ISTITUTO TECNOLOGIE DIDATTICHE

Tackling the digital divide: Exploring ICT access and usage patterns among final-year upper secondary students in Italy

Affrontare il divario digitale: esplorare i modelli di accesso e utilizzo delle TIC tra gli studenti dell'ultimo anno della scuola secondaria superiore in Italia

Donatella Papa[A,*], Marta Desimoni[B]

[A] *Istat, Rome, Italy, donatella.papa@istat.it**
[B] *Invalsi, Rome, Italy, marta.desimoni@invalsi.it*
**Corresponding author*

HOW TO CITE Papa, D., & Desimoni, M. (2024). Tackling the digital divide: Exploring ICT access and usage patterns among final-year upper secondary students in Italy. *Italian Journal of Educational Technology*, *32*(2), 49-64. https:// doi.org/10.17471/2499-4324/1360

Received: August 17, 2024; *Accepted:* October 28, 2024; *First Published:* November 6, 2024

ABSTRACT This study examines the access and usage of Information Communication Technologies (ICTs) outside the school environment among upper secondary students in Italy, based on data from the 2021-2022 INVALSI Field Trial. The study investigates the availability of digital devices such as desktops, laptops, and smartphones, and explores usage patterns through a questionnaire addressing the first and second digital divides, socio-demographics, and other relevant factors. The findings provide food for thought for those who need to manage technology and enhance learning. Notably, 96% of students reported having access to a computer at home for both learning and non-learning activities, and 88% had internet connectivity at home. While initial results suggest a reduction in the digital access gap, logistic regression models indicate that the first-level digital divide remains challenging for certain socio-economic groups. Using association rules data mining techniques, therefore, specific activities were identified as the most influential among students. Most of the grade 13 students possessed ICT tools and used them primarily for leisure activities such as social media, online communication platforms, entertainment videos and music, and web browsing.

KEYWORDS Digital Divide; Information Communication Technologies; Digital Home Environment; Educational Data Mining; Association Rules.

SOMMARIO Questo studio esamina l'accesso e l'uso delle Tecnologie dell'Informazione e della Comunicazione (TIC) al di fuori dell'ambiente scolastico tra gli studenti delle scuole secondarie superiori in Italia, basato sui dati del Field Trial INVALSI 2021-2022. Lo studio indaga la disponibilità di dispositivi digitali come desktop, laptop e smartphone, e esplora i modelli di utilizzo tramite un questionario che affronta il primo e il secondo divario digitale, le variabili socio-demografiche e altri fattori rilevanti. I risultati offrono spunti di riflessione per chi deve gestire l'uso della tecnologia e migliorare le esperienze di apprendimento. È significativo che il 96% degli studenti abbia riferito di avere accesso a un computer a casa per attività di apprendimento e non, e l'88% avesse connettività a Internet a casa. Sebbene i risultati iniziali suggeriscano una riduzione del divario di accesso digitale, i modelli di regressione logistica indicano che il primo livello di divario digitale rimane una sfida per alcuni gruppi socio-economici. Utilizzando tecniche di data mining come le regole di associazione, sono state quindi identificate le attività più influenti tra gli studenti. La maggior parte degli studenti di grado 13 possedeva strumenti TIC e li utilizzava principalmente per attività ricreative come i social media, le piattaforme di comunicazione online, i video e la musica di intrattenimento, e la navigazione web.

PAROLE CHIAVE Divario Digitale; Tecnologie dell'Informazione e della Comunicazione; Ambiente Domestico Digitale; Data Mining Educativo; Regole di Associazione.

1. Introduction

The rapid digitization of society, accelerated by the COVID-19 pandemic, has had profound implications for adolescents and young adults worldwide. In Italy, this shift has been particularly pronounced, with significant changes in educational practices, parental involvement, and access to digital technologies. While the pandemic has undoubtedly contributed to increased digital adoption, it's essential to recognize that the digital divide – the disparity in access to and use of technology – existed long before the crisis.

Socio-economic status (SES), in particular, plays a critical role in shaping digital inequality. Reports show that students from low SES backgrounds frequently have less access to computers and the internet, resulting in limited opportunities for educational engagement compared to their wealthier peers. For instance, studies highlight that these students may spend considerably less time utilizing digital technologies for educational purposes, primarily due to access constraints and differing levels of digital literacy. Furthermore, the Italian National Institute of Statistics (ISTAT) has documented these inequalities, emphasizing that they persist despite efforts to bridge the digital divide (ISTAT, 2020b; Di Pietro, 2021). Similarly, the European Centre for the Development of Vocational Training (Cedefop, 2021) reports that low-SES students are 1.5 times more likely to lack the necessary digital skills to fully engage with remote learning platforms during the pandemic. These disparities have significant implications for educational outcomes, social mobility, and overall well-being, with digital exclusion perpetuating existing inequalities.

Previous studies have extensively documented the digital divide, which consists of understanding differences in access to Information, Communication and Technologies (ICTs) (Attewell, 2001; DiMaggio et al., 2001; Riggins & Dewan, 2005; van Dijk, 2005), highlighting persistent inequalities along the lines of social class, age, sex, and geographic location. For example, research from Goudeau et al. (2021) and ISTAT (2020a) reveals that certain groups, particularly those from lower-income families and rural areas, need to improve regarding access to and proficiency with digital technologies. These disparities can have far-reaching consequences for educational opportunities, social mobility, and overall well-being. Research on students' access to ICT outside of school shows mixed results. Chiu (2020) highlights that ICT access is mediated by socioeconomic status (SES), leading to differences in learning outcomes. Heo and Kang (2010), along with Fernàndez-Gutièrrez et al. (2020), note that using ICT outside of school can improve academic performance. SANFO (2023) confirms this, showing that ICT use supports learning, though its impact varies based on socio-economic factors. ICT use by upper secondary students can have both positive and negative effects (Olofsson et al., 2018), with challenges related to equity and integration into formal education (Nachmias et al., 2001). European studies (Wastiau et al., 2013; Ola Lindberg & Sahlin, 2011) emphasize the need for a balanced use of ICT in and out of school to maximize educational benefits.

Despite the wealth of existing research, important gaps remain in our understanding of the digital divide among Italian youth. Further, many studies focus on broad sociodemographic factors, but less is known about the specific ways in which access to and use of digital technologies vary within this population. For instance, what are the patterns of device ownership and usage among Italian adolescents and young adults? How do these patterns differ based on factors like age, sex, socioeconomic status, and educational level? Furthermore, while some research has explored the impact of the pandemic on digital adoption, more nuanced studies are needed to disentangle the effects of the crisis from longer-term trends in the digital divide.

Our study aims to fill these gaps by providing a detailed analysis of access to and use of digital technologies among Italian upper secondary school students during the 2021-2022 academic year. We will go beyond simple measures of device availability and investigate the complex interplay between educational and leisure use of digital media. By examining students' digital habits in depth, we will explore the nature of the digital divide and its implications for this key demographic.

To analyse this complex data, we will employ Association Rules Mining (ARM), a powerful data mining technique that can uncover hidden patterns and relationships within the data. ARM will allow us to capture the nuanced ways in which access to and use of digital technologies intersect with students' sociodemographic characteristics and activities. By exploring these previously unknown patterns, our study will contribute some insights to the ongoing research on digital divides and provide issues for future investigations.

The following research questions will guide our analysis:

Does students' access to ICT vary as a function of their sociodemographic characteristics? We will examine multiple devices and different types of access to capture the full picture of digital inequality.

What patterns exist among key items relating to students' activities, as well as among these items and students' sociodemographic characteristics? By investigating both educational and leisure use of digital media, we can explore the dynamics of the digital divide.

Through this comprehensive analysis, we will provide a clearer understanding of the digital divide among Italian young adults and contribute to the broader conversation on digital inequality in the context of rapid technological change.

2. Materials and methods

2.1. Participants and procedures

The present study is part of a larger research project on ICT-related constructs and digitally assessed mathematics among students in their final year of upper secondary school, conducted within the INVALSI 2022 Field Trial. The final sample comprised 3,254 students (49% males, 51% females; 4% first-generation immigrants, 5% second-generation immigrants, 91% natives), with 76% aged 19 years. Geographically, 29% attended schools in central Italy, 12% in the north-east, 25% in the north-west, and 34% in the south. The questionnaire and INVALSI tests were administered by INVALSI at school with an external observer present, and all data collection was anonymous.

2.2. Measures

First-level digital divide was assessed using two blocks of items: "What kind of internet connection do you have at home?" and "Do you have access to the following digital devices at home?" For internet connection, students could choose from: "slow," "medium," "fast," "I do not have access to the internet," or "I don't know/I prefer not to answer." For ICT access, devices included desktop computers,

DOI: 10.17471/2499-4324/1360

Table 1. 95% Confidence boundaries for Cronbach's alpha.

Method	Lower Bound	Alpha	Upper Bound
Feldt	0.84	0.85	0.86
Duhachek	0.84	0.85	0.86
Bootstrapped	0.84	0.85	0.86

laptops, tablets, smartphones, smart TVs, game consoles, and e-readers. Responses were: 1 = "No"; 2 = "Yes, and only I use it"; 3 = "Yes, but it is a shared device"; 4 = "Yes, but I don't use it" (labelled as Not access, Alone, With others, and Not use, respectively).

Second-level digital divide was measured by the ICT Usage at Home (ICTUH) item, which included 24 items. These items assessed how and how often students engage in ICT-related activities outside of school. The ICTUH scale was developed by reviewing the literature on ICT use in secondary school, with a special focus on existing measures of ICT use in student populations, such as the PISA ICT Familiarity Questionnaire (OECD, 2017) and ICILS Student questionnaire (Fraillon et al., 2019). Items were tailored to Italian grade 13 students. Responses were on a five-point scale: 1 = "Never", 2 = "Once or twice a month", 3 = "Once or twice a week", 4 = "Almost every day" and 5 = "Every day". Items were reviewed for relevance, comprehensiveness of content, clarity of presentation, and ease of administration by experts in questionnaire development, researchers with expertise on students' use of ICT and digital inequalities, and secondary school teachers. Scale reliability was empirically tested. Specifically, given the ordinal nature of the raw scale, we computed ordinal alpha, which is more suitable for this type of data than the traditional Cronbach's alpha (Tavakol & Dennick, 2011). The ordinal alpha value was consistently found to be above 0.85 for each method employed, indicating good reliability.

ESCS was an index of economic, social, and cultural status computed by INVALSI, based on students' home educational resources, the highest level of education of the student's parents (PARED), converted into years of schooling, and the highest level of the parents' International Socio-Economic Index of Occupational Status (HISEI). Further details on the INVALSI methodology can be found in (Campodifiori et al., 2010).

Additional variables included student sex (0 for females, 1 for males), immigrant background (0 for natives, 1 for students born outside Italy or whose parents were born abroad), and school career (1 for repeating grades, 0 for regular students). The geographical location of the school was categorized as North-West, North-East, South, or Centre. These variables were analyzed to determine their impact on access to and use of digital devices.

2.3. Data analysis

To answer the first research question, we used logistic regression analyses to identify significant predictors of ICT access. In the logistic analyses, the dependent variable was access to each device ("0" corresponded to categories "not having access" and "not using" the device, and "1" to having access to the device, also including those shared with others). Further, a logistic regression was performed contrasting those having access neither to a desktop nor laptop computer (0) and other students (1). To account for the potential inflation of Type I error rates due to multiple comparisons, we applied the Bonferroni correction to our significance thresholds. Specifically, we divided the conventional alpha level of 0.05 by the number of tests conducted (in this case, the number of devices analysed) to determine a more stringent threshold for significance. This adjustment helps mitigate the risk of falsely identifying significant predictors and ensures a more robust interpretation of the results. This approach allowed us to systematically evaluate the influence of various sociodemographic factors on access to ICT while maintaining the integrity of our statistical findings.

To address the second research question, we employed Association Rules Mining (ARM) to uncover significant patterns in our ICTUH questionnaire data. ARM is designed to identify correlations and frequent patterns in datasets using an "if-then" approach. Unlike multivariate techniques, ARM focuses on finding associations between items. The process involves two main steps: identifying frequent items in the transactional database and generating association rules from these items (Agrawal et al., 1993; Attewell & Monaghan, 2015). The goal is to discover rules that meet specified minimum support and confidence thresholds (Abdullah et al., 2011):

- $Support = \frac{n(X \cup Y)}{N}$
- $Confidence = \frac{n(X \cup Y)}{n(X)}$

where $n(X \cup Y)$ is the number of events in which both X and Y are found together, N is the number of events and n(X) stands for the number of all events in which X was found.

Rather than verifying specific rules, our focus is on discovering all rules. The relationship between support and confidence represents a trade-off too little support can lead to many unattractive rules, while too much confidence can cut out. Experts typically set minimal support and minimal confidence, as noted by Zhang and Zhang (2002), which will be the approach in our subsequent study.

The data mining techniques employed in the research used R Studio and Python software, both widely used open-source software, selected because they are popular and easily reproduced in the data mining community. Specific libraries such as "caTools" for logistic regression and "mlxtend" for association rules were essential components of our analysis. (Tuszynski & Khachatryan, 2013; Raschka, 2018).

3. Results and discussion

3.1. Description of access to digital devices

This subsection illustrates the descriptive statistics for grade 13 students' access to digital devices and the internet at home. As shown in Table 2, 50.1% of students did not have a desktop computer at home, and a further 11.6% owned a desktop computer but did not use it. Otherwise, there was an increase in the percentage of laptops. Our questionnaire also considers that ICT access has evolved with mobile solutions such as tablets and smartphones replacing more traditional devices such as personal computers (henceforth PC). For tablets, 50.8% of the sample reported having access to and using them, whereas 33.7% of the sample reported not having access, and 15.5% reported not using these devices. Unsurprisingly, most students in the sample (98.3%) had access to and used a smartphone, although 9.5% shared the device with others.

The 96.1% of the sample had access to a personal computer (either a desktop or a laptop). The diagonal value in Table 3 for the intersection of desktop and laptop, denoted by the label "no access", indicates that 3.9% had no access to a PC (either a desktop or a laptop). The 27.6% of the sample used the

DOI: 10.17471/2499-4324/1360

Table 2. Distribution of digital device usage: Percentage breakdown.

	Desktop	Laptop	Smartphone	Smart TV	Game console	e-reader	Tablet
Alone	15.5	48.6	88.8	15.4	27.9	10.1	28.6
With other	22.8	33.4	9.5	64.5	22.6	9.0	22.2
Not use	11.6	7.5	0.8	5.4	17.5	13.9	15.5
Not access	50.1	10.5	1.0	14.7	32.0	67.0	33.7
Tot.	100	100	100	100	100	100	100

Table 3. Relationship between desktop and laptop PC usage: Percentage breakdown.

Desktop/Laptop	Alone	With other	Not use	Not access	Tot.
Alone	6.4	3.2	2.9	3.0	15.5
With other	9.8	8.2	1.7	3.1	22.8
Not use	7.3	2.8	1	0.5	11.6
Not access	25.1	19.2	1.9	3.9	50.1
Tot.	48.6	33.4	7.5	10.5	100

PC (desktop and laptop) alone or shared it with others (sum of the labels ’alone’ and ’with others’ for desktop and laptop).

Regarding Internet access (missing values = 11%), only 1.2% of our sample reported having no access to the Internet at home and 2% reported having a slow connection. The internet connection was fast for 51.7% of the sample and medium for 35.9%.

3.2. Sex, socioeconomic, and geographical disparities in digital device access among late adolescent students

The digital divide between males and females is a topic that has garnered much attention in recent years. According to Table 4, late adolescent males tend to own and use desktop computers twice as often. However, this gap is offset by the fact that females tend to own more laptops and tablets. Considering desktop and laptop computers together, no sex gap emerged. Late-adolescent males were much more likely than females to have access to and use game consoles. This finding aligns with previous research showing that boys are more likely to use ICT heavily for entertainment purposes (Xiao & Sun, 2022).

The logistic regression analysis confirms existing literature that access to digital devices is strongly influenced by students’ SES. Students in the first quartile of ESCS are significantly less likely than more affluent students to own and use a variety of digital devices, including smartphones, tablets, and PCs. This result highlights the persistent digital divide along socioeconomic lines.

The analysis suggests that students with an immigrant background show no significant differences in access to most digital devices compared to their native peers after adjusting for ESCS and other sociodemographic characteristics. These results may be partially explained by the fact that the study focuses on late adolescents in their final year of upper secondary school, a group less likely to include students who have dropped out. In Italy, dropout rates are higher among students with non-Italian citizenship, which might influence the findings (Cesareo, 2022). Further research is needed to explore \

Table 4. Odds ratios for access to digital devices: Logistic regression analysis (Bonferroni corrected).

	Desktop	Laptop	Smartphone	Smart TV	Console	e-Reader	Tablet	PC
Male	2.051***	0.505***	0.665	0.895	6.308***	0.954	0.754***	0.901
	(0.074)	(0.097)	(0.279)	(0.090)	(0.078)	(0.088)	(0.071)	(0.140)
ESCS (1st quartile)	0.589***	0.505***	0.328***	0.582***	0.863	0.691***	0.704***	0.260***
	(0.089)	(0.101)	(0.278)	(0.098)	(0.092)	(0.110)	(0.083)	(0.142)
Immigrant background	0.940	0.775	0.512	0.746	0.630	0.895	0.877	0.778
	(0.136)	(0.158)	(0.387)	(0.145)	(0.142)	(0.166)	(0.128)	(0.219)
Repeating	0.941	0.663***	1.003	1.042	1.085	0.891	0.868	0.536***
	(0.107)	(0.123)	(0.358)	(0.124)	(0.112)	(0.131)	(0.102)	(0.167)
North-East	0.834	1.137	1.026	0.757	0.814	0.855	1.045	0.892
	(0.125)	(0.161)	(0.486)	(0.145)	(0.133)	(0.154)	(0.121)	(0.245)
North-West	0.721	1.533	1.156***	0.757	0.844	1.081	1.073	1.400
	(0.101)	(0.136)	(0.391)	(0.118)	(0.107)	(0.119)	(0.097)	(0.215)
South	0.890	0.875	0.775	1.344	0.944	0.920	1.083	0.607
	(0.093)	(0.115)	(0.339)	(0.119)	(0.099)	(0.112)	(0.090)	(0.1728)
Constant	0.588***	8.611***	5.212***	5.212***	0.472***	0.293***	1.314***	30.165***
	(0.084)	(0.115)	(0.104)	(0.104)	(0.088)	(0.099)	(0.081)	(0.180)
Akaike Inf. Crit.	4,229	2,928	557	3,191	3,879	3,252	4,482	1,571

$^{***}p < 0.00625$; $^{**}p < 0.01$; $^{*}p < 0.05$.

digital access among late adolescents with an immigrant background who are not attending upper secondary school.

Geographical differences also emerged in the data, with students in the South of Italy being significantly less likely to have access to and use PCs, a finding that remains robust even after controlling for sociodemographic factors.

In conclusion, our results confirm that access to digital devices is heavily shaped by students' socioeconomic and cultural background, consistent with previous research on first-level digital divides (Benecchi et al., 2021). The geographical and gender differences, particularly in access to specific devices, with males more frequently using desktop computers and game consoles, while females tend to own laptops and tablets, highlight ongoing challenges in ensuring equitable digital access.

3.3. ICT usage at home items description

As technology continues to advance, it becomes increasingly important to understand and recognize how ICT is used in different aspects of daily life. Figure 1 shows the distribution of students' responses to the ICTHU questionnaire, providing a general overview of their ICT use outside of school time. Focusing on activities performed "almost every day' and "every day", no item has a frequency rate of zero or close to it.

Not surprisingly items related to communicating with others, using social media, and engaging in entertainment activities (Q2, Q4 and Q9), had the highest percentages.

Most of the grade 13 students also used ICT for school-related activities, such as interacting with classmates and teachers and searching for information or materials for school assignments (Q3, and Q6). More than 40% of the sample reported using ICT for doing homework (Q1) and for uploading and downloading learning material from the internet (Q8).

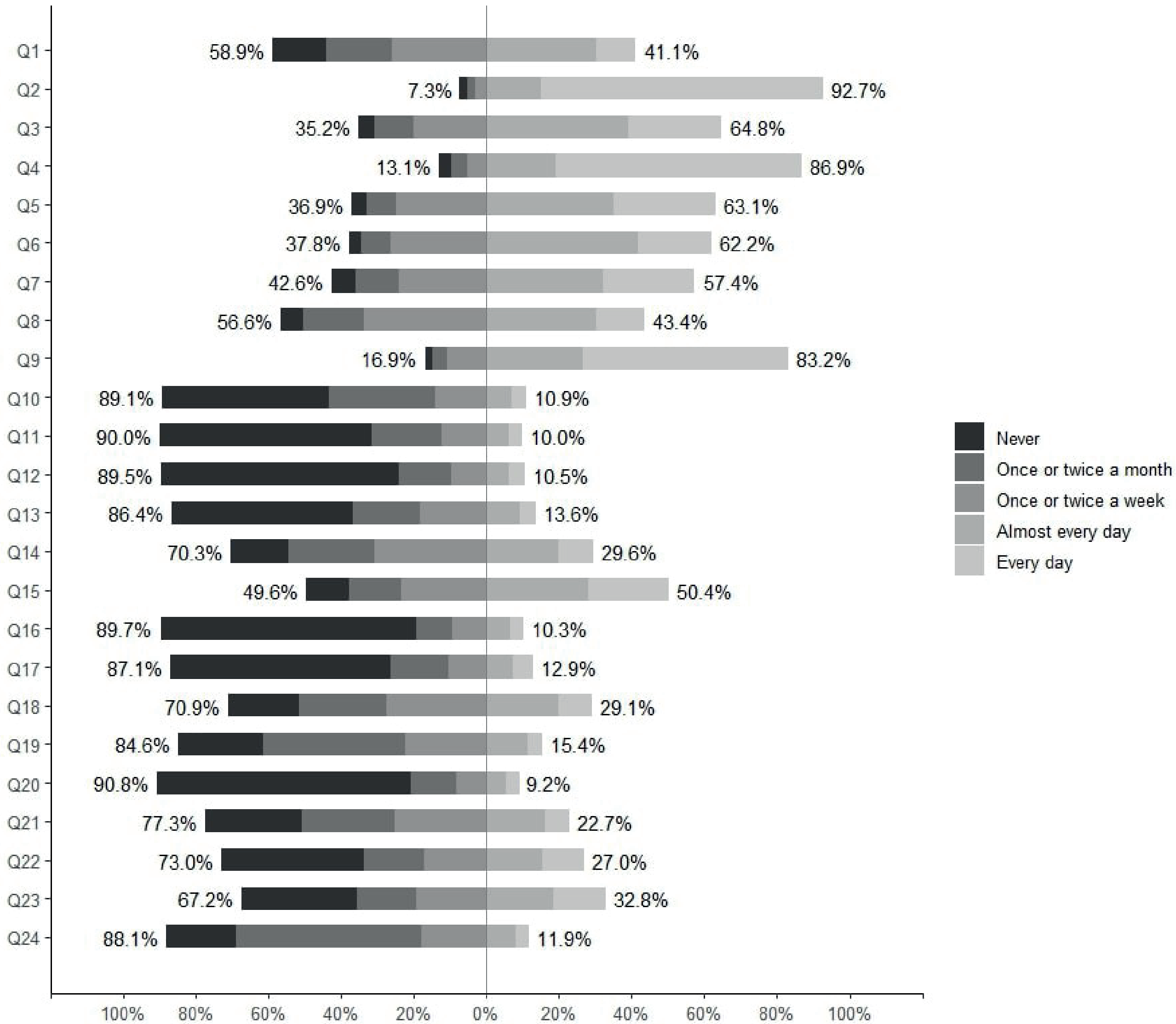

Figure 1. ICT Usage at Home items descriptive statistics (n = 3,254 students).
Legend: Q1=Doing homework with software or web applications; Q2=Communicating with friends, family or other people via chat or email; Q3=Interacting with classmates or teachers at school activities; Q4=Sharing or accessing content on social networks; Q5=Searching for information about places and events for the free time; Q6=Searching for information or materials for school assignments; Q7=Read online news or newspapers; Q8=Uploading or downloading educational material from the internet; Q9=Listening to music or watching streaming or downloading films; Q10=Accessing online courses for personal interest; Q11=Using educational games; Q12=Participating in forums or discussion groups on topics of personal interest; Q13=Doing maths homework with dedicated software on a PC, tablet or smartphone; Q14=View tutorials for personal interest; Q15=Deepen their knowledge on topics of personal interest; Q16=Write computer programs, scripts or apps; Q17=Produce creative content (music, poems, etc.); Q18=Search for reviews online about products or services before buying; Q19=Working in groups with other students in educational activities; Q20=Reading ebooks in free time; Q21=Writing or editing documents for educational activities; Q22=Playing online with others; Q23=Playing alone; Q24=Creating a presentation for learning activities.

These data are consistent with the heavy reliance on ICT in the context of the COVID-19 pandemic, even after most schools had reopened. Further, most students reported daily use of ICT for seeking information (Q5), such as reading news online (Q7) or finding information about free-time activities (Q5), and for deepening their knowledge of topics of personal interest (Q15).

3.4. Exploring association rule mining techniques for analyzing student activity patterns

The initial assumption of ARM was that a student had to engage in an activity at least once a day to be considered active in a transaction. The students' responses were converted to a binary format (0 for scores 1-3 and 1 for scores 4-5) to fit the model. In addition, we also included dummy variables for sociodemographic characteristics as suggested by Attewell and Monaghan (2015), such as ESCS (0 for scores 3-4 lower quartile and 1 for scores 1-2 higher quartile), sex (0 for female and 1 for male), immigrant background (0 for native and 1 for students born outside Italy), geographical area (each area category is represented as a one-hot vector, e.g., where 0 for those living in the south and 1 otherwise), student's school career (0 for regular students and non-zero values for other categories), and access to digital devices (each device is represented as a one-hot vector, where 0 for who owns one and 1 for other categories).

Initially, the Apriori algorithm was considered for AR analysis but was replaced by the FP-growth algorithm due to Apriori's high memory demands. FP-growth, which uses an FP tree and a divide-and-conquer method to find frequent item sets (Han & Pei, 2000), was more efficient. Although FP-growth initially generated 13,000 rules, refining support and confidence parameters led to 29 quality rules, focusing on those with a lift greater than 1, indicating independence between rules and elements.

To explore the strength of relationships between demographic variables and survey responses (Q1-Q24), we used Cramér's V, an index that measures the association between categorical variables. The results were visualized in a heatmap (Figure 2), where the colours represent the intensity of the associations: darker shades of blue indicate weaker associations, while brighter colours suggest stronger relationships. Overall, most associations between the survey questions and sociodemographic variables were weak, as reflected by the predominance of dark blue tones. For instance, variables like "not access to PC" (no_access_PC) "ESCS (4st quartile" (high_ESCS) and "not access to PC" (no_tablet) showed little correlation with the survey questions. However, a few moderate associations emerged, such as between the variable "student repeating a grade" (repeating) and other characteristics, although these cases were relatively rare. The heatmap allowed us to quickly identify these relationships and focus the association rule analysis on variables with significant associations. This approach ensured that we only considered the most relevant relationships, minimizing the risk of including random or insignificant associations in the ARM analysis.

3.4.1. Analyzing patterns of ICT engagement among grade 13 students: Insights from Association Rule Mining

Table 5 serves as a comprehensive repository of results for the exploration of key activities outside school hours among grade 13 students, shedding light on the various influences shaping their everyday lives.

Communication-related activities, such as engaging with friends and family (Q2), exhibit a strong connection with academic pursuits like information-seeking (Q5, Q6) and homework completion (Q1). This suggests a close relationship between interpersonal communication and academic engagement, highlighting the multifaceted nature of students' ICT usage, where social interactions are intertwined with scholarly activities.

Entertainment activities (Q9) emerge as central in the ICT engagement network, showing links not only with communication (Q2) but also with searching for materials (Q6) and homework (Q1). Using the FP-Growth algorithm, the analysis identified correlations between entertainment activities

DOI: 10.17471/2499-4324/1360

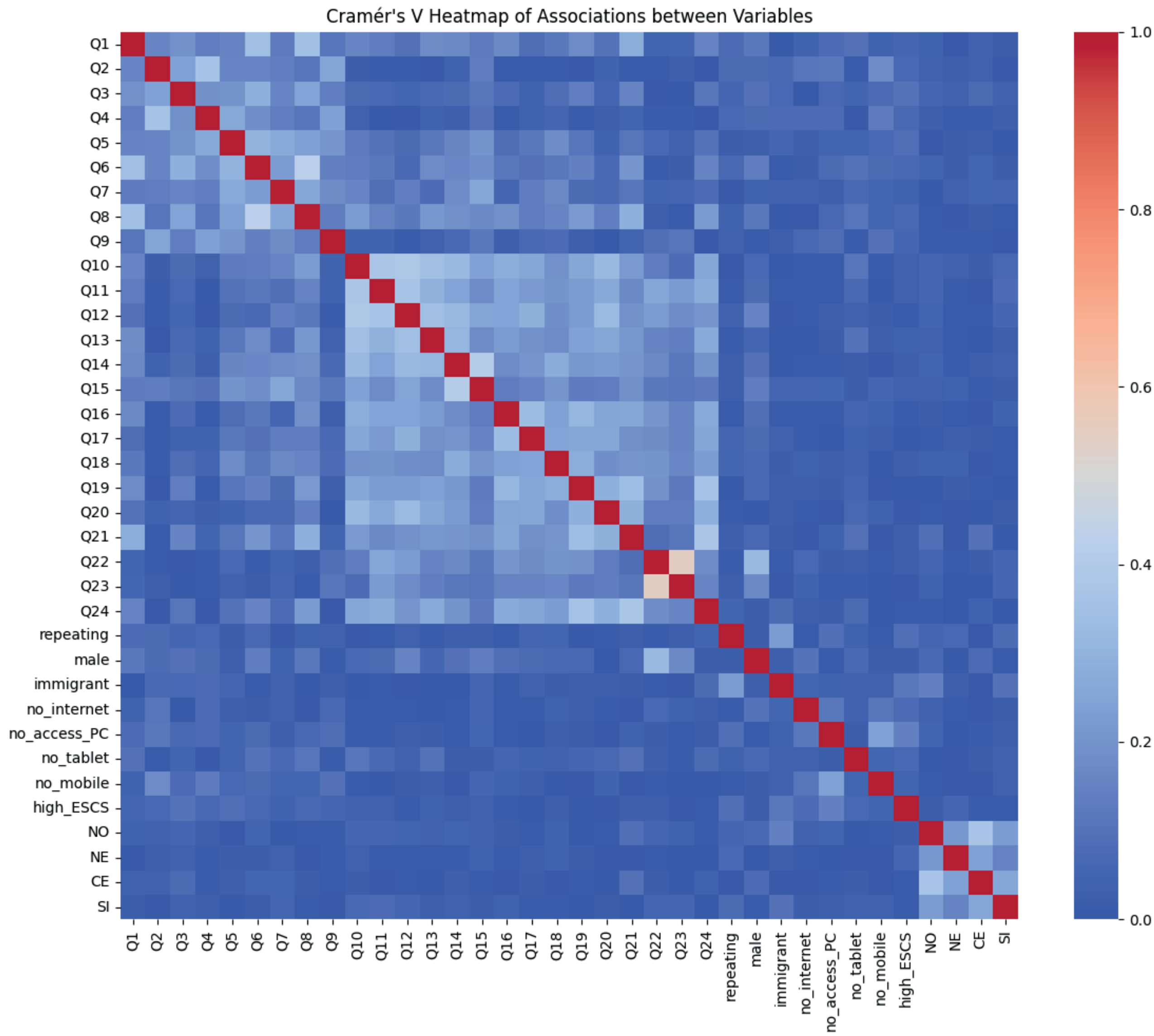

Figure 2. ICT usage at home items descriptive statistics (n = 3,254 students).
Legend: Q1=Doing homework with software or web applications; Q2=Communicating with friends, family or other people via chat or email; Q3=Interacting with classmates or teachers at school activities; Q4=Sharing or accessing content on social networks; Q5=Searching for information about places and events for the free time; Q6=Searching for information or materials for school assignments; Q7=Read online news or newspapers; Q8=Uploading or downloading educational material from the internet; Q9=Listening to music or watching streaming or downloading films; Q10=Accessing online courses for personal interest; Q11=Using educational games; Q12=Participating in forums or discussion groups on topics of personal interest; Q13=Doing maths homework with dedicated software on a PC, tablet or smartphone; Q14=View tutorials for personal interest; Q15=Deepen their knowledge on topics of personal interest; Q16=Write computer programs, scripts or apps; Q17=Produce creative content (music, poems, etc.); Q18=Search for reviews online about products or services before buying; Q19=Working in groups with other students in educational activities; Q20=Reading ebooks in free time; Q21=Writing or editing documents for educational activities; Q22=Playing online with others; Q23=Playing alone; Q24=Creating a presentation for learning activities.

and broader academic contexts. While these associations suggest potential overlaps between leisure and educational tasks, it is important to note that the method reveals frequent co-occurrences rather than causality. Additional qualitative research would be required to explore the underlying dynamics

Table 5. Association rules filtering.

n.	antecedents	consequents	antecedents s.	consequents s.	support	confidence	lift	leverage	conviction	zhangs
1	Q2, Q6, Q9	Q1	0.527	0.411	0.301	0.572	1.389	0.084	1.374	0.592
2	Q4, Q3	Q2	0.594	0.927	0.584	0.983	1.061	0.033	4.302	0.141
3	Q4, Q9, Q3	Q2	0.526	0.927	0.518	0.985	1.063	0.031	4.831	0.125
4	Q2, Q6, Q5, Q4	Q3	0.428	0.648	0.352	0.823	1.270	0.075	1.993	0.372
5	Q9, Q2, Q5, Q4, Q6	Q3	0.392	0.648	0.323	0.824	1.271	0.069	1.997	0.351
6	Q2	Q4	0.927	0.869	0.837	0.904	1.040	0.032	1.358	0.519
7	Q9	Q4	0.832	0.869	0.753	0.905	1.041	0.030	1.381	0.236
8	Q2, Q9	Q4	0.795	0.869	0.731	0.920	1.058	0.040	1.624	0.266
9	Q4, Q6, Q9	Q5	0.509	0.632	0.403	0.792	1.255	0.082	1.774	0.413
10	Q4, Q5, Q9	Q6	0.534	0.622	0.403	0.755	1.214	0.071	1.545	0.379
11	Q6, Q9, Q5	Q7	0.418	0.574	0.309	0.740	1.288	0.069	1.635	0.384
12	Q2, Q6, Q9, Q5	Q7	0.406	0.574	0.301	0.742	1.293	0.068	1.652	0.381
13	Q2, Q15, Q9	Q7	0.427	0.574	0.312	0.730	1.272	0.067	1.579	0.373
14	Q6, Q3	Q8	0.470	0.434	0.303	0.645	1.486	0.099	1.594	0.617
15	Q6, Q5	Q8	0.463	0.434	0.305	0.658	1.514	0.103	1.652	0.633
16	Q2, Q5	Q9	0.605	0.832	0.545	0.900	1.083	0.042	1.692	0.194
17	Q4, Q5	Q9	0.592	0.832	0.534	0.901	1.084	0.041	1.708	0.190
18	Q2, Q5, Q4	Q9	0.573	0.832	0.520	0.907	1.090	0.043	1.806	0.194
19	Q15, Q9	Q14	0.440	0.297	0.215	0.488	1.645	0.084	1.373	0.701
20	Q2, Q15, Q9	Q14	0.427	0.297	0.208	0.487	1.641	0.081	1.370	0.682
21	Q2, Q7, Q9	Q15	0.494	0.504	0.312	0.633	1.256	0.064	1.351	0.402
22	Q7	Q18	0.574	0.291	0.206	0.358	1.229	0.038	1.104	0.437
23	Q5, Q9	Q18	0.563	0.291	0.203	0.362	1.241	0.040	1.110	0.444
24	Q2	Q21	0.927	0.227	0.212	0.229	1.008	0.002	1.002	0.105
25	Q4	Q21	0.869	0.227	0.205	0.236	1.037	0.007	1.011	0.271
26	male	Q22	0.515	0.270	0.210	0.408	1.511	0.071	1.233	0.697
27	Q23	Q22	0.328	0.270	0.202	0.616	2.283	0.114	1.902	0.837
28	male	Q23	0.515	0.328	0.209	0.407	1.239	0.040	1.132	0.397
29	Q22	Q23	0.270	0.328	0.202	0.749	2.283	0.114	2.681	0.770

Legend: Q1=Doing homework with software or web applications; Q2=Communicating with friends, family or other people via chat or email; Q3=Interacting with classmates or teachers at school activities; Q4=Sharing or accessing content on social networks; Q5=Searching for information about places and events for the free time; Q6=Searching for information or materials for school assignments; Q7=Read online news or newspapers; Q8=Uploading or downloading educational material from the internet; Q9=Listening to music or watching streaming or downloading films; Q10=Accessing online courses for personal interest; Q11=Using educational games; Q12=Participating in forums or discussion groups on topics of personal interest; Q13=Doing maths homework with dedicated software on a PC, tablet or smartphone; Q14=View tutorials for personal interest; Q15=Deepen their knowledge on topics of personal interest; Q16=Write computer programs, scripts or apps; Q17=Produce creative content (music, poems, etc.); Q18=Search for reviews online about products or services before buying; Q19=Working in groups with other students in educational activities; Q20=Reading ebooks in free time; Q21=Writing or editing documents for educational activities; Q22=Playing online with others; Q23=Playing alone; Q24=Creating a presentation for learning activities.

of these relationships more fully. While this correlation highlights a potential overlap between entertainment and academic engagement, further research would be needed to understand the nature and implications of this relationship.

Analysis of students' online news reading habits (Q7) reveals associations with interacting with classmates (Q6), listening to music (Q9), and leisurely information seeking (Q5). These connections emphasize the importance of a holistic approach to understanding information behaviour, where academic, social, and personal aspects converge in the digital realm.

The gender disparity in gaming activities (Q22, Q23), with males showing higher participation, highlights the importance of investigating how gamification elements, rather than pure gaming for entertainment, can be integrated into educational contexts to improve learning outcomes and address gender dynamics in student engagement. Unlike games designed for entertainment, gamification applies game-like elements to enhance motivation and engagement in educational tasks. While existing research does not indicate a direct link between gaming and academic achievement (Dindar, 2018), the differences in how various genders engage with gaming may provide insights into developing tailored educational strategies.

Group interaction (Q19) appears as an isolated aspect of students' ICT use, with no significant associations found with other activities. This suggests that collaborative efforts in educational activities may not be closely linked to other ICT-related behaviours. Exploring the factors contributing to this isolation could provide insights into the dynamics of collaborative learning beyond the traditional classroom. Recent studies (Gasaymeh, 2018; Chugh & Ruhi, 2018) highlight how specific online resources, such as Wikipedia and Facebook, support group work, suggesting that the choice of platform plays a crucial role in shaping collaborative interactions in ICT. Nonetheless, the rapid and significant rise in the adoption of Learning Management Systems (LMS) in educational settings deserves closer consideration. LMS platforms have become essential not only for course management but also for fostering structured, coordinated collaboration among students within a controlled and secure environment. This shift has been largely motivated by concerns over privacy, particularly in response to regulations like the General Data Protection Regulation (GDPR), which mandates the creation of safer, more regulated spaces for student interactions. As a result, it is important to reassess how these platforms might further influence collaborative dynamics in educational contexts.

Extending our analysis of association rules, key metrics such as leverage, conviction, and Zhang's metric were examined in Table 5 to identify patterns and relationships between different ICT-related activities.

Leverage measures the deviation from expected co-occurrence frequencies between activities. High leverage values, such as the association between Q1 (homework) and Q2 (communicating), indicate a strong likelihood of these activities occurring together, signifying a strong link between academic tasks and communication.

Conviction scores reveal the strength of dependency between activities, indicating the likelihood of one activity occurring when another is present. For instance, the association between Q4 (social networks) and Q8 (educational materials) suggests a strong association between social networks and access to educational resources, with conviction values greater than one.

Zhang's metric, which measures statistical significance, highlights robust and meaningful patterns. The association between Q2 (communication) and Q6 (seeking educational information) suggests that engagement in communication often coincides with the search for educational information, indicating a significant relationship between these activities.

This study also assesses the influence of sociodemographic characteristics such as ESCS, migrant background, repeat students, geography, and gender. Notably, none of these characteristics, except for being male and gaming, show a significant association with digital activities. This finding suggests that the relationship between sociodemographic variables, access to digital devices, and engagement in digital activities may be complex and context-dependent.

4. Conclusions

This study enriches the literature on ICT access by examining Italian grade 13 students' digital experiences post-pandemic, a period relatively less studied than earlier stages (OECD, 2023).

First, we examined whether students' sociodemographic characteristics were associated with differences in their access at home to a range of digital devices. On the one hand, our results showed that very few students reported having no access to a PC (neither a desktop computer nor a laptop). Most students reported having a PC at home and using it, although for some students, the PC is a shared device used by other family members. We also provided a picture of access to other devices, with smartphones being the most common, owned by almost all students in the sample.

On the other hand, the main results from our logistic regression analyses highlighted that there is still a digital divide in access to ICT between students from more disadvantaged backgrounds and their peers. This finding emerged not only when focusing on devices traditionally addressed in digital divide research (i.e., the PC) but also on other digital devices, except game consoles. These differences underscore the complex interplay between digital access and socioeconomic and cultural factors, necessitating strategies to close the gaps (Kenny, 2017; Vassilakopoulou & Hustad, 2023).

The current study also found no significant relationship between students' sex and their access to and actual use of PCs and almost all other devices. However, male late adolescents were more likely to have access to and use game consoles than their female peers; this finding aligns with existing literature on ICT use for entertainment among younger students (Burgess et al., 2007; Greenberg et al., 2010; Phan et al., 2012; Gómez-Gonzalvo et al., 2020).

Second, we examined how students use ICT outside school and the differences across sociodemographic groups using a data-mining approach. Association rule mining helped identify patterns in ICT activities and their connections to students' sociodemographic characteristics and digital device ownership. One notable finding was that ICT activities often bridged different dimensions, such as learning and leisure. This is consistent with Ludvìk et al. (2020), who found that learning with ICT can be influenced by its use in other areas. However, activities like playing games alone or with others were isolated and not strongly linked to other ICT activities. Contrary to expectations, we did not find a strong association between ICT use and students' ESCS, suggesting the need for further research. An exception was the significant association between being male and frequent ICT use for gaming, aligning with recent findings on the narrowing digital sex gap (Gebhardt et al., 2019). This underscores the importance of addressing potential risks and benefits associated with online gaming among male students. As we continue to navigate the rapidly changing landscape of ICT in education and other areas relevant to young people, it is critical that we remain mindful of the digital divide within the "digital youth" and work to create a more inclusive digital environment for all students. It is also important to understand how students engage with ICT. Data mining techniques can help discover patterns of ICT use in everyday life, providing useful insights to create a safe and supportive environment that encourages them to make the most of their ICT experiences.

DOI: 10.17471/2499-4324/1360

4.1. Limitations and future directions for research

To make our findings more objective, we should recognize their limitations. First, the generalizability of our results is subject to certain limitations. Data were collected on a large and nationally representative sample of the target population, namely students attending the last year of upper secondary school in Italy. However, our results could not be fully generalizable to ICT access and usage among late adolescents and young adults from all walks of life. For instance, recent data (Crosier & Sigalas, 2022) suggest that early school leaving challenges the Italian education system, especially in the South of Italy and among the foreign-born population. Further research is needed to provide a more complete picture of digital inequalities among young people, also reaching early leavers from education and training. Second, the initial assumption of AR was that a student had to engage in an activity at least once a day to be considered active in a transaction; this allowed us to detect patterns of co-occurrence among more frequent activities. However, a further study may capture more detailed patterns in ICT uses, also including activities that are less likely to be carried out every day (such as coding), to provide more nuanced associations between sociodemographic characteristics and ICT pattern of usage. Third, the study is mainly based on students' self-reported data. Further research also integrating survey data from other sources (e.g. territorial data) would be a useful way of providing a more detailed picture of ICT access and use among students.

4. Acknowledgement

The authors would like to thank INVALSI for granting access to the data. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of INVALSI.

5. Authors' contributions

All authors contributed to the study conception, design and writing. Data preparation and data analysis were performed by Donatella Papa. The first draft of the manuscript was written by Donatella Papa except for the conclusion, written by Marta Desimoni; and all authors commented and wrote on previous versions of the manuscript. All authors read and approved the final manuscript.

6. Data availability

Data sets that have been analysed as part of this study and that are not in breach of data protection legislation can be requested from the institution that owns the data set (INVALSI).

7. Consent to participate

The protocol of data collection, also including the consent to participate, was handled by INVALSI. We obtained from INVALSI the formal consent to use the anonymous database to carry out all secondary analyses reported in the present paper.

8. References

Abdullah, Z., Herawan, T., Ahmad, N., & Deris, M. M. (2011). Mining significant association rules from educational data using critical relative support approach. *Procedia Social and Behavioral Sciences*, *28*, 97–101. https://doi.org/10.1016/j. sbspro.2011.11.020

Agrawal, R., Imielinski, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *ACM SIGMOD Record*, *22*, 207–216. https://doi.org/10.1145/170036.170072

Attewell, P. (2001). Comment: The first and second digital divides. *Sociology of Education*, *74*, 252-259. https://doi.org/10.2307/2673277

Attewell, P., & Monaghan, D. (2015). *Data mining for the social sciences: An introduction*. University of California Press. https://doi.org/10.1525/9780520960596

Benecchi, A., Ciapanna, E., Bottoni, C., Frigo, A., Milan, A., & Scarinzi, E. (2021). Digitalisation in Italy: Evidence from a new regional index. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4016669

Burgess, M. C., Stermer, S. P., & Burgess, S. R. (2007). Sex, lies, and video games: The portrayal of male and female characters on video game covers. *Sex roles*, *57*, 419-433. https://doi.org/10.1007/s11199-007-9250-0

Campodifiori, E., Figura, E., Papini, M., & Ricci, R. (2010). *Un indicatore di status socio-economico-culturale degli allievi della quinta primaria in Italia*. Invalsi.

Cedefop (2021). Digital skills: challenges and opportunities during the pandemic. *Cedefop*, https://www.cedefop.europa.eu/en/news/ digital-skills-challenges-and-opportunities-during-pandemic

Cesareo, V. (2022). Ventisettesimo rapporto sulle migrazioni 2021. *Ventisettesimo rapporto sulle migrazioni 2021*, 1–301. https://www.ismu.org/ ventisettesimo-rapporto-sulle-migrazioni-2021/

Chiu, M.-S. (2020). Exploring models for increasing the effects of school information and communication technology use on learning outcomes through outside-school use and socioeconomic status mediation: The ecological techno-process. *Educational Technology Research and Development*, *68*(1), 413–436. https://doi. org/10.1007/s11423-019-09707-x

Chugh, R. & Ruhi, U. (2018). Social media in higher education: A literature review of facebook. *Education and Information Technologies*, *23*, 605–616. https://doi.org/10.1007/s10639-017-9621-2

Crosier, D., & Sigalas, E. (2022). Towards equity and inclusion in higher education in Europe: Eurydice report. *Luxembourg: Publications Office of the European Union, 2022*. https://hdl.handle.net/11162/222272

Di Pietro, G. (2021). Changes in Italy's education-related digital divide. *Westminster Research*. https://doi.org/10.1111/ecaf.12471

DiMaggio, P., Hargittai, E., Neuman, W. R., & Robinson, J. P. (2001). Social implications of the internet. *Annual Review of Sociology*, *27*, 307–336. https://doi.org/10.1146/annurev.soc.27.1.307

Dindar, M. (2018). An empirical study on gender, video game play, academic success and complex problem solving skills. *Computers & Education*, *125*, 39–52. https://doi.org/10.1016/j.compedu.2018.05.018

Fernàndez-Gutiérrez , M., Gimenez, G., & Calero, J. (2020). Is the use of ICT in education leading to higher student outcomes? Analysis from the spanish autonomous communities. *Computers & Education*, *157*. https://doi.org/10.1016/j.compedu.2020.103969

Fraillon, J., Ainley, J., Schulz, W., Duckworth, D., & Friedman, T. (2019). *IEA International computer and information literacy study. 2018 Assessment Framework*. Springer International Publishing. https://doi.org/10.1007/ 978-3-030-19389-8

Gasaymeh, A. (2018). A study of undergraduate students' use of Information and Communication Technology (ICT) and the factors affecting their use: a developing country perspective. *EURASIA Journal of Mathematics, Science and Technology Education*, *14*(5), 1731–1746. https://doi.org/10.29333/ejmste/85118

Gebhardt, E., Thomson, S., Ainley, J., && Hillman, K (2019). What have we learned about gender differences in ICT? In *Gender differences in computer and information literacy: An in-depth analysis of data from ICILS* (pp. 69–73). https://doi.org/10.1007/ 978-3-030-26203-7_6

Gómez-Gonzalvo, F., Molina, P., & Devìs-Devìs, J. (2020). Which are the patterns of video game use in spanish school adolescents? gender as a key factor. *Entertainment Computing*, *34*. https://doi.org/10.1016/j.entcom.2020. 100366

Goudeau, S., Sanrey, C., Stanczak, A., Manstead, A., & Darnon, C. (2021). Why lockdown and distance learning during the covid-19 pandemic are likely to increase the social class achievement gap. *Nature Human Behaviour*, *5*(10), 1273–1281. https://doi.org/10.1038/s41562-021-01212-7

Greenberg, B. S., Sherry, J., Lachlan, K., Lucas, K., & Holmstrom, A. (2010). Orientations to video games among gender and age groups. *Simulation & Gaming*, *41*(2), 238–259. https://doi.org/10.1177/1046878108319930

Han, J., & Pei, J. (2000). Mining frequent patterns by pattern-growth. *ACM SIGKDD Explorations Newsletter*, *2*, 14–20. https://doi.org/10.1145/ 380995.381002

Heo, H., & Kang, M. (2010). Impacts of ICT use on school learning outcome. In F. Scheuermann, & F. Pedró (Eds.), *Assessing the effects of ICT in education. Indicators, criteria and benchmarks for international comparisons* (pp. 189-198). European Commission Joint Research Centre. https://erte.dge.mec.pt/sites/default/files/Recursos/Estudos/assessingtheeffectsofictineducation.pdf

ISTAT. (2020a). Il rapporto Istat sul BES. *ISTAT*. https://www.istat.it/it/ files//2021/03/BES_2020.pdf

ISTAT. (2020b). Italian multipurpose survey on households. *ISTAT*. https://www.istat.it/wp-content/uploads/2014/08/ISTAT_MFR_AVQ_2020_IT-2.zip

Kenny, E. (2017). Settlement in the digital age: Digital inclusion and newly arrived young people from refugee and migrant backgrounds. *Centre for Multicultural Youth*. https://www.cmy.net.au/wp-content/uploads/2020/03/ Settlement-in-the-digital-age_Jan2017.pdf

Ludvìk, E., Łukasz, T., Milan, K., Maria, P., & Gabriela, P. (2020). How do first year university students use ICT in their leisure time and for learning purposes? *International Journal of Cognitive Research in Science, Engineering and Education*, *8*(2), 35–52. https://doi.org/10.5937/IJCRSEE2002035E

Nachmias, R., Mioduser, D., & Shemla, A. (2001). Information & Communication Technologies usage by students in an Israeli high school: Equity, gender, and inside/outside school learning issues. *Education and Information Technologies*, *6*, 43–52. *h*ttps://doi.org/10.1023/A:1011367212148

OECD. (2017). *Pisa 2018 ICT familiarity questionnaire*. OECD Publishing. https://www.oecd.org/pisa/data/2018database/CY7_201710_QST_MS_ICQ_ NoNotes_final.pdf

OECD. (2023). *PISA 2022 Assessment and Analytical Framework*. OECD Publishing.
https://doi.org/https://doi.org/10.1787/dfe0bf9c-en

Ola Lindberg, J., & Sahlin, S. (2011). Bridging school-subjects and distances in upper secondary schools. *Campus-Wide Information Systems*, *28*(3), 144–153. https://doi.org/10.1108/10650741111145670

Olofsson, A. D., Lindberg, O. J., & Fransson, G. (2018). Students' voices about information and communication technology in upper secondary schools. *The International Journal of Information and Learning Technology*, *35*(2), 82–92. https://doi.org/10.1108/IJILT-09-2017-0088

Phan, M. H., Jardina, J. R., Hoyle, S., & Chaparro, B. S. (2012). Examining the role of gender in video game usage, preference, and behavior. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol.56 (pp.1496– 1500). Sage Publications. https://doi.org/10. 1177/1071181312561297

Raschka, S. (2018). Mlxtend: Providing machine learning and data science utilities and extensions to python's scientific computing stack. *Journal of Open Source Software*, *3*(24), 638.

Riggins, F., & Dewan, S. (2005). The digital divide: Current and future research directions. *Journal of the Association for Information Systems*, 6:298–337. https://doi.org/10.17705/1jais.00074.

SANFO, J.-B. M. B. (2023). Examining student ICT use and learning outcomes: Evidence from Japanese Pisa data. *Computers and Education Open*, *4*. https://doi.org/10.1016/j.caeo.2023.100141

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53. https://doi.org//10.5116/ijme.4dfb.8dfd

Tuszynski, J., & Khachatryan, M. H. (2013). Package 'Catools'. https://cran.r-project.org/web/packages/caTools/caTools.pdf

van Dijk, J. (2005). *The deepening divide: Inequality in the information society*. SAGE Publications. https://doi.org/10.4135/9781452229812

Vassilakopoulou, P., & Hustad, E. (2023). Bridging digital divides: A literature review and research agenda for information systems research. *Information Systems Frontiers*, *25*(3), 955–969. https://doi.org/10.1007/s10796-020-10096-3

Wastiau, P., Blamire, R., Kearney, C., Quittre, V., Van de Gaer, E., & Monseur, C. (2013). The use of ICT in education: a survey of schools in europe. *European Journal of Education*, *48*(1), 11–27. https://doi.org/10.1111/ejed.12020

Xiao, F. & Sun, L. (2022). Profiles of student ICT use and their relations to background, motivational factors, and academic achievement. *Journal of Research on Technology in Education*, *54*(3), 456–472. https://doi.org/10.1080/15391523. 2021.1876577

Zhang, C. & Zhang, S. (2002). *Association rule mining: models and algorithms*. Springer. https://doi.org/10.1007/3-540-46027-6