

Article

Not Just a Screen: Understanding Students' Engagement with Digital Technology in Educational Settings

Costanza Baviera ¹, Nicla Cucinella ^{2,*}, Francesco Preiti ³, Francesca Liga ⁴, Cristiano Inguglia ²
and Sonia Ingoglia ²

¹ Department of Research and Innovation in Humanities, University of Bari "Aldo Moro", 70121 Bari, Italy; c.baviera@phd.uniba.it

² Department of Psychology, Educational Science and Human Movement, University of Palermo, 90128 Palermo, Italy; cristiano.inguglia@unipa.it (C.I.); sonia.ingoglia@unipa.it (S.I.)

³ Department of Psychology, University of Campania "Luigi Vanvitelli", 81100 Caserta, Italy; francesco.preiti@unicampania.it

⁴ Department of Clinical and Experimental Medicine, University of Messina, 98124 Messina, Italy; francesca.liga@unime.it

* Correspondence: nicla.cucinella@unipa.it

Abstract

This study explores students' attitudes towards technology for learning, their cellphone use in class, and their digital distraction during educational activities, also considering the potential role of some sociodemographic characteristics. Participants were 803 Italian middle school students ($M_{\text{age}} = 12.2$ years, $SD = 0.9$; 53% female). Using Latent Profile Analysis (LPA), we identified five profiles: *Low-engagement users*, *Highly distracted*, *Disengaged distracted users*, *Self-regulated users*, and *Moderate users*. Results highlighted small differences between profiles associated with age and maternal educational level. These findings underscore the dual nature of technology as both a valuable tool and a source of distraction from school activities, highlighting the importance of tailored strategies to promote balanced and mindful technology use. Future research should further explore how these profiles interact with broader psychosocial and developmental factors.

Keywords: digital technology; cellphone use; digital distraction; latent profile analysis; students

1. Introduction

Youth involvement with digital technology has sharply increased, especially among recent generations who have grown up as digital natives. This constant exposure has shaped how they communicate, learn, and face daily challenges [1,2]. In educational settings, digital technologies can support learning processes by facilitating access to resources, communication, and collaborative activities [3,4]. Digital tools may also help students organize study activities and engage with learning materials, although their benefits depend on how they are integrated into educational practices [5,6].

Although young people grow up surrounded by digital technology, their engagement with digital technology in education varies across individuals. Understanding both positive and problematic technology behaviors is crucial. This study aims to deepen knowledge of early adolescents' engagement with digital technology in educational settings by examining attitudes, behaviors, distraction, gender, and age.



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1.1. Students' Attitudes Towards Technology for Learning

Youth belong to a highly digitalized generation [7], and the impact of technology on their lives is massive from an early age. This early exposure to digital technologies significantly shapes youth familiarity with them. Notwithstanding, young people's relationship with digital technologies is shaped by several factors, one of which is their attitude towards technology. This is a significant aspect, as it influences the ways in which they engage with and use technological tools. Indeed, attitudes lead to a preference for certain technologies for learning, with students tending to choose technologies they are more familiar with [8].

Staddon [9] has outlined that the factors that most strongly influence students' overall attitudes towards technology for learning are confidence and perceived utility. Confidence in technology is a perception that increases with usage [10]. The literature indicates that students' greater confidence in technology is also associated with a higher perceived ease of use of a given technology as well as their self-efficacy and perseverance [11]. Perceived utility refers to how students use the technology and how useful they consider technology for a specific purpose, in agreement with Sun et al. [12], who suggest that students evaluate which technology best suits a given task, and that this evaluation, in turn, shapes their attitude toward it. At the core of students' attitude towards technology—expressed in terms of confidence and perceived utility—Staddon [13] found that students choose to use a technology based on its purpose and convenience.

1.2. Students' Cellphone Use During School

Unlike previous generations, contemporary adolescents are among the first to be raised with portable touchscreen devices [14,15]. Cellphones are constantly present in students' lives, often used even during class despite school restrictions [16]. Research has highlighted its psychological effects, frequently pointing to signs of abuse [17]. While cellphone use can have both positive and negative impacts on students' well-being, including life satisfaction and academic performance, the risks remain significant [18]. Montag et al. [19] also referred to problematic cellphone use as similar to addiction. It is therefore crucial to bear in mind how the use of such a device is integrated into the everyday lives of youth, so that we can develop a greater awareness related to the correct use of the tools of the digital world.

1.3. Students' Digital Distraction in School Activities

One of the undesirable effects of digital technology in school contexts is the increase in the distraction of students in carrying out homework, both in the classroom and at home. In fact, it has been shown that being constantly surrounded by digital devices increases the likelihood of distraction [20,21].

The emergence of new technologies has posed a novel challenge to students' ability to stay focused while completing assignments [21]. Evidence from different studies [16,22] suggests that the use of digital devices in the classroom is prevalent and causes significant distraction in learning and that, in addition, students who use cellphones in the classroom also tend to distract their classmates [23]. In terms of the relationship between distraction and students' attitudes towards technology, Scherer and Hatlevik [24] found that perceived distraction from digital devices was negatively related to perceived usefulness. In other words, when students felt distracted by technology, they were less likely to perceive it as useful. This reduced perceived usefulness, in turn, was associated with lower levels of technology use in class and decreased self-efficacy. Conversely, students who perceived technology as useful tended to use it more and reported greater confidence in using it.

1.4. Sociodemographic Differences in Students' Engagement with Digital Technology in Educational Settings

Two personal characteristics that can play an important role in students' engagement with digital tools are students' gender and age. In terms of attitudes, Cai et al. [25] highlighted that males hold more favorable attitudes towards technology use than females. Accordingly, Yau and Cheng [26] found that male students report greater confidence in using technology for learning than female students, while results from Suri and Sharma [27] showed that no significant relationship was found between gender and attitudes towards technology and e-learning. Findings from Hilao and Wichadee [28] showed that male and female students did not differ in their usage and attitudes towards cellphone for language learning, but another study [29] indicates that females exhibited significantly higher degrees of cellphone dependence compared to males. In terms of distraction, one of the main differences between male and female students is the type of activity they choose, as it emerged that female students engaged with social media significantly more than male students, whereas male students played games significantly more than female students [30].

Another important factor to consider alongside gender is age, which has been shown to influence students' attitudes and behaviors related to technology use. Research indicates that younger students tend to use technologies more frequently [9]; moreover, older students may initially show lower confidence in their digital skills, which improves over time with experience [31]. Finally, there is not much empirical evidence regarding the relationship between students' age and digital distraction during school activities.

Beyond gender and age, family sociodemographic characteristics may also contribute to students' engagement with digital technology. In particular, parental educational level is commonly used as an indicator of socioeconomic background [32], whereas the number of children in the family and firstborn status capture additional aspects of the family context.

To integrate these dimensions within a coherent conceptual framework, the present study draws on a self-regulated learning perspective [33,34]. From this perspective, confidence and perceived utility can be understood as motivational and cognitive beliefs that shape whether and how students engage with digital technologies for learning. Cellphone use in class represents the behavioral expression of this engagement, whereas digital distraction reflects the attentional and behavioral difficulties that may arise when technology use is not effectively regulated in relation to academic goals. Importantly, positive attitudes toward technology do not necessarily result in purposeful or well-regulated use. Students may feel confident in using technology and perceive it as useful while simultaneously engaging in frequent cellphone use that interferes with attention and learning activities. Conversely, limited cellphone use and low distraction may coexist with low confidence and perceived utility, reflecting limited digital engagement rather than effective self-regulation. Attitudes, cellphone use, and distraction can therefore be conceptualized as interconnected but distinct components of students' digital engagement in educational settings.

Taken together, these strands of research suggest that students' engagement with digital technology in educational settings cannot be fully understood by considering attitudes, cellphone use, and digital distraction as isolated dimensions. Students may simultaneously report positive attitudes toward technology and experience high levels of distraction, whereas others may show limited use and low distraction but also low confidence and perceived utility. In this sense, variable-centered approaches may overlook meaningful combinations of attitudes and behaviors that characterize different groups of students. A person-centered approach is therefore useful because it allows the identification of distinct patterns of digital engagement, capturing how confidence, perceived utility, cellphone use, and distraction co-occur within individuals.

1.5. The Present Study

The general aim of the study was to better understand students' engagement with digital technology in educational settings by examining the relationship among their attitudes towards technology for learning, their cellphone use in class and their digital distraction during educational activities at school and at home, also considering the possible role of some sociodemographic characteristics, such as gender, age, paternal and maternal educational levels, number of children and firstborn status, with respect to these variables. Specifically, based on the theoretical premises and empirical studies reported previously, we aimed at identifying latent profiles of students related to (a) attitudes towards technology, in terms of confidence in using technology and its perceived utility, (b) cellphone use in the classroom, and (c) digital distraction during school activities in class and at home. We expected these dimensions to combine in heterogeneous patterns, reflecting different forms of digital engagement and self-regulation among students.

Our second aim was to explore the association of student profiles with gender, age, paternal and maternal educational levels, number of children and firstborn status. Given the limited and inconsistent evidence regarding how these sociodemographic characteristics relate to combinations of digital attitudes, behaviors and distraction, these associations were examined exploratorily.

This study adopts a person-centered approach to jointly examine the relationship between attitudes towards technology, behaviors and distractions. By capturing the heterogeneity of student experiences, this approach allows for a more nuanced and targeted interpretation of how attitudes, behaviors, and sociodemographic characteristics combine in shaping students' experience.

2. Materials and Methods

2.1. Participants

Participants were 803 students from southern Italy (53% female; 99.5% were Italian nationals) aged between 10 and 14 years ($M = 12.2$ years, $SD = 0.9$). Most participants (95.8%) attended middle school, 3.8% attended high school, and 0.4% attended elementary school. Moreover, 22.5% of participants were only children, and 39.4% had a brother or a sister, while 38.1% lived in a family with three or more children; three responses were inconsistent with the reported birth order and were therefore treated as missing in analyses. Regarding the birth order, 50.1% of participants were first born, 36.4% were second-born, and 13.5% were third-born or more. This variable was dichotomized as firstborn and non-firstborn. Finally, regarding parents' educational degrees, 1.5% of fathers had a primary school diploma, 21.5% had a middle school diploma, 49.3% had a high school diploma, 25.8% had a university degree, and 1.9% had a postgraduate degree; 1% of mothers had a primary school diploma, 17.2% had a middle school diploma, 45.8% had a high school diploma, 34.7% had a university degree, and 1.3% had a postgraduate degree.

2.2. Procedure

The study was conducted using an online survey created with PsyToolkit (version 3.6.2). Participants were recruited using a non-probability snowball sampling method. Specifically, psychology students and research assistants, primarily based in Southern Italy, were invited to share the survey link within their personal and academic networks. Participation was voluntary and anonymous, and no incentives were provided. Informed consent was obtained from all participants, and parental consent was required for minors. The study was approved by the Research Ethics Committee of the University of Campania "Luigi Vanvitelli" and conducted in accordance with the Declaration of Helsinki and the ethical guidelines of the Italian Association of Psychology (AIP).

2.3. Measures

2.3.1. Attitudes Towards Technology for Learning

Students were administered a section of the Technology Attitudes Questionnaire (TAQ; [9]). It taps students' attitudes towards technology. The scale consists of 17 items articulated in two subscales: (a) *Confidence in using technology* (8 items, e.g., "I generally feel confident working with technology"), and (b) *Perceived utility of technology for learning* (9 items, e.g., "Technology can help me organize my studies"). Items were rated on a 7-point Likert scale ranging from 1 (Entirely disagree) to 7 (Entirely agree). Two total scores were obtained as the mean of item scores for each subscale. In the present study, the internal consistency was good for both subscales: Cronbach's α was 0.84 and 0.88, for Confidence in using technology and for Perceived utility of technology for learning, respectively.

2.3.2. Cellphone Use Time in Class

Students were administered the Cellphone Use Questionnaire (CPU; Ref. [35,36]). It is a 4-item scale measuring students' cellphone usage time during class activities, asking for how many minutes (from 0 to 60) students use cellphones in class to read or send emails or text messages, visit social networks, access the Internet, check the calendar, and play games. A total score was obtained as average of item scores. In the present study, the internal consistency was good: Cronbach's $\alpha = 0.83$.

2.3.3. Digital Distraction During School Lessons

Students were administered the Digital Distraction Intensity (DDI; Ref. [20]). It is a 5-item scale assessing distraction from digital devices for non-classroom related activities, such as surfing the web, reading/sending text messages and visiting social networking sites. Items were rated on a 5-point Likert scale ranging from 1 (Never) to 5 (Very frequently). A total score was obtained as average of item scores. In the present study, the internal consistency was excellent: Cronbach's $\alpha = 0.92$.

2.3.4. Digital Distraction During Homework

Students were administered the Tech-related distraction subscale of the Homework Distraction Scale (HDS; Ref. [37,38]), assessing their distraction while carrying out homework, such as interrupting homework assignments to send text messages or play games. It consists of 3 items which were slightly modified for the needs of the study and the sample: "Stop homework to play online games or video games", "Stop homework to use social network", and "Stop homework to send or receive text messages". Items were rated on a 5-point Likert scale ranging from 1 (Never) to 5 (Routinely). A total score was obtained as average of item scores. In the present study, the internal consistency was adequate: Cronbach's $\alpha = 0.75$.

2.4. Data Analyses

The analyses conducted to achieve our research objectives consisted of two steps: Latent Profile Analysis (performed in Mplus, version 8) and examination of the associations between profile membership and sociodemographic variables (performed using SPSS, version 25).

2.4.1. Latent Profile Analysis

Latent Profile Analysis was selected because it is a model-based person-centered approach that identifies unobserved subgroups of individuals based on their responses to continuous indicators. Compared with traditional cluster analytic procedures, such as k-means or hierarchical clustering, LPA offers a probabilistic classification of individuals, allows alternative profile solutions to be compared through likelihood-based fit indices and statistical tests, and enables the quality of classification to be formally evaluated through indices such

as entropy and posterior membership probabilities [39,40]. These features were considered particularly appropriate for the present study, which aimed to identify empirically derived patterns of students' digital engagement rather than to impose predefined groups.

In order to identify students' digital engagement profiles that best describe the heterogeneity within the current sample, we performed a LPA including these five dimensions as observed indicators (after saving the relevant factor scores): confidence in using technology, perceived utility of technology for learning, cellphone use time in class, digital distraction during school lessons and digital distraction during homework. The LPA thus aimed to identify the different ways (i.e., profiles) in which these five variables interplay in our sample.

We examined fit indices of measurement models, beginning with one profile and adding profiles incrementally. To reduce the risk of local maxima, the number of random starting values was progressively increased as the number of profiles increased, and models were re-estimated until the best log-likelihood value was replicated. Although no empirical under-identification or convergence problems were encountered, we stopped estimating additional profiles to the 10-profile model because the groups had become too small. As suggested by Sorgente et al. [41], selecting the optimal fitting model was based on descriptive measures of relative model fit and statistical tests.

As descriptive measures of relative model fit, we adopted five information criteria: Akaike Information Criterion (AIC), Consistent AIC (CAIC), Approximate Weight of Evidence Criterion (AWE), Bayesian Information Criterion (BIC), and the Sample-size adjusted BIC (ssBIC). For all criteria, lower values indicate a better fit.

As statistical tests, we adopted the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT; Refs. [42,43]) and the adjusted Lo-Mendell-Rubin likelihood ratio test (adjusted LMR-LRT; Ref. [42]). These two tests compare a $(k - 1)$ -class model with a k -class model; a statistically significant p -value suggests that the k -class model fits the data significantly better than a model with one less class. Conversely, if it is not significant, the k -class model is as good as the $(k - 1)$ -class model, so the $(k - 1)$ class model is preferred according to parsimony criterion.

After selecting the best model, the quality of its classification (i.e., assignment of people to profiles) must be evaluated [39]. The most common diagnostic classification is Entropy (E_k), where values closer to 1 indicate a better classification of cases. Furthermore, the quality of the classification needs to be evaluated by checking the Class Proportion (CP_k or π_k), the modal class assignment Proportion ($mcaP_k$), the Average Posterior Probability ($AvePP_k$), and the Odds of Correct Classification ($OCCK$). In particular, classification can be considered good when the $mcaP_k$ for each profile is included in the 95% CI of the π_k , $avePP_k$ values are equal to 0.70 or higher and $OCCK$ values are above 5 [39,41].

2.4.2. Analysis of Sociodemographic Differences Across Profiles

After identifying the best LPA model, we saved the most likely profile membership for each individual, thereby obtaining an observed variable representing each participant's membership in a specific digital engaged group. We used this profile membership variable to test the relationship each profile has with students' sociodemographic characteristics.

In particular, a chi-square test was performed in SPSS to describe the attitudes towards technology and behaviors profiles in relation to gender (male vs. female) and firstborn status (firstborn vs. non-firstborn). Furthermore, one-way analyses of variance (ANOVA) were conducted to examine differences across profiles in age, maternal and paternal educational levels, and the number of children in the family. Maternal and paternal educational levels were coded on a five-point scale ranging from 1 (Primary school diploma) to 5 (Postgraduate degree), with higher scores indicating higher educational attainment. Partial eta squared was reported as an effect-size measure. When the homogeneity of variance assumption was violated, Welch's robust test was used. Post hoc analyses were performed using the Bonferroni test.

3. Results

3.1. Descriptive Statistics

First of all, descriptive statistics and correlations between the study variables were estimated; the results are summarized in Table 1. The observed values of skewness and kurtosis for these variables were mostly within the acceptable range of -1.00 to $+1.00$ [44], with a few exceptions. Overall, the distributions can be considered approximately normal. Regarding the correlation, confidence in using technology and perceived utility showed only weak, non-significant associations with digital distraction variables. Cellphone use time in class showed moderate positive associations with both digital distraction during school lessons and during homework, while digital distraction during lessons and homework were strongly correlated.

Table 1. Mean, standard deviation, skewness, kurtosis, and Pearson correlation coefficients of study variables.

	1	2	3	4	5	6	7
1 Confidence in Using Technology	–						
2 Perceived Utility of Technology for Learning	0.64 **	–					
3 Cellphone Use Time in Class	−0.06	0.04	–				
4 Digital Distraction during School Lessons	0.06	0.16 **	0.37 **	–			
5 Digital Distraction during Homework	0.05	0.10 **	0.27 **	0.49 **	–		
6 Age	0.02	0.02	0.02	0.13 **	0.12 **	–	
7 Gender	0.01	−0.06	−0.09 *	0.03	0.01	0.03	–
M	5.56	5.07	14.01	2.62	2.93	12.24	1.53
SD	1.00	1.23	13.96	1.32	1.09	0.89	0.50
S	−0.98	−0.42	1.04	.30	0.01	0.04	−0.14
K	1.09	−0.31	0.23	−1.14	−0.80	−0.80	−1.99

Note. Gender was coded as 1 = male, 2 = female. * $p < 0.05$, ** $p < 0.01$.

Additionally, independent samples t-tests were conducted to examine group differences by gender. Results indicated that male students reported significantly higher cellphone use time in class compared to female students [$t(800) = 2.44$, $p = 0.015$], whereas no significant gender differences emerged for confidence in using technology, perceived utility of technology for learning, or digital distraction during school lessons and homework.

3.2. Identification of Latent Profiles

Ten different measurement models were performed, from the one with only one profile for the entire sample to the one with ten different profiles. As shown in Table 2, both the 5-profile and the 8-profile solutions performed better than the other solutions across multiple fit indices. In particular, the two statistical tests (i.e., the VLMR-LRT and the adjusted LMR-LRT) suggest that both the 5- and the 8-profile solutions are acceptable. Among the five information criteria, the AWE indicates the 6-profile solution as the best one, whereas the other four criteria (AIC, CAIC, BIC and ssBIC) are not fully informative as they continue to decrease with the increase in the number of profiles. Although the 8-profile solution also showed acceptable fit according to the likelihood-ratio tests, the additional profiles were small and less theoretically interpretable. Similarly, although the AWE criterion favored the 6-profile solution, this model did not provide a substantively clearer or more parsimonious representation of students' digital engagement patterns. Therefore, the 5-profile solution was retained because it offered the best balance between statistical adequacy, classification quality, parsimony, profile size, and theoretical interpretability.

As suggested by Masyn [39] we evaluated the classification quality of this 5-profile solution; in other words, we assessed the accuracy of participants' classification. First, as reported in Table 3, we found that Entropy was sufficiently high to suggest a high-quality classification.

Furthermore, the other classification diagnostics (i.e., Class Proportion; modal class assignment Proportion; Average Posterior Probability; Odds of Correct Classification) too indicated that the 5-profile solution produces well-separated and highly differentiated groups, whose members have a high degree of homogeneity in their responses on the profile indicators.

The five latent profiles (see Figure 1), representing five patterns of digital engagement in educational settings, were named as follows: *Low-engagement users* ($n = 70$; 9%), *Highly distracted* ($n = 176$; 22%), *Disengaged distracted users* ($n = 87$; 11%), *Self-regulated users* ($n = 272$; 34%), *Moderate users* ($n = 198$; 24%).

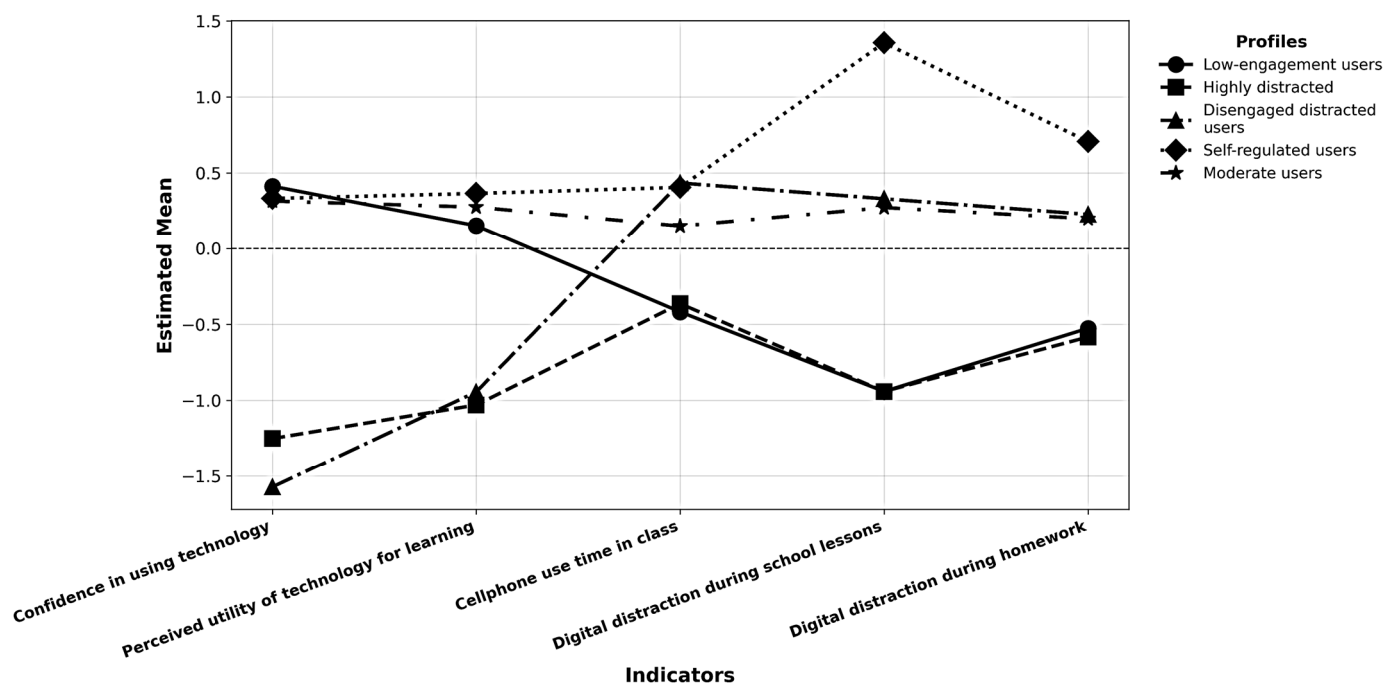


Figure 1. Estimated means of the five indicators included in the Latent Profile Analysis across the five-profile solution.

Low-engagement users had poor attitudes towards technology (very low confidence and perceived utility of technology for learning), low tendency to use cellphones in class and, consequently, low levels of distraction during both lessons and homework.

An opposite trend was found for the second latent profile presented in our sample (*Highly distracted*). It characterizes those with the highest levels of distraction and with high levels of cellphone use in the classroom; furthermore, this cluster reports high perceptions of confidence and utility in the use of technology.

The third latent profile (*Disengaged distracted users*) represents individuals with the lowest levels of confidence using technologies and with very low levels of perceived utility; but they score very high on cellphone use in class and, consequently, high distraction scores during both lessons and homework.

In contrast, the fourth latent profile (*Self-regulated users*) consists of individuals with high levels of confidence using technologies and with average levels of perceived utility; but they score very low on distraction during both lessons and homework with low tendency to use cellphones in class.

Finally, the last latent profile (*Moderate users*) includes individuals who had average levels in all five observed indicators.

Table 2. Absolute and Relative Model Fit Indices for Ten Latent Profile Models.

Model	LL	AIC	CAIC	AWE	BIC	ssBIC	SIC	BF	cmP	VLMR-LRT Test	LMR-LRT Test	BLRT Test
1-profile	−5468.979	10,957.958	11,014.842	11,101.725	11,004.842	10,973.086	−5502.421	0.00	6.9981×10^{-218}			
2-profile	−5236.416	10,504.832	10,595.846	10,734.859	10,579.846	10,529.037	−5289.923	0.00	1.3541×10^{-125}	$p < 0.001$	$p < 0.001$	$p < 0.001$
3-profile	−5093.048	10,230.096	10,355.240	10,546.384	10,333.240	10,263.377	−5166.620	0.00	4.80225×10^{-72}	$p < 0.001$	$p < 0.001$	$p < 0.001$
4-profile	−5040.824	10,137.648	10,296.922	10,540.196	10,268.922	10,180.006	−5134.461	0.00	4.44522×10^{-58}	$p = 0.0326$	$p = 0.0348$	$p < 0.001$
5-profile	−4975.007	10,018.014	10,211.418	10,506.822	10,177.418	10,069.449	−5088.709	0.00	0.00	$p = 0.0004$	$p = 0.0005$	$p < 0.001$
6-profile	−4921.667	9923.334	10,150.868	10,498.402	10,110.868	9983.846	−5055.434	0.00	0.00	$p = 0.2908$	$p = 0.2999$	$p < 0.001$
7-profile	−4884.238	9860.476	10,122.140	10,521.805	10,076.140	9930.064	−5038.070	0.00	0.00	$p = 0.0715$	$p = 0.0754$	$p < 0.001$
8-profile	−4849.455	9802.910	10,098.704	10,550.499	10,046.704	9881.575	−5023.352	0.00	0.00	$p = 0.0154$	$p = 0.0169$	$p < 0.001$
9-profile	−4816.059	9748.118	10,078.043	10,581.967	10,020.043	9835.860	−5010.021	0.00	0.00	$p = 0.0881$	$p = 0.0946$	$p < 0.001$
10-profile	−4788.376	9704.752	10,068.807	10,624.861	10,004.807	9801.570	−5002.403	/	1.00	$p = 0.0522$	$p = 0.0557$	$p < 0.001$

Note. LL = Loglikelihood; AIC = Akaike Information Criterion; CAIC = Consistent AIC; AWE = Approximate Weight of Evidence Criterion; BIC = Bayesian Information Criterion; ssBIC = Sample-Size Adjusted BIC; SIC = Schwarz Information Criterion; BF = Bayesian Factor; cmP = Approximate Correct Model Probability; VLMR-LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test; LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrapped Likelihood Ratio Test.

Table 3. Classification Diagnostics for the Five-Profile Model.

Entropy	Class (N)	CP _k	mcaP _k	AvePP _k	OCC _k
0.844	Profile 1 (70)	0.095 (0.060 – 0.157)	0.087	0.877	67.923
	Profile 2 (176)	0.220 (0.185 – 0.259)	0.219	0.932	48.594
	Profile 3 (87)	0.107 (0.064 – 0.145)	0.108	0.860	51.267
	Profile 4 (272)	0.331 (0.266 – 0.379)	0.339	0.923	24.228
	Profile 5 (198)	0.246 (0.203 – 0.291)	0.247	0.867	19.980

Note. CP_k = Class Proportion; mcaP_k = modal class assignment Proportion; AvePP_k = Average Posterior Probability; OCC_k = Odds of Correct Classification.

3.3. Relationship Between Profiles and Sociodemographic Variables

We saved the most likely class membership for each individual to use as an observed variable representing each participant's membership in a specific technology use attitudes and behaviors profile. We further tested how the technology use attitudes and behaviors profiles were related to gender and firstborn status (by a chi-square test), and to age, paternal and maternal educational levels and number of children (by a one-way ANOVA).

The association between latent profiles and gender was not significant [$\chi^2(4) = 3.806$, $p = 0.433$]. Profile membership was significantly associated with age [$F(4, 798) = 5.832$, $p < 0.001$, partial $\eta^2 = 0.028$]. Specifically, a significant difference was found between the Low-engagement users profile (composed of younger students) and the Highly distracted profile (composed of older students). Maternal educational level differed significantly across profiles [$F(4, 798) = 3.099$, $p = 0.015$, partial $\eta^2 = 0.015$]. However, Bonferroni-adjusted post hoc comparisons did not identify any significant pairwise differences. For paternal educational level, the homogeneity of variance assumption was not met. Welch's robust test showed no significant differences across profiles [Welch's $F(4, 267.66) = 2.099$, $p = 0.081$, partial $\eta^2 = 0.011$]. No significant differences in the number of children in the family emerged across profiles [$F(4, 795) = 0.937$, $p = 0.442$, partial $\eta^2 = 0.005$], and firstborn status was also not significantly associated with profile membership [$\chi^2(4) = 5.585$, $p = 0.232$].

4. Discussion

The present study examined students' engagement with digital technology in educational settings by exploring the relationships among their attitudes towards technology for learning, cellphone use in class, and digital distraction at school and at home, while also considering the role of gender and age. Five distinct student profiles were identified, offering a nuanced view of how students interact with technology in these contexts.

The first profile, labeled *Low-engagement users*, was characterized by very low confidence and perceived utility of technology for learning, minimal cellphone use in class, and correspondingly low distraction levels. This suggests limited engagement with educational technologies both attitudinally and behaviorally. Although this pattern may appear less problematic than highly distracted profiles, it is theoretically and educationally relevant because it may indicate reduced familiarity with digital tools, fewer opportunities to develop digital confidence, or broader disengagement influenced by prior negative experiences or contextual barriers. As Staddon [13] highlights, students often avoid technology they find difficult to use, unreliable, or poorly implemented by instructors. In school contexts increasingly characterized by the integration of digital tools, students in this profile may, therefore, require support not primarily in reducing distraction but in developing confidence, perceived usefulness, and meaningful opportunities to engage with technology for learning purposes.

The second profile, named *Highly distracted*, showed high confidence and perceived utility of technology but also the highest levels of cellphone use and digital distraction. This suggests that while these students are engaged with digital tools, they may struggle to regulate their use during academic tasks. Supporting Malureanu et al. [11], greater confidence relates to ease of use and perseverance, explaining their positive attitudes. However, frequent device use – especially cellphones in class – is linked to significant distraction affecting both users and peers [23]. Scherer and Hatlevik [24] found distraction usually reduces perceived usefulness and self-efficacy, but this profile shows that high confidence can coexist with distraction, highlighting the complexity of digital engagement where positive attitudes do not always lead to focused technology use.

The third profile, labeled *Disengaged distracted users*, showed low confidence and perceived utility of technology but high cellphone use and distraction. This pattern may be interpreted as a less regulated form of cellphone use rather than as a simple expression of positive digital engagement. Prior research has linked frequent cellphone use in learning contexts with distraction and poorer learning-related outcomes [23], while broader literature on problematic smartphone use suggests that frequent or automatic use may occur even when individuals do not evaluate such use positively [19,45]. Therefore, this profile should be interpreted cautiously as potentially reflecting difficulties in regulating cellphone use during academic activities.

The fourth profile, named *Self-regulated users*, includes students with high digital confidence and average perceived utility of technology, but low levels of cellphone use and distraction. This group may represent the “ideal” technology users – those who are comfortable with digital tools and able to effectively self-regulate their use during learning activities. The benefits of technology – like knowledge acquisition, communication, and collaboration – are greatest for students who use digital tools strategically and regulate their use to minimize distractions, maximizing learning potential [3,4].

Finally, the fifth profile, labeled *Moderate users*, reflected moderate levels across all dimensions, suggesting a more balanced or relatively undifferentiated pattern of technology use in education. This profile may capture a large group of students whose digital engagement is neither clearly problematic nor optimal. Although these students may not require intensive or highly targeted intervention, they should not be overlooked. Universal classroom strategies aimed at strengthening digital self-regulation, promoting intentional use of digital tools, and preventing moderate distraction from becoming more disruptive over time may be particularly useful for this group.

The second aim of the study was to explore whether students’ profiles differed by some sociodemographic characteristics. Findings revealed significant, although modest, age differences across profiles. Specifically, students in the Low-engagement users profile were younger, whereas those in the Highly distracted profile tended to be older. This age difference may be interpreted in light of developmental changes occurring during early adolescence, a period characterized by increasing autonomy, broader access to digital environments, and greater involvement in peer-related online activities [15]. Developmental research indicates that increasing autonomy from adults and the growing salience of peer relationships may expand adolescents’ opportunities and motivation for independent digital engagement. At the same time, self-regulatory capacities continue to develop and remain particularly sensitive to social and motivational cues during this period [46–48]. Younger students may have more restricted or supervised access to technology, possibly due to parental control, leading to less frequent use and lower distraction. In contrast, older students may have broader access to digital tools and longer experience with digital environments. Staddon [9] found that attitudes toward digital technology are similar across ages, but younger students use a wider variety of tools more frequently, while older

students use fewer technologies but have longer experience. Thus, older students' membership in the profile characterized by positive attitudes and high distraction may reflect not only greater familiarity with technology, but also the developmental challenge of regulating digital opportunities in increasingly autonomous learning contexts. However, the small magnitude of the observed age effect indicates that age had limited discriminatory value across profiles. Therefore, this finding should be interpreted cautiously and should not be taken to suggest clearly distinct developmental groups. Rather, age may represent only one of several factors contributing to profile membership, which was primarily defined by students' attitudes, cellphone use, and digital distraction. By contrast, no significant associations were found between profile membership and gender. This suggests that students' attitudes toward technology, behaviors, and levels of distraction are not strongly influenced by gender, aligning with recent literature indicating that gender gaps in digital engagement are becoming less pronounced, particularly among younger generations [49,50].

Maternal educational level also showed a statistically significant association with profile membership. However, the magnitude of this effect was small, and none of the pairwise comparisons remained significant after Bonferroni correction. Therefore, the finding appears to reflect limited overall variability across profiles rather than a clear difference involving specific groups and should be interpreted cautiously. Paternal educational level, family size, and firstborn status were not significantly associated with profile membership. Overall, these findings suggest that the identified profiles were only weakly differentiated by the family sociodemographic characteristics examined in this study. Nevertheless, the small overall association with maternal education suggests that family socioeconomic resources may contribute modestly to students' patterns of digital engagement, although parental education alone cannot provide a comprehensive assessment of socioeconomic background.

From a practical perspective, the identification of five profiles suggests that educational strategies should be differentiated. Students in the Low-engagement users profile may benefit from activities designed to increase confidence and perceived usefulness of technology for learning. Students with positive attitudes but high distraction may need support in digital self-regulation and classroom norms for focused technology use. Students with negative attitudes and high distraction may require more intensive guidance, combining support for meaningful educational technology use with strategies to reduce problematic or automatic cellphone use. Students with positive attitudes and low distraction may be encouraged to act as models of balanced technology use, whereas students with average attitudes and distraction may benefit from universal preventive strategies aimed at maintaining moderate and intentional digital engagement.

These findings should also be interpreted in light of the school policy context in which the data were collected. Data collection preceded the stricter nationwide restriction introduced in Italy for the 2024/2025 school year, which prohibited smartphone use in classrooms, including for educational purposes, except in specific cases related to accessibility and individualized educational needs [51]. At the time of data collection, students' cellphone use in class may, therefore, have been more dependent on school- and teacher-level rules. Accordingly, the profiles identified in this study reflect students' digital engagement before the implementation of this stricter national policy and may not fully capture patterns emerging under the current regulatory context.

Several limitations should be considered. The cross-sectional design prevents causal conclusions about the links between student profiles, technology use, and distraction. Self-reported data may introduce biases affecting accuracy. Although maternal and paternal educational levels were included as sociodemographic indicators, parental education represents only a partial proxy for socioeconomic background [52]. Other potentially

relevant contextual factors, such as household income, parental occupation, access to digital resources, parental mediation and supervision, school-level policies, and teaching quality, were not examined and may influence students' technology engagement and distraction. Future studies could use longitudinal designs to assess causality, include objective measures alongside self-reports, and explore contextual influences for a fuller understanding of students' digital engagement in education. Moreover, the use of non-probability snowball sampling limits the generalizability of the findings. The sample was drawn exclusively from Southern Italy using non-probability snowball sampling and should therefore be regarded as context-specific rather than representative of the broader Italian student population. Although focusing on a geographically defined context provides insight into patterns of digital engagement within this particular educational and sociocultural setting, the distribution and characteristics of the identified profiles may differ across regions with different educational resources, digital practices, and socioeconomic conditions. Accordingly, the findings should not be generalized to students from other Italian regions or national contexts. Future studies should replicate these findings using probability-based recruitment strategies and more geographically, socioeconomically, and culturally diverse samples.

In conclusion, this study sheds light on the diverse ways students engage with technology, revealing distinct profiles characterized by varying attitudes, behaviors and levels of digital distraction. The findings highlighted small differences associated with age and maternal educational level, whereas gender, paternal educational level, number of children and firstborn status were not significantly associated with profile membership. Understanding these patterns can inform tailored educational approaches aimed at fostering productive and focused use of technology in educational settings.

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