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Digital Capital and Cultural Capital in education: Unravelling intersections and distinctions that shape social differentiation

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Abstract

This article seeks to provide a clearer understanding of Digital Capital in education. It introduces a comprehensive analytical framework that explores the relationship between Digital Capital and Bourdieu's Cultural Capital Theory. Instead of treating digital skills and resources as separate entities, it integrates them into Cultural Capital Theory as complementary elements. This approach helps shed light on the disparities in ICT usage. Data from the 2018 OECD-PISA survey conducted in Italy are analysed to assess whether Digital Capital can be considered a component of Cultural Capital. The findings indicate that differences in Cultural Capital do not significantly impact the possession and usage of digital assets. Instead, distinctions become apparent through students' behaviours within the school environment. This underscores the connection between digital competencies and various dimensions of cultural and educational capital. The article posits that status and cultural disparities stem not solely from digital competencies but also from their interplay with social and cultural resources. This offers deeper insights into how the digital divide intersects with broader societal power dynamics.

KEYWORDS

Cultural Capital Theory, Digital Capital, ICT, LPA, PISA-OECD, school

Key insights

What is the main issue that the paper addresses?

The paper aims to clarify the concept of Digital Capital (DC) in the framework of Bourdieu's Cultural Capital Theory within the context of education. It seeks to investigate whether digital resources, skills, abilities and Internet usage contribute to establishing boundaries among social groups.

What are the main insights that the paper provides?

The paper sheds light on the relationship between digital competencies, Cultural Capital, school choice and school achievement, providing valuable insights for understanding the role of digital technologies in shaping educational opportunities and outcomes.

INTRODUCTION

In the last 20 years, a debate has arisen about the relevance of digital inequalities in the production and reproduction of social disparities. In this framework, Digital Capital (DC) arises as a key concept. Nevertheless, this concept is highly polysemous as it is used to talk about very different things, such as the 'amount' of digital-related individual skills and abilities, as well as the digital assets of a company that can boost or protect its activities and business.

In the sociological field, the concept of DC has gained significant attention and has been studied in relation to various aspects of society and education. Scholars have explored how individuals' digital skills and competencies contribute to their social and economic capital in the digital age. Additionally, the concept has been used to analyse the digital resources and infrastructures available to educational institutions and how they impact educational outcomes.

Despite growing popularity, DC lacks a precise and universally accepted definition. Scholars and researchers have used the concept differently, often drawing from different theoretical frameworks and disciplinary perspectives(Robinson, 2009; Ragnedda, 2017; Ragnedda and Ruiu, 2020). This polysemy has resulted in a certain level of confusion and ambiguity surrounding the concept.

In this article, we aim to contribute to clarifying the concept of DC within the context of education. By doing so, we seek to enhance our understanding of the role of digital technologies in shaping educational opportunities and outcomes. Our aims are twofold; firstly, we seek to clarify the appropriateness of using the notion of DC within the framework of Bourdieu's Cultural Capital Theory. Secondly, we aim to test the hypothesis of DC as a component or form of Cultural Capital by exploring the associations between variables related to digital skills, abilities and usage and other variables pertaining to cultural and educational choices and behaviours.

We hypothesise that if digital resources, skills, abilities and Internet use contribute to establishing boundaries among social groups with similar social, cultural and educational characteristics, then the hypothesis of DC may be considered validated. In other words, the digital assets, coherently with Bourdieu's Cultural Capital frame, should differentiate social groups and be consistent with other strategies for accumulating educational credentials related to Cultural Capital.

To test this hypothesis, we draw on statistical analysis from the 2018 OECD survey conducted for the Program for International Student Assessment (PISA) in Italy. The interest in studying the Italian case lies in the association between family school choices and school characteristics. The Italian school system is characterised by the diversity of secondary school programmes that generate a symbolic and educational stratification among schools, setting the so-called academic school programmes at the top and the vocational programmes at the bottom. In other words, school choices shape the structure of the school field in Italy. Therefore, we will highlight if family school strategies, family Cultural Capital and DC are associated with defining the school field structure (Pitzalis & Porcu, 2017).

Adopting a probabilistic classification model for latent variables, we aim to determine whether DC should be considered a significant component of Cultural Capital. While identifying specific groups of students based on their possession of Cultural Capital as an intangible asset, the results indicate that these groups are not significantly differentiated in their possession of digital assets. Instead, differentiation arises from their distinct school behaviours, perspectives and choices. Through the empirical analysis, we shed light on the potential linkages between digital competencies, Cultural Capital, school choice and school achievement.

This paper is articulated as follows: the next two sections examine the digital dimension of the Cultural Capital debate; subsequently, we present data and methods, and discuss empirical evidence, and a final section contains concluding remarks.

SETTING THE BACKGROUND

In the last 20 years, a debate has emerged regarding digital inequalities, shifting the focus from availability and access to usage (DiMaggio et al., 2004; DiMaggio & Hargittai, 2001). Evidence has been found regarding the relationship between individuals' Internet usage and other social and cultural variables (van Deursen & van Dijk, 2014). Hargittai and Hinnant (2008), in their study of a young adult population in the USA, shed light on the role of cultural background in explaining the propensity to engage in activities that could enhance their human, financial, political, social and Cultural Capital. They also highlighted the role of 'online skills' as a mediating factor in determining the online activities that people pursue. This research agenda addresses the question of which digital skills and uses enable socially, culturally, educationally and economically advantaged individuals to gain further advantages. The above-mentioned articles employ the notion of skills, with Hargittai and Hinnant (2008) operationalising DC as the self-reported ability to use the web and understand Internet-related terms. Nonetheless, these studies emphasise the multidimensionality of digital-related skills and abilities. Recent publications have also emphasised that, despite the diffusion of user-friendly Internet interfaces, skills continue to be an important shaper of Internet usage (Hargittai & Micheli, 2019).

Following Bourdieu's theory of habitus, Robinson (2009) has shown the persistence of an association between the quality and autonomy of Internet access and particular orientation in Internet use. Based on qualitative research, Calderón Gómez (2021) analyses feedback and reconversion mechanisms between economic, social and cultural forms of capital and DC, considering it a specialised form of Cultural Capital.

Ragnedda (2017), Ragnedda et al. (2019) and Ragnedda and Ruiu (2020) have comprehensively analysed and operationalised the concept of DC. They aim to consider the multidimensionality of digital inequalities and how they intersect with other social, cultural and economic capitals. They assert that the individual level of DC influences the quality and types of online activities and the benefits and tangible outcomes of accessing and using the Internet. These scholars emphasise that DC plays a crucial role in shaping individuals' experiences and opportunities in the digital realm, influencing educational achievements and various aspects of social life. By recognising the multidimensional nature of digital inequalities, researchers can better understand the complex dynamics between digital skills, social capital and digital outcomes. This conceptualisation upgrades the discussion on digital inequalities, moving beyond the focus on inequalities in access to digital devices or the Internet (the 'first-level' of the digital divide; Attewell, 2001; Selwyn, 2004) and inequalities in usage (the 'second level' of the digital divide). Instead, it considers the effects of cultural, educational and social advantages derived from possessing a higher level of digital competencies. The existence of a 'third level' of the digital divide is undoubtedly a critical issue in current research. Scholars are witnessing a growing gap that may impact individuals' capacity to participate in democratic life and exercise their civil rights actively (van Deursen & Helsper, 2015).

The notion of DC has also emerged within the scientific debate to explain how digital skills and competencies can impact educational and social outcomes and the evolution of digital inequalities today. Paino and Renzulli (2013), for instance, argue that students who possess digital skills present themselves as culturally competent members of the information-age society, thereby increasing their likelihood of educational success. They view DC as a new form of Cultural Capital that acts as a valuable social signal.

In this ongoing debate, the notion of DC has assumed a central position. This concept has the advantage of synthesising a complex set of elements. However, owing to its metaphorical strength, it runs the risk of being more suggestive than explanatory from a sociological standpoint. In conclusion, the concept of DC is multifaceted and has gained attention in both management/business and sociological fields. However, further theoretical and empirical work is needed to establish a clear and unified definition, explore its implications for educational practices and policies, and take into account current and future issues, such as the impact of Artificial Intelligence on education and society.

Cultural Capital and its digital dimension

Bourdieu and Passeron's influential work *Reproduction in Education, Society and Culture* (1977) explored the link between school selection and Cultural Capital. They revealed the persistence of selectivity within educational systems, even after the expansion and democratisation of schools following the 1968 protests. Surprisingly, the new, more open system did not significantly benefit hard-working lower-class students, as teachers continued to value the cultural familiarity and embodied distinctiveness of middle- and upper-class students. This advantage stemmed from the relaxed and confident attitude towards the culture that these students acquired through their family experiences, which makes membership in a status group evident for their teachers. Bourdieu's interpretation highlights how Cultural Capital, encompassing highbrow cultural activities and habitus, shapes the social dynamics of education and challenges notions of social domination within schools.

Our previous study criticised the use of Cultural Capital (Pitzalis & Porcu, 2017) as a causal variable directly affecting educational achievement. Instead, we considered Cultural Capital as a theoretical construct representing a latent variable encompassing a range of factors influencing the likelihood of a student choosing a particular school programme associated with similar cultural behaviours. Here, we test the hypothesis that variables related to the possession of technological devices, digital behaviour and digital consumption should be included within the ensemble of factors associated with the notion of Cultural Capital. Consistent with Bourdieu's theoretical standpoint and following Lareau and Weininger (2003), we consider Cultural Capital as a notion that indicates a set of factors producing social effects in social distinction and closure processes. Cultural Capital should be viewed in its dimension of a ‘signal’ and its capacity to define the boundaries of dominant social groups (Lamont & Lareau, 1988). Lamont and Lareau highlighted two fundamental elements that we consider essential. First, Cultural Capital is not intended solely as an individual asset; its effectiveness lies in its social dimension. This social dimension is primarily represented by the alignment of the highbrow Cultural Capital of the middle and upper-middle classes with the legitimate ‘culture’ promoted by educational agents. Second, the school field, as a space of institutional and symbolic differences, shapes how parents from different social classes utilise their resources (economic, social and cultural) to gain access to high-status schools (Lareau et al., 2016). Within this framework, possession of technological devices, digital behaviour and digital consumption should or should not be considered variables included in the ensemble of factors associated with the notion of Cultural Capital itself.

With the increasing integration of information and communication technologies (ICT) in classrooms over the past two decades, the digital aspects of Cultural Capital have gained prominence in the school environment. The DC could represent a theoretical frame appropriate to exploring how students combine their technical knowledge and skills with their academic curriculum, thereby reshaping power relations in the classroom. Paino and Renzulli (2013) propose the notion of DC to examine Cultural Capital and assess the impact of ICT in schools, specifically focusing on its role as a cultural resource in teacher–student interactions. This perspective aligns with a dynamic understanding of Cultural Capital that emphasises individuals’ agency and ability to challenge the status quo rather than a static view that sees social actors as constrained by structural factors. Accordingly, digital skills can be seen as a cultural resource influencing power dynamics within different contexts. Paino and Renzulli suggest that these skills and knowledge should be considered a distinct dimension of Cultural Capital. Regarding teacher–pupil interaction, Paino and Renzulli argue that DC is a valuable resource that can enhance student achievement, even among individuals with lower levels of Cultural Capital. However, the utilisation and value attributed to digital skills also depend on students’ academic inclination and overall educational environment. This was evident in ethnographic research conducted in Italy by Pitzalis et al. (2016), where it was observed that in schools with general academic programmes, students and teachers collaborated using digital devices to enhance school achievement. Instead, in vocational schools, students’ digital skills were only valued for slightly boosting their involvement in classroom activities. Consistently with this finding, Comi et al. (2017) demonstrate that practices requiring active student participation in ICT-based classes may negatively affect student learning outcomes unless teachers demonstrate their ability to integrate it within their teaching activities. Consequentely, we believe that DC should not be considered a dimension of Cultural Capital since it does not function as a sign of cultural distinction that aligns with teachers’ highbrow cultural and aesthetic values. Instead, teachers value it as part of their internal strategies to address the challenges of managing a classroom with diverse cultural and academic backgrounds. In any case, these studies emphasise the mediating role of teachers and schools.

Another element pertains to the ‘second level’ digital divide, which concerns technological skills and ICT knowledge. The emergence of new means and methods through digital skills has the potential to exacerbate existing social differences. While the first level of digital inequality persists among certain segments of the adult population, it is less pronounced among younger generations. Consequently, there is growing interest in studying second-level digital inequalities related to ICT usage and how it can amplify pre-existing social and cultural disparities (DiMaggio & Garip, 2012; Robinson et al., 2015; Sparks, 2013). This exploration prompts reflection on how social inequalities may be further compounded by differential access to the Internet and technological devices and variations in their usage (Hargittai, 2010; Selwyn, 2004; Yuen et al., 2016). Following Robinson et al. (2015), Micheli (2015), and Calderón Gómez (2021), students’ social and cultural backgrounds probably significantly impact their aptitude to leverage Internet opportunities more than their digital skills alone. Consequently, disparities in expertise in using these tools may intensify existing social and cultural differences. Then, following Bourdieu, this reference to the social background leads Ignatow and Robinson (2017) to underline the notion of habitus to explain different dispositions towards the use of the Internet among students from different social groups and to explain that different uses reinforce previous social inequalities. This explanation is consistent with the Bourdesian framework; nevertheless, it is not directly focused on the role of Cultural Capital as the latent factor that shapes social distinction.

In summary, the perspectives discussed above shed light on different aspects of the issue. Adopting the Cultural Capital theory, one should demonstrate how culturally distinct digital practices contribute to the reproduction of inequalities, leading to social distinction and distance (Cultural Capital is related to the concept of distinction as a mechanism for creating social distance). Instead, DC should be considered a valuable resource that can enhance individual productivity and earning capacity. This aligns with the human capital theory, emphasising skills and knowledge's economic value.

Our objective is to examine whether and under what conditions DC can be considered a dimension of Cultural Capital per se. In this case, we hypothesise that its effects should align with other indicators of Cultural Capital in predicting educational strategies, trajectories and the formation of groups with similar cultural and social characteristics. Conversely, if digital skills and resources, as well as educational skills and resources, do not consistently explain cultural and educational strategies and fail to delineate boundaries between groups with similar cultural and educational behaviours, it suggests that digital competencies are not a dimension of Cultural Capital. While they are undoubtedly valuable individual resources, they do not carry the same social significance as other cultural attributes that signify belonging to different social groups.

Operationalising Cultural (and Digital) Capital

In the literature, a different angle of research exists into the operationalisation of the theoretical concept of Cultural Capital (Jæger, 2009, 2011; Kingston, 2001; Noble & Davies, 2009). Beginning with DiMaggio (1982), many authors have looked at individuals' (also parents') involvement in highbrow cultural activities (Aschaffenburg & Maas, 1997; de Graaf, 1986; DiMaggio & Mohr, 1985; Dumais, 2002; Flere et al., 2010; Graetz, 1988; Kalmijn & Kraaykamp, 1996; Katsillis & Richard, 1990; Sullivan, 2001; van de Werfhorst & Hofstede, 2007); others have examined individuals' reading practices (a practice rewarded by teachers at school; de Graaf, 1986; de Graaf et al., 2000; Georg, 2004; Jæger & Holm, 2007) or cultural resources at home (e.g. books, computers, etc.; Downey, 1995; Roscigno & Ainsworth-Darnell, 1999; Teachman, 1987) or participation in activities like foreign language or music classes (Covay & Carbonaro, 2010; Kaufman & Gabler, 2004).

With respect to DC, there have been several attempts to operationalise it. Various studies have examined the relationship between socio-economic and cultural resources and the profile of computer users, yielding contrasting results (Helsper, 2012; Tondeur et al., 2010; van Deursen et al., 2014, 2015). In prticular, Ragnedda et al. (2022) have made an empirical effort, within a diverse theoretical framework, to provide a foundation for the construct of DC. These authors consider DC a specific form of capital resulting from digital competencies and access to digital technology. They design a 'circular' process where DC is both the outcome of an accumulation process influenced by other social, political and cultural resources and an autonomous form of capital considered important for enhancing other forms of capital. In any case, in this understanding, DC is an individual resource that does not have the specific character of Cultural Capital in Bourdieusian understanding, which is represented by the dynamics of 'social recognition' and social closure, the production of legitimated culture and the selection of social and school elites in a specific society.

In this paper, we consider DC as an ensemble of factors related to digital behaviours and resources that produce their effects on other valuable facts such as school choice, school achievement, social boundaries, cultural behaviours, etc. We adopt a probabilistic approach that will permit us to analyse the ensemble of factors that could sort out groups with homologous social, cultural, digital, and school characteristics founded on statistical evidence. In this way, we do not put at the beginning of the process the hypothesis of DC as an independent asset, nor as a component of the Cultural Capital, which could lead to a circular and self-referential reasoning. Therefore, we will consider the behaviours and the possession of cultural goods (traditional or digital-related) as a whole, with the aim of testing if the digital-related assets sum up with traditional ones in explaining the strategies for the accumulation of Cultural Capital of families, particularly the educational strategy of the school choice.

DATA AND METHODS

We considered data from the 2018 Italian survey from PISA carried out by the OECD. The PISA survey is an internationally recognised assessment conducted every 3 years to assess the knowledge and skills of students (enrolled in private or public schools) in various domains, such as reading, mathematics and science. Its target population is students between 15.25 and 16.25 years old at the time of the survey. The PISA survey goes beyond academic performance and collects valuable data on students' attitudes, motivations and beliefs about learning and education. The survey explores various factors influencing educational outcomes, including students' socio-economic backgrounds, home environments and overall school learning environment. The OECD-PISA database contains significant information that can be useful for operationalising and measuring Cultural Capital. Indeed, some scholars have already used the PISA data in relation to Cultural Capital (Jæger, 2009; Pitzalis & Porcu, 2017; Tramonte & Willms, 2010). Furthermore, among the variables available in the database, there are several related to the possession of ICT devices and their use, both in school activities and everyday activities. These can provide valuable information to operationalise the DC construct.

In this analysis, we will consider Cultural (Digital) Capital as a *latent* variable whose value can be inferred (through a statistical model) by considering the values of a set of *manifest* (i.e. observed) variables. We assume the latent variable is discrete and consists of two or more categories (or classes). Individuals (in our study, the students) are grouped into different categories (classes) based on the values they exhibit in the manifest variables. Each category corresponds to a different value of the latent Cultural Capital variable (or a different amount—or endowment—of it). The manifest variables we consider are a batch of indicators available in the OECD-PISA database that may act as proxies of the 'objectified' and 'embodied' forms of Cultural Capital (Bourdieu, 1986).

Furthermore, our analysis will consider additional information as *post-classification* variables to interpret the model-fitting results. These include the socio-demographic characteristics of the interviewed students, the educational level of their parents, indicators related to the family's socio-economic status, the occupational status of the student's parents and the availability of ICT within the family's household.

In the following, we describe the variables considered in the analysis, discussing those classified as *manifest* or *post-classification controls*. Table A1 in the Appendix reports descriptive statistics. These variables are indexes available in the PISA database derived from students' responses to survey questionnaires and obtained using model-based scaling procedures belonging to the family of item response theory, IRT (applied to dichotomous or Likert-type responses to questionnaire items; OECD, 2022), or by principal component analysis. Indexes are centred on the average for OECD countries (OECD, 2022). Extensive sampling design and procedure information is available in thematic and technical reports at http://www.pisa.oecd.org.

Manifest variables

The manifest variables are:

- WEALTH: *family wealth possessions*. The index was scaled (by IRT) from students' reporting of the availability of 14 household items at home plus three specific country household items (considered as relevant measures of family wealth within each country's context; for Italy, antique furniture, alarm system, air conditioning). Higher values indicate higher family wealth.
- CULTPOSS: *cultural possessions at home*. The index was scaled (by IRT) from students' reporting of the availability at home of culture-related goods such as classic literature, books of poetry or works of art (e.g. paintings). Higher values indicate a higher endowment of cultural items at home.
- HEDRES: *educational resources at home*. The index was scaled (by IRT) from students' reporting of the availability of resources such as a desk and a quiet place to study, a computer for schoolwork, educational software, dictionaries, technical reference books or books helpful for schoolwork. Higher values indicate higher availability of educational resources at home.
- HOMEPOS: *home possessions*. The index was scaled (by IRT) from students' reporting of the availability at the home of items such as a desk to study at, a room of the student's own, books on art, music or design, a computer, Internet access, antique furniture, an alarm system and air-conditioning.
- HOMSCH: *ICT use at home for school-related tasks*. To construct an index (by IRT), seven items were used to obtain information on the use of ICT outside the school for school-related tasks. Higher values indicate greater use of home ICT resources for school tasks.
- ENTUSE: *ICT entertainment use*. The index was scaled (by IRT) through the answers given by the students on the frequency with which they engage in activities such as surfing the Internet, using e-mail, playing games, participating in social networks, etc. Higher values indicate a higher intensity of ICT use for entertainment.
- AUTICT: *ICT perceived autonomy*. The index was scaled (by IRT) through the answers given to the question related to students' experience with digital media and digital devices, in particular, the student's ability to instal software, independently solve equipment malfunctions and choose new applications. Higher values point to a greater perceived autonomy in ICT use.
- COMPICT: *ICT perceived competence*. The index was scaled (by IRT) from the student's answers to the question related to the student's ability to use equipment with which she/he is less familiar, advise on digital device usage to friends or relatives, easily use the digital equipment available in their own home and troubleshoot problems with digital devices. Higher values indicate a higher perceived competence.
- ICTRES: *ICT resources availability at home*. The index, obtained through IRT, is constructed based on the students' responses to the question about the availability of equipment such as smartphones, computers, tablets, e-book readers, software and internet connectivity in their homes. Higher values point to a greater availability of ICT resources at home.
- INTICT: *ICT interest*. The index (scaled by IRT) is based on students' responses to questions about their experience using digital devices and digital media. Higher values of the index indicate a greater student interest towards ICT.

- SOIACT: *ICT in social interactions*. The index was scaled (by IRT) and is constructed based on questions about social interactions related to ICT use. It measures to what extent ICT are a topic in daily social life. Higher values indicate a greater importance of ICT in daily social interactions.

Post-classification control variables

To better interpret the classification of an individual within the different categories of the latent variable Cultural Capital, some other variables have been considered as *post-classification controls*. By including these post-classification controls, we can examine how the latent class membership relates to specific characteristics of interest beyond what was captured by the manifest variables included in the model. This can provide additional insights into the relationship between latent classes and external variables, enhancing understanding of the underlying structure and its associations with other variables. The description of these post-classification controls is listed below:

- ICTHOME: *ICT availability at home*. The index (ranging from 0 to 11) is calculated as the number of all 11 items included in the question related to the availability of devices that the student agreed upon (either response category 'Yes, and I use it' or 'Yes, but I don't use it'). Higher values indicate a greater presence of ICT devices in the home.
- HISEI: *highest occupational status of parents*. The PISA survey collects occupational data for both of a student's parents. Responses are then mapped to the international socio-economic index of occupational status (ISEI) (OECD, 2013, 2022). The index HISEI corresponds to the higher ISEI score of either parent or to the only available parent ISEI score.
- ESCS: *PISA index of economic, social, and cultural status*. The ESCS scores were obtained (by principal component analysis) taking account of domestic possessions, the most prestigious occupation of parents and parents' highest educational level. Higher values indicate higher socio-economic and cultural status. The index may be considered as a proxy for the 'institutionalised' form of Cultural Capital because it encompasses parents' educational credentials.

In addition to these variables, we also considered the student achievement in reading and mathematics assessed through the survey. Note that rather than one measure of achievement, the PISA database provides 10 plausible values for each student's score in reading and 10 in mathematics. The plausible values for each student's score in reading and mathematics represent the likely distribution of a student's proficiency and are provided to consider the uncertainty associated with the estimates (Monseur & Adams, 2009; OECD, 2013, 2022). The values have been averaged out for each student and the corresponding variables are:

- ACHIEVREAD: *PISA score in reading*.
- ACHIEVMATH: *PISA score in mathematics*.

Moreover, the following categorical variables that account for the socio-demographic characteristics of the students have been considered as post-classification controls:

- SEX.
- SCHTYPE: *type of school*. In Italy, upper secondary school programmes last 5 years, after which all students take a final exam that allows them to access university studies (provided she/he passes the admission test if required). The main subdivision is between the

'Liceo', Technical institutes and Vocational schools. The 'Liceo' are academic schools oriented towards studying the classics and sciences and designed to train students for tertiary education programmes. The Technical programmes are oriented towards more practical subjects (such as business administration, computer science, chemistry, nautical disciplines and aeronautics). The Vocational programmes are even more specific, focusing on practical subjects. Both technical and vocational programmes enable students to enter the job market as soon as they have completed their school career. According to the International Standard Classification of Education (ISCED-1997) drawn up by the United Nations, most of the sample units in the Italian survey are enrolled in an ISCED 3A/B (93.3%) school programme (i.e. upper secondary); those enrolled in a ISCED 2C programme (i.e. lower secondary aiming for direct access to the labour market) account for 5.0% while only 1.7% are still enrolled in an ISCED 2A programme (i.e. lower secondary aiming for access to upper secondary education). The ISCED 2A level in Italy is normally completed at age 13 or 14.

- AREA: *Geographical area*. Northwest, Northeast, Centre, South and Main Islands (Sicily and Sardinia). Among OECD countries, Italy displays one of the highest levels of regional socio-economic inequality. In addition, the northern regions have better-performing schools (and generally better public services) than the South and Islands (Agasisti & Cordero-Ferrera, 2013). Students in the northern regions have higher reading and mathematics scores; the average scores differ markedly among the northern and southern regions. These considerable discrepancies produce a wide north–south literacy divide (Quintano et al., 2012).
- NONATIVE: *native Italian or immigrant*, divides students into native or non-native Italian (Ress & Azzolini, 2014).
- LANGHOME: *language spoken at home*. Students are classified into Italian, Dialect and Other according to what they declared in the corresponding questionnaire item. The question of language is a central one from a Bourdieusian perspective, so the systematic reduction in the importance of dialects and regional languages resulting from the affirmation of a national school system recalls both the question of domination and symbolic violence (Bourdieu & Passeron, 1977).
- PARED: parents' highest educational level. The index is the (highest) estimated number of years of schooling for a student's parents converted into a three-category variable: lower-secondary, higher-secondary and tertiary.

The statistical model

This work uses latent profile analysis (LPA) to define groups (classes) of students with similar cultural environments and analogous behaviours. Latent profile analysis is a classification method linked to latent class analysis (Agresti, 2002; Hagenaars & McCutcheon, 2002; Vermunt, 2008). It is a mixture model designed to identify class membership probabilities of statistical units (or individuals) by considering their responses to a set of observed (manifest) variables (or indicators). The latent classes are assumed to be comprehensive and mutually exclusive. In classical latent class analysis, manifest variables are categorical, whereas LPA uses continuous variables as latent class indicators. Assuming that the '*y*' indicators are conditionally independent within the latent classes, the latent class model for '*y*' indicators is:

$$f\left(\mathbf{y}_i | \theta\right) = \sum_{k=1}^{K} \pi_k \prod_{j=1}^{J} f_k\left(y_{ij} | \theta_{jk}\right) \tag{1}$$

where $\mathbf{y}_i$ is an individual's score on a set of manifest indicators, K is the number of latent classes, π_k is the estimated prior probability of membership to latent class k, J is the total number of indicators, and j is a specific indicator. Given the model parameters of θ, the distribution of $\mathbf{y}_i$ is assumed to be a mixture of class-specific densities (Vermunt & Magidson, 2002). The appropriate univariate distribution function for each element y_{ij} of $\boldsymbol{y}_i$ is set to be Normal. By fitting such a model, we can group individuals within a probabilistic model rather than a deterministic one (thus accounting for statistical uncertainty in defining an individual's class membership). Unlike standard cluster analysis, whose aim is similar to LPA or LCA, groups are not predetermined and are not shaped by choice of a metric designed to measure the distances between them (Porcu & Giambona, 2016). Consequently, LPA or LCA can be considered a probabilistic clustering method.

RESULTS

The analysis was conducted in STATA using `gsem` command and maximum likelihood estimation (Rabe-Hesketh et al., 2004; StataCorp, 2021). Starting with the one-class model, we continued to estimate different models by gradually increasing the number of classes. The summary of the model results used for model selection is reported in the Appendix in Table A2.

Figure A1 in Appendix shows how the models with five or more classes display only a slightly better fit than the one with four latent classes, which we ultimately decided to select. As stated by Nylund et al. (2007), there is no consensus on the best criteria for determining the number of latent classes in mixture models; in this application, we based the choice of the number of classes on the parsimony principle and the interpretability of the latent classes.

Our application considers 11 manifest variables to model the latent response, and the four latent classes represent different endowments of Cultural Capital. We also estimate the probabilities of being clustered in each latent class; Table 1 reports the latent class marginal probabilities, that is, the expected proportions of the population in each group. More than half (54.2%) of the students are classified in Class 2, 21.7% in Class 1, 12.9% in Class 3 and 11.2% in Class 4.

Interpreting the latent classes

Table 2 reports the estimated parameters for the four latent classes model. We assume that errors are uncorrelated and that the variances do not differ across classes. For each manifest variable, the null hypothesis, which states that the effect of each indicator is zero, should be rejected. Thus, the individual's value for each manifest variable contributes significantly to discriminating between clusters. Table 2 helps in interpreting the classes. Values

TABLE 1 Latent class marginal probabilities.

Latent class	Margin	Standard error	95% Confidence interval	
1	0.2165	0.0066	0.2038	0.2298
2	0.5424	0.0067	0.5293	0.5555
3	0.1286	0.0052	0.1188	0.1391
4	0.1125	0.0042	0.1045	0.1210

TABLE 2 Estimated parameters for the four-latent classes model solution.

Manifest variable	Class 1		Class 2		Class 3		Class 4	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
WEALTH	−0.8167	0.0134	−0.1206	0.0099	0.8122	0.0192	−0.1024	0.0184
CULTPOSS	−0.4710	0.0161	0.2760	0.0121	0.8606	0.0185	0.2326	0.0239
HEDRES	−0.6297	0.0227	0.4325	0.0134	0.8690	0.0225	0.4307	0.0277
HOMEPOS	−0.9651	0.0148	0.0634	0.0124	1.2336	0.0193	0.0710	0.0209
HOMESCH	−0.1636	0.0238	−0.0340	0.0141	0.2182	0.0298	0.6574	0.0368
ENTUSE	−0.1214	0.0225	−0.0349	0.0136	0.2837	0.0299	1.1432	0.0365
AUTICT	−0.4418	0.0212	−0.3584	0.0132	0.0125	0.0293	1.2311	0.0307
COMPICT	−0.3480	0.0213	−0.2934	0.0132	0.0387	0.0284	1.2614	0.0287
ICTRES	−0.9857	0.0158	−0.1853	0.0112	0.9388	0.0255	−0.0985	0.0221
INTICT	−0.3760	0.0218	−0.3105	0.0131	−0.0477	0.0277	1.1300	0.0318
SOIAICT	−0.1796	0.0209	−0.1243	0.0126	0.1228	0.0276	1.1457	0.0315

represent the mean of the corresponding variable predicted for the individuals classified in each cluster.

Figure 1 displays the latent profile plot of the fitted four-class model. The analysis reveals distinct clusters within the model, characterised by variations in cultural possessions and wealth-related variables. However, it appears that these clusters are not directly associated with ICT possessions or usage, or at least not in a straightforward manner. The application of LPA has isolated four groups (latent classes) characterised by different values in the manifest indicators (see Table A1). In this way, each of the four classes clusters individuals according to their different resources and practices, linked with different Cultural (and Digital) Capital dimensions.

Let's now try to understand better what the different classes represent. For economic capital, the index for the WEALTH manifest variable shows that the second (Class 2) and fourth (Class 4) groups have similar characteristics that are very close to the sample average. On the other hand, the first (Class 1) and third (Class 3) groups have opposite behaviours and are far from the average: Class 1 is characterised by a low level of economic capital, while Class 3 comprises individuals with a high endowment of economic capital. This evidence is confirmed (Table A1) by the control variables HISEI and ESCS. Both indexes—which express both economic and social status—show a marked differentiation: Class 3 has much higher scores than Class 1, while Class 2 and 4 group individuals with values of the two variables very close to each other and very close to the sample average as well. This is also confirmed by the control variable PARED (parents' highest educational level): up to 65% of Class 3 parents have tertiary education qualifications, but the rate falls to 30% for Class 1.

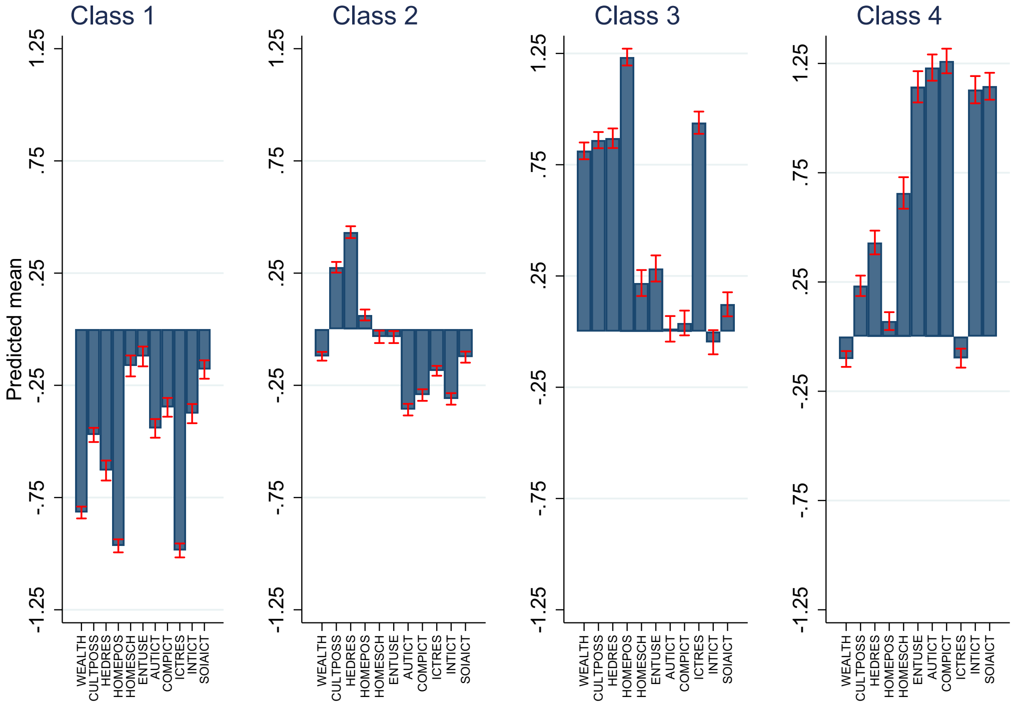

FIGURE 1 Profile plot for the four-latent classes model. The *y*-axis represents the estimated parameter (mean) values corresponding to each manifest variable for the individuals classified in the four latent classes. Confidence intervals of the estimates are plotted in red. [Corrections made on 25 July 2024, after first online publication: Figure A1 was published as Figure 1 and has been corrected in this version.]

Also, for this variable, Classes 2 and 4 have similar compositions, aligning with the average values recorded for the entire sample. Considering the objectified component of Cultural Capital, Class 3 differs from the others; the indices related to the availability of cultural goods (CULTPOSS), the availability of resources useful for education (HEDRES), and especially, the possession in the household of goods (HOMEPOS) (which denotes investment in goods that create a favourable environment for the student, or what Bourdieu refers to as a conversion of economic capital into educational and Cultural Capital) are much higher than the other classes. Also, Classes 2 and 4 are very similar for these objectified components of Cultural Capital, while Class 1 shows significantly lower values.

The four classes differ notably when considering the type of school where the clustered students are enrolled. This is one of the key features of an educational strategy (Bourdieu & Passeron, 1977): school choice is one of the essential components of a family's cultural and educational strategy for social reproduction in modern societies. Families in Italy differ in school choice strategies (Checchi, 2010; Parziale, 2016); we can detect a ranking division in terms of social standing and school prestige among the school programmes grouped into three broad categories. At the top comes the Liceo, with Technical schools in the middle ground and the Vocational schools at the bottom. Students with lower economic and Cultural Capital mainly choose a vocational school career. Liceo programmes tend to have the highest proportion of students from families with above-average socio-economic status. Classes 1 and 3 differ notably when considering the type of school: not surprisingly, Class 3 students tend to be enrolled in Liceo schools; in contrast, Class 1 students attend vocational and technical programmes or are in job training (see Table 3, variable SCHTYPE). It appears that the school strategies of Class 1 are more likely to be motivated by an economic investment than a cultural one. Classes 2 and 4 differ notably from the other two groups, displaying proportions of the different school types very close to each other.

The control variable LANGHOME (language spoken at home) indicates the extent to which Italian is used as a first language in the household; students grouped in Class 3 have the highest probability of speaking Italian at home rather than a dialect, regional language or foreign language. Since proficiency in Italian is a key factor in school success (Gui et al., 2014), it is a proxy for a specific feature of family Cultural Capital rewarded by schoolteachers. Class 1 had the highest share of students who did not speak Italian at home and, as expected, the highest rate of non-Italian natives, with one out of five students of foreign origins. Again, Classes 2 and 4 show quite similar behaviour for this post-classification control variable.

That said, concerning the endowment of economic capital and the objectified form of Cultural Capital, we can effectively define three groups of students: Classes 2 and 4 appear entirely overlapping. Let us explore the distinguishing factors that set the four groups apart.

The estimated values of the manifest variables related to availability, usage and attitudes towards ICT significantly differentiate the four groups. Concerning the variable that measures the availability of ICT resources (ICTRES), we observe how Class 3, which groups students with the highest economic and material resources, presents much higher values than the remaining classes, effectively anchoring device ownership to economic availability.

Nonetheless, focusing on the variables related to the use of ICT, it is particularly interesting to observe Class 4. Students grouped in Class 4 show particularly high values in both HOMESCH (use of ICT for school-related tasks) and ENTUSE (use of ICT for entertainment) variables. Moreover, Class 4 includes students who also present relatively high values for variables related to their perception of ICT issues in terms of familiarity in use (AUTICT, COMPICT), interest in them (INTICT) and consideration of their importance in social interactions (SOIAICT).

The four classes effectively differentiate students based on their possession of economic capital and cultural goods, including ICT devices. Classes 1 and 3 exhibit contrasting

TABLE 3 Post-classification control variables and four-latent classes classification.

Variable	Class 1	Class 2	Class 3	Class 4
Cluster size				
n	2438	6543	1450	1087
%	21.17	56.81	12.59	9.44
ICTHOME				
Mean	7.2729	8.8005	9.7412	9.0656
SD	2.4143	1.8747	1.7633	1.6408
HISEI				
Mean	36.6474	48.2303	60.7773	47.4682
SD	17.1575	20.6246	19.8056	20.6773
ESCS				
Mean	−0.9927	−0.1547	0.7774	−0.1725
SD	0.6990	0.7407	0.6907	0.7917
ACHIEVREAD				
Mean	439.1723	490.3874	506.5580	490.5699
SD	93.2086	87.2280	87.5743	85.9967
ACHIEVMATH				
Mean	452.9905	502.9185	524.3562	507.9670
SD	86.4725	79.6458	80.0323	83.2928
	%			
SEX				
Female	46.76	51.95	48.28	30.63
Male	53.24	48.05	51.72	69.37
SCHTYPE				
Liceo	28.84	51.93	65.79	46.64
Technical	31.17	31.03	24.90	37.72
Vocational	20.63	8.05	3.59	8.37
Job training	17.72	8.56	5.66	6.72
Low-secondary	1.64	0.43	0.07	0.55
AREA				
Northwest	11.24	11.80	14.00	10.58
Notheast	33.84	34.16	30.55	30.08
Centre	20.67	22.67	22.83	20.33
South	13.17	10.41	9.66	12.33
Islands	21.08	20.97	22.97	26.68
NONATIVE				
Native Italian	79.87	92.99	96.92	91.26
Non-native Italian	20.13	7.01	3.08	8.74
LANGHOME				
Italian	60.16	75.73	82.38	72.60
Other	18.71	8.87	6.57	10.61

(Continues)

TABLE 3 (Continued)

Variable	Class 1	Class 2	Class 3	Class 4
Dialect	21.14	15.40	11.06	16.79
PARED				
Low-secondary	26.19	13.35	4.36	14.33
High-secondary	43.71	43.67	30.89	42.42
Tertiary	30.10	42.98	64.75	43.25

Note: number of clustered observations = 11,518; number of missing observations = 267.

characteristics and significantly differ from Classes 2 and 4. However, the latter two classes share a similar profile regarding economic capital and pthe ossession of culturally significant goods; the distinguishing factor between them lies in the estimated values for variables related to the use and ownership of ICT.

In the following, we label the four categories (classes) of students differentiated according to their different latent Cultural Capital variable endowments. Summarising the descriptions of the four classes, we have the following:

- Class 1—this class is characterised by a low endowment of economic and Cultural Capital and limited access to educational and ICT resources.
- Class 2—members of this class have relatively low economic capital, but they invest in Cultural Capital and educational resources. Their access to ICT resources is slightly below the average.
- Class 3—in this class, individuals possess high economic capital and invest substantially in Cultural Capital and educational resources. They have high availability of ICT resources but show usage aligned with the sample average.
- Class 4—this class consists of individuals with relatively low economic capital. However, they invest in Cultural Capital and educational resources, like Class 2. The distinguishing feature of this class is their intensive use of ICT, despite having access to ICT resources very close to the sample average.

It is interesting to observe the behaviour of Class 3 concerning ICT. As we recall, this class groups students more endowed with economic capital and cultural goods, with high availability of ICT devices, who attend the 'Liceo' and have more educated parents. Well, observing the variables related to ICT for this class, we observe that even though students use ICT for both school-related and entertainment purposes, they do not differ from the general average in terms of their interest in technology, their familiarity in use and in attributing importance to ICT for social interactions.

Classes 2 and 4 should be particularly observed as they are almost identical regarding the availability of economic and cultural resources but are opposite in their relationship with digital technology. By observing the control variables, we can note that Class 4 differs from Class 2 (and the other classes) concerning the composition for gender, for which a clear prevalence of male students (70%) is recorded.

Although our primary objective was not to evaluate the relationship between Cultural Capital and achievement (ACHIEVREAD, ACHIEVMATH), it is interesting to observe the differing trends in achievement measured by the OECD-PISA tests in mathematics and reading among the four groups. The Class 3 group exhibits the highest scores in both tests, while Class 1 has the lowest scores. Particularly notable is that the groups categorised based on their cultural and school characteristics also display distinct educational outcomes. The two intermediate classes, Classes 2 and 4, can be considered segments of the same social cluster, with the most significant difference being the gender composition. Class 2 has a higher proportion of females, while the other class has a higher proportion of males. This distinction indicates that variations in digital behaviour and resources are related to gender rather than social or cultural backgrounds. Nevertheless, both classes demonstrate similar scores in literacy and numeracy, with Class 2 slightly outperforming Class 4 in literacy and Class 4 showing a slightly better performance in mathematics. This is consistent with evidence reported by OECD-PISA (OECD, 2023). Overall, it appears that school achievement is directly associated with the family's Cultural Capital, and we did not find a strong association between the hypothetical latent variable DC and school achievement. Indeed, Classes 2 and 4, which are quite similar with respect to their academic achievement, display notable differences in assets related to the ICT domain.

DISCUSSION AND CONCLUDING REMARKS

Extensive research has delved into the significance of digital skills (or DC) in the broader context of social stratification, social mobility processes and employability within a digitally driven society and economy (Hargittai & Micheli, 2019; Ragnedda et al., 2022). This article aims to contribute to the academic debate by analysing the unequal distribution of ICT resources and their utilisation in schools—a system deeply entrenched in a hierarchy from cultural and symbolic viewpoints—where families deploy their social reproduction strategies in choosing educational pathways. We propose a comprehensive model to investigate the impact of digital resources and behaviours on these strategies. Our model encompasses (i) the structure of the school field and (ii) the distribution of students within this field based on their individual cultural and digital resources.

Based on our analysis, we find no substantial evidence to support the hypothesis that DC should be regarded as a distinct dimension within the Cultural Capital construct, as stated by Paino and Renzulli (2013) or as a new form of capital, as stated by Ragnedda et al. (2022). Unlike cultural resources and educational choices, digital-related indexes do not effectively discriminate between classes. However, it is worth noting that the distribution of digital resources (and uses) varies among the students. Nevertheless, we cannot definitively claim that digital skills and practices are inherently linked to other cultural resources, nor can we assert that they reinforce or underpin cultural and educational disparities.

The primary evidence supporting this observation is the widespread and increasing use of Internet-connected devices in recent years. This shift necessitates re-evaluating how we perceive the digital divide, as Holmes (1999) highlighted. Undoubtedly, digital skills hold significant value and are beneficial within educational settings and broader contexts (Angus et al., 2004). Students' digital competencies have become increasingly crucial in schools where ICT has assumed a central role. They hone their digital skills and seamlessly integrate them into school and classroom activities, a trend highly appreciated and valued by teachers, albeit not in terms of a valued signal of cultural and class distinction.

As demonstrated elsewhere (Pitzalis & Porcu, 2017), the school choice process perpetuates the reproduction of Cultural Capital, shaping the structure and dynamics of the school field as a space with significant differences among schools and actors. Understanding the specific structure and rules within the school field becomes crucial for parents who seek to leverage their capital and secure access to esteemed institutions for their children (Lareau et al., 2016).

The analyses here presented classify students into four distinct classes, each exhibiting similar characteristics in terms of school choices and economic and cultural backgrounds. This classification aligns with the Bourdieusian theory of Cultural Capital. However, the same cannot be said for DC, as there is no correspondence between digital skills and the possession of digital devices on the one hand and academic achievement and school choice on the other. Moreover, digital resources and behaviours seem to shape the distinction between groups based on gender, even when these groups share similar educational, social and cultural backgrounds. This observation indirectly implies that digital resources cannot be equated with other forms of capital, like cultural and economic capital, which often rely on familial inheritance.

In conclusion, our findings indicate that ICT possessions and use (the DC) do not function as a determining factor in explaining the perpetuation of structural divisions within schools, such as the choice of school programmes, in the same way that Cultural Capital does. While we consider that digital skills can be valuable resources within the classroom setting, they do not significantly contribute to shaping the overall social structure at school. In addition, scant evidence supports the hypothesis that digital skills directly and positively influence academic performance and educational achievement. This is due to schools serving as highly institutionalised social environments where various factors intersect or conflict, mediating the role and function of digital skills within different schooling conditions and yielding varied effects for students with different backgrounds. Nonetheless, further research is needed to understand schools' role in fostering digital competencies and how these competencies enhance learning outcomes and overall academic success.

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CONFLICT OF INTEREST STATEMENT

None of the authors have a conflict of interest to disclose.

DATA AVAILABILITY STATEMENT

The data supporting this study's findings are openly available in PISA 2018 Database—Student questionnaire data files—at https://www.oecd.org/pisa/data/2018database/, reference number 29APR19 (accessed on 14 March 2023).

ETHICS STATEMENT

This research study, which involved the analysis of OECD-PISA data, was conducted with strict adherence to ethical principles and guidelines. The following ethical considerations were paramount throughout the research process: Confidentiality and anonymity—the OECD-PISA data used in this study is publicly available and anonymised. No personally identifiable information was accessed or disclosed during the analysis process. Data integrity—the integrity of the OECD-PISA data was upheld throughout the analysis process, ensuring that the findings accurately reflected the information provided in the dataset. Non-discrimination—this research was conducted without bias or discrimination against any individual or group based on demographic characteristics, including but not limited to gender, ethnicity, or socioeconomic status. Our analysis focused solely on identifying patterns and trends within the OECD-PISA data for research and policy-related purposes. Transparency—we are committed to transparency in reporting our research methods, findings, and interpretations. Ethical approval—this research was conducted in accordance with institutional guidelines and regulations.

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APPENDIX

TABLE A1 Summary statistics of variables considered in the analysis.

Variable name	Description	Summary statistics: Mean	SD	Number missing
Manifest variables				
WEALTH	Family wealth possessions	−0.1494	0.6778	276
CULTPOSS	Cultural possessions at home	0.1845	0.7598	299
HEDRES	Educational resources at home	0.2585	0.9391	280
HOMEPOS	Home possessions	−0.0079	0.7850	271
HOMESCH	ICT use at home for school-related tasks	0.0543	0.9780	2208
ENTUSE	ICT entertainment use	0.1248	1.0034	1649
AUTICT	ICT perceived autonomy	−0.1360	0.9427	2817
COMPICT	ICT perceived competence	−0.0742	0.9303	2786
ICTRES	ICT resources availability at home	−0.2043	0.8060	286
INTICT	ICT interest	−0.1184	0.9334	2571
SOIAICT	ICT in social interactions	0.0495	0.8877	2981
Post-classification controls				
ICTHOME	ICT availability at home	8.6268	2.1087	675
HISEI	Parents' highest occupational status	47.3739	21.0053	732
ESCS	PISA index of economic, social and cultural status	−0.2159	0.8878	310
ACHIEVREAD	Achievement in reading	481.0910	91.0670	—
ACHIEVMATH	Achievement in mathematics	495.0658	84.4156	—
		n	**%**	
SEX				
Female		5680	48.20	
Male		6105	51.80	
SCHTYPE				
Liceo	Type of school	5669	48.10	
Technical		3633	30.83	
Vocational		1212	10.28	
Job training		1196	10.15	
Low secondary		75	0.64	
AREA				
Northwest	Geographical area	1426	12.10	
Northeast		3921	33.27	
Centre		2566	21.77	
South		1292	10.96	
Islands		2580	21.89	

TABLE A1 (Continued)

Variable name	Description	Summary statistics Mean	SD	Number missing
NONATIVE				
Not Italian native	Native Italian or immigration background	1071	9.09	
Italian native		10,283	87.25	
Missing		431	3.66	
LANGHOME				
Italian	Language spoken at home	8386	71.16	
Dialect		1861	15.79	
Other		1243	10.55	
Missing		295	2.50	
PARED				
Low-secondary or less	Parents' highest educational level	1717	14.57	
High-secondary		4798	40.71	
Tertiary		4924	41.78	
Missing		346	2.94	

TABLE A2 Summary of model results used for model selection.

Model	LL	d.f.	AIC	BIC	Number of observations
1—Class	−144,070.0	22	288,184.0	288,345.8	11,518
2—Classes	−137,343.8	34	274,755.7	275,005.6	11,518
3—Classes	−133,950.8	46	267,993.6	268,331.8	11,518
4—Classes	−130,899.2	58	261,914.3	262,340.7	11,518
5—Classes	−129,443.4	70	259,026.8	259,541.4	11,518
6—Classes	−127,735.9	82	255,635.8	256,238.6	11,518

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; d.f., degrees of freddom; LL, log-likelihood.

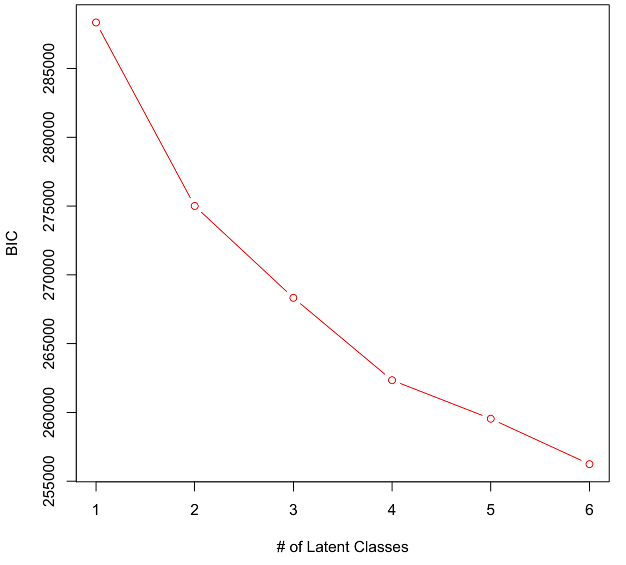

FIGURE A1 Scree plot of BIC value by each model specification. BIC, Bayesian information criterion. [Corrections made on 25 July 2024, after first online publication: Figure 1 was published as Figure A1 and has been corrected in this version.]