



Tracing Educational Inequalities in Primary and Secondary Schools

Insights from a Systematic Review of Longitudinal and Repeated Cross-sectional Studies

WP2 - Deliverable 2.1 *Literature Review Report*

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1. Abstract

Background: Ensuring equal access to quality education is deemed crucial for fostering more inclusive and just societies across the European Union. However, despite numerous policy initiatives, educational inequalities remain a key challenge within and between countries. The study of educational inequalities is particularly enriched by the use of longitudinal and repeated cross-sectional data, as it allows exploring the heterogeneity in change and determining the casual relationship between specific factors and their evolution over time.

Objectives: This systematic literature review aims to provide answers to three research questions: (i) to identify studies on educational inequalities in school education with a longitudinal and/or repeated cross-sectional research design and the related datasets, (ii) to identify methods and techniques used for analysing this type of data, and (iii) to identify and cluster the variables that are factors or predictors of educational inequalities.

Review methodology: The systematic review covers academic and grey literature and followed PRISMA 2020 reporting guidelines and workflow steps. After applying predefined inclusion/exclusion criteria, 157 records were identified and analysed in-depth through a review matrix. Three inter-rater reliability checks ensured that the researchers involved labelled and analysed the literature homogeneously and comparably.

Key findings: The review results indicate that despite many policy initiatives to promote equity, conceived as fairness and inclusion, educational inequalities remain a considerable challenge across Europe. Overall, the systematic review resulted in the identification of (i) 77 datasets (69 longitudinal and eight repeated cross-sectional) of various sizes, focuses and geographical scope, (ii) 54 statistical and causal analysis methods (complement in some cases by qualitative methods), and (iii) 70 variables contributing to educational inequalities, which were systematically categorised into a conceptual model comprising four clusters (student, family, teacher and school/education system) and ten sub-clusters.

Discussion: Educational inequalities represent a complex and critical topic with many interrelated and interconnected variables many variables. The review also confirmed a strong relationship between academic achievement, which is often at the centre of educational policies and practices, and students' school engagement and well-being, which emerge as a key intervention area closely linked to students' performance.

Implications: Policy interventions to tackle educational inequalities can benefit from evidence based on longitudinal and repeated cross-sectional data as it allows understand how early experiences, attitudes and results impact later outcomes. The research community could intensify and broaden the collection and analysis of such data to better study the dynamic nature of educational inequalities across Europe. Finally, schools and teachers could play an essential role in tackling inequalities through early interventions targeting students at risk of falling behind.

Table of content

Abstract.....	4
Executive summary	7
Introduction	7
Review methodology	7
Key findings	8
Discussion and conclusions.....	9
Implications for policy research and practice.....	10
Report structure	10
1. Introduction	11
1.1 Background and rationale.....	11
Equity and quality in education	11
The European research and policy context	11
Academic achievement in basic skills	13
The rationale for identifying and analysing longitudinal data.....	14
1.2 Objectives and research questions	16
2. Review methodology	18
2.1 Search and identification strategy and open data approach	18
2.2 Screening and inclusion process	21
Step 1 – title-abstract-keywords screening.....	21
Step 2 – full-text screening	22
Step 3 - inclusion and in-depth analysis	22
2.3 Inter-rater reliability.....	23
2.4 Data extraction and synthesis	26
3. Results	28
3.1 Overview of analysed studies.....	28
3.2 RQ1: The mapping of existing datasets from studies with a longitudinal or repeated cross-sectional research design	32
Geographical coverage.....	32
Data collection methods	37
Timeframe and sample	39
3.3 RQ2: Methods and techniques used to assess inequalities over time	41
3.4 RQ3: Variables identified as factors and predictors of educational inequalities	47
Student cluster.....	56
Family cluster.....	61
Teacher cluster	63
School and education system cluster	64
4. Discussion.....	68

4.1	Limitations of the literature review	68
4.2	Synthesis of findings	69
	Academic achievement.....	70
	School engagement.....	71
	Well-being	71
	The essential role of teachers, families, schools and education systems	71
4.3	Implications for policy, research and practice	72
	Implications for policy	72
	Implications for research.....	73
	Implications for practice	73
5.	Conclusions	74
5.1	Next steps.....	75
6.	References.....	76
7.	Appendices	89
	Appendix A: Datasets identified through the in-depth analysis	89
	Appendix B: Quantitative methods identified through the in-depth analysis	101
	Appendix C: Mapping of analysed studies to the variables of educational inequalities	111

2. Executive summary

Introduction

Education is recognised globally as a fundamental human right. In the European Union (EU), ensuring equal access to quality education is considered pivotal for creating more equitable and inclusive societies. Still, the disparity in educational attainment between advantaged and disadvantaged groups of students has scarcely diminished within and between countries, despite the introduction of numerous “equalising” policies.

Academic underachievement, low school engagement and early school leaving cannot be attributed to a single cause or factor. These issues are complex and multi-faceted, with numerous interrelated drivers. Identifying the factors and predictors of educational inequalities and taking an evidence-based approach to policy design and implementation is of outmost importance for education systems across Europe.

When studying dynamic concepts of educational inequalities, such as student achievement in basic skills and school engagement, which are at the centre of the LINEup project, longitudinal and repeated cross-sectional data are particularly important as they take into consideration ‘time’ as a crucial variable. In the context of the LINEup project and the systematic review presented in this report, we analysed studies with a longitudinal research design on inequalities in primary and secondary education in several European countries. Studies with repeated cross-sectional design were also included as they provide comparable data on factors influencing school performance and engagement over time, covering also countries where longitudinal data is unavailable. Identifying and deepening the analysing of this type of datasets can significantly contribute to designing and implementing effective compensatory policies and interventions to foster students’ learning outcomes.

This systematic literature review aims to provide answers to three research questions (RQs): (i) to identify studies on educational inequalities in school education with a longitudinal and/or repeated cross-sectional research design and the related datasets, (ii) to identify methods and techniques used for analysing this type of data, and (iii) to identify and categorise the variables that are factors or predictors of educational inequalities.

Review methodology

The LINEup research team conducted a systematic review of studies on educational inequalities with a longitudinal and repeated cross-sectional research design in primary, lower- and upper-secondary education, general and vocational, between February and June 2024. The systematic review was documented by using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting items and workflow steps (Identification, Screening, Inclusion), increasing the dependability and reliability of the collected data.

The research team searched scientific literature databases and portals, such as Scopus, to locate the relevant academic literature (e.g., peer-reviewed journal articles, conference papers, edited book chapters, etc.) reporting studies from the 32 countries covered by the project. In addition, the research team searched international and national databases (such as Google Scholar) to identify relevant grey literature (e.g. project reports, theses, and policy documents), which are an additional important source of evidence.

The screening and inclusion process was organised in three steps. In Step 1, the title, abstract and keywords of 1399 publications were screened based on five inclusion/exclusion criteria. In Step 2, the full text of 843 publications was screened based on seven inclusion/exclusion criteria. Finally, 157 publications were selected for in-depth analysis in Step 3 through a review matrix. The review

matrix approach is a well-established method for conducting an in-depth comparative analysis of the selected publications to extract relevant information and insights to answer the research questions. The quality assurance strategy of LINEup's systematic review included Inter-Rater Reliability (IRR) exercises in each of the three steps, thus ensuring that the involved researchers labelled and analysed the literature homogeneously and comparably.

All the publications identified, screened and analysed were stored in a Zotero library, which will be hosted by the end of the project in the EU Open Repository for EU-funded Research in Zenodo. In this way, the publications collected and analysed in the context of LINEup can become valuable references for future studies, particularly for researchers and policymakers interested in using longitudinal data and studying educational inequalities in Europe.

Key findings

Overall, the body of relevant literature includes 129 academic (82,1%) and 28 grey (17.8 %) literature documents. Approximately two-thirds (110 publications, 70%) of the analysed literature were published in the last decade (2015-2024), while most of them (24) were published in 2023. This could reveal that interest in the topic or the availability of studies with longitudinal and/or repeated cross-sectional design has grown recently. As expected, most of the publications identified, included, and analysed through the review matrix were written in English (94 out of 157 publications or 60%), followed by French (30 publications, 19%) and German (21 publications, 13%). Overall, relevant studies from 16 countries were identified through the review process. Almost one out of four studies (38 publications, 24%) refers to Germany, followed by France (28 publications, 18%) and Italy (21 publications, 14%). Finally, 27 publications (16%) present studies where data was collected in more than one of the 32 countries covered by LINEup. One hundred twenty-nine studies (82%) had a longitudinal research design and 25 (16%) a repeated cross-sectional research design, while only three (2%) followed a different design. The in-depth analysis of the 157 publications through the review matrix identified 77 datasets, 69 (90%) longitudinal and eight (10%) repeated cross-sectional ones.

For **RQ1**, the systematic review highlights that (i) longitudinal and repeated cross-sectional data are widespread only in some European countries, and the data collection can happen through different means (e.g. standardised competency-based tests, surveys, etc.) and at different levels (national, regional and local); (ii) there is a growing body of literature and studies with a longitudinal or repeated cross-sectional research design; (iii) these studies are mainly quantitative, even though in few cases they are based on a mixed-method approach, (iv) the available studies differ significantly as some are based on significant larger dataset and/or longer timespan, compared with others.

For **RQ2**, the systematic review highlights a wide range of statistical and causal analysis methods and techniques (54 in total) that are chosen depending on the research questions of each study, the processes the researcher wishes to explore, the underlying technical or theoretical assumptions, the restrictions posed by the nature of the data, or by the type of data collected or available. The review also identified a few qualitative methods that complement the quantitative ones.

For **RQ3**, the systematic review confirms the complexity and multifaceted nature of inequalities in education, with a wide range of factors related to students, families, schools, teachers, and the (education) system. The variables identified through the systematic review are presented through a conceptual model (see next section) that highlights how each of them plays an important role individually and in connection with others, making the design and implementation of effective policies and interventions even more challenging.

Discussion and conclusions

Educational inequalities represent a complex and critical topic with many interrelated and interconnected variables. The review results indicate that despite many policy initiatives to promote equity, conceived as fairness and inclusion, educational inequalities remain a considerable challenge across Europe. With more details, the analysis of 157 publications confirms the importance of academic achievement as well as school engagement and well-being.

Academic performance and students' engagement and well-being: two sides of the same coin

The review results show that educational inequalities often emerge early in a child's life and persist throughout their educational journey. For example, children from lower socioeconomic and disadvantaged cultural backgrounds start school with fewer cognitive and socio-emotional skills than their more privileged peers, and these initial gaps tend to persist or even grow over time. Overall, the review shows worrying trends in acquiring reading, mathematics and science skills in European countries correlated with educational inequalities. Analyses relying on longitudinal data from several European countries show that a considerable proportion of students (at all education levels) is still not proficient in these key areas, which are fundamental for personal development, employability, and active citizenship.

On the other side, school engagement emerges as a critical factor in academic achievement and overall educational outcomes. The review shows that students who engage with their schoolwork, participate in extracurricular activities and connect to their school community are more likely to achieve better academic outcomes and less likely to drop out. Students' well-being also emerges from the literature as essential for their school engagement and academic performance. A strong sense of belonging and subjective well-being is linked to better educational outcomes and helps creating more supportive learning environments, particularly for disadvantaged students.

LINEup conceptual model of educational inequalities

Research in the sociology and economics of education has mainly focused on the individual factors affecting students' educational achievement and attainment, such as students' gender, social origin, and migratory background. In the literature, these factors producing differences in students' learning outcomes have been interpreted as sources of 'primary' and 'secondary' effects: students' characteristics directly influence their educational achievement and are also connected to students' and parents' choices at turning points in education careers, beyond their performances.

A more recent strand of research has then introduced the concept of 'tertiary effects' to refer to the role that school's community members, and in particular teachers, can play through their expectations, evaluations and suggestions towards students with different backgrounds. In fact, inequalities can also be reinforced and reproduced by a complex set of micro-mechanisms at play within the school context and between school players (teachers and school leaders) and families. Moreover, specific policies and characteristics of the education system also shape educational inequalities. Examples include, among others, the level of schools' autonomy and public expenditure on education.

One original contribution of the systematic review of academic and grey literature presented in this report is the clustering of the 70 variables identified as factors or predictors of educational inequalities in primary and secondary education across Europe. The proposed conceptual model offers a comprehensive overview and an initial categorisation of the identified variables. Apart from the variables associated with individual students (primary and secondary effects), the model stresses the importance of the teacher-related variables and those referring to the role of family, school and system (tertiary effects).

Implications for policy research and practice

The review findings highlight that longitudinal and repeated cross-sectional data offer valuable insights into educational inequalities. Although the review identified and analysed in depth 157 related publications, it is evident that the available longitudinal or repeated cross-sectional datasets do not cover all European countries and/or all the variables that are predictors of educational inequalities. Therefore, there is a **need for intensifying the collection and analysis of longitudinal and repeated cross-sectional data** to monitor and understand the evolution of educational inequalities, their predictors, and the impact of related policies. The insights derived from the review also indicate that policymakers and school practitioners should monitor academic achievement but also design and implement **strategies to increase students' engagement**. This may involve creating a supportive school environment, inclusive teaching practices and targeted support for students at risk of falling behind, including counselling, mentoring and special education resources.

Report structure

Section 1 presents the research and policy context and this systematic review's objectives and research questions. Section 2 details the review methodology, including the screening strategy, the quality control mechanisms, and the open data approach. Section 3 provides an overview of the studies analysed in-depth through a review matrix and outlines the key findings for each of the three research questions. The synthesis of the results and the implications for policy, research and practice are discussed in Section 4, along with the study's limitations. The conclusions and next steps are presented in Section 5.

Appendix A contains the complete list of the 77 longitudinal or repeated cross-sectional datasets identified through the systematic review. Appendix B includes the complete list of the 54 data analysis methods and techniques. Finally, Appendix C presents the 70 factors and predictors of educational inequalities identified through the 157 studies analysed in depth in this systematic review.

The report is complemented by a Zotero library, which is going to be a living infrastructure, updated and constantly curated during the LINEup project. The library will be hosted by the end of the project in the EU Open Repository for EU-funded Research in Zenodo. Access to the Zotero library can be granted before the end of the project upon request to the project coordinator and/or corresponding author of this this systematic review.

3. Introduction

3.1 Background and rationale

Equity and quality in education

Globally, education is recognised as a fundamental human right². Better education systems are linked to improved human development indicators such as enhanced well-being and better health (e.g., Estes & Sirgy, 2019; Spencer et al., 2019). However, as indicated already in 1966 by the Coleman Report (1966), schools can partially reproduce inequalities arising in societies. Research shows that the disparity in educational attainment between advantaged and disadvantaged students within and between countries has scarcely diminished (e.g., Erikson, 2020). Even in developed countries and regions, some young people leave school with no worthwhile qualifications or drop out (e.g., Ainscow, 2020), while socioeconomic background and parental education still strongly affect educational outcomes and labour market participation. Although schools can reproduce inequalities, at the same time, they are one of the most important levers in minimising inequalities (e.g., Gingrich, 2019). To this end, equity and quality are key elements of a well-functioning education system and a high priority across countries (OECD, 2024b).

Equity in education refers to its degree of fairness and inclusion (European Commission/EACEA/Eurydice, 2020a; OECD & The World Bank, 2015). Inclusion is “when all students receive at least a minimum amount of good quality education”, whereas fairness is “when student performance is largely independent of socioeconomic background” (European Commission/EACEA/Eurydice, 2020a, p. 3). This definition of equity, as a combination of fairness and inclusion, does not imply that all students should achieve the same learning outcomes, nor does it entail teaching the same content or providing identical resources to all students (OECD, 2024b). Equity is recognised as laying the foundations for quality education for all (Ainscow, 2020; UNESCO, 2015), as lack of inclusion and fairness can result in poor retention and/or school dropout, both incurring significant economic and social costs (Belfield, 2008; Brunello & Paola, 2014; OECD, 2024b).

Quality education for all is one of the seventeen Sustainable Development Goals (SDGs)³ adopted by the United Nations Member States in 2015 “to build a greener, fairer, better world by 2030”. Although quality education is a key enabler of most other SDGs (UNESCO, 2015), global progress in education has not been fast enough (United Nations, 2024). As with all significant policy priorities, advancing equity and quality in education necessitates an effective implementation strategy focusing on personalising the learning offer and identifying and addressing barriers that marginalise some children due to contextual factors (Ainscow, 2020). Overcoming these barriers is essential for developing educational practices that benefit all students.

The European research and policy context

In the European Union (EU), ensuring quality education and equal access is considered pivotal for creating more equitable and inclusive societies. Reducing underachievement in basic skills and early school leaving remain key targets of European cooperation in education and training. The initiative *Pathways to School Success* addresses these issues holistically, recognising the multifaceted and complex nature of underachievement and early leaving (European Commission, 2022c). Along the same line, the European Education Area (EEA) aspires to build resilient and inclusive education and

² <https://www.un.org/en/about-us/universal-declaration-of-human-rights>

³ <https://sdgs.un.org/goals/goal4> and <https://www.globalgoals.org/goals/4-quality-education/>

training systems where equity and quality are mutually reinforcing (European Commission, 2022d). Significant progress has been achieved across the EU over the past years as we witness a decline in early school leaving and increased attainment in early childhood education and care (ECEC) and higher education (European Commission, 2023a). Most European educational systems have implemented significant initiatives and policies to promote quality in education and support disadvantaged students.

For instance, a recent Eurydice report (European Commission/EACEA/Eurydice, 2020a; 2020b) examines key education policies and structures across the EU Member States, assessing how these affect equity and quality levels in education systems. These policies and structures are interrelated (often interdependent) and can be clustered into three broad categories: stratification, standardisation, and support elements (European Commission/EACEA/Eurydice, 2020b).

Stratification, resulting from educational differentiation, refers to grouping students into different classes, schools, or programmes based on ability, interest, or other characteristics (European Commission/EACEA/Eurydice, 2020a; 2020b). This grouping often involves tracking but can also result from grade retention, school types, choice policies, or selective schooling. Stratification concentrates students of similar abilities and characteristics within the same schools or classes, increasing academic segregation (Parker et al., 2016). In highly stratified systems, the impact of socioeconomic background on achievement is more significant, resulting in larger gaps between students from different socioeconomic backgrounds (Strietholt et al., 2019). *Standardisation* refers to the consistency of quality standards within an education system, encompassing both ‘input’ and ‘output’ dimensions (European Commission/EACEA/Eurydice, 2020a; 2020b). Input standardisation is often associated with school autonomy in setting curricula and allocating resources, while output standardisation involves accountability measures like standardised tests and school evaluations. Finally, *support measures* aim to promote equity and mitigate disadvantage in schools. Many education systems have segregated schools with high proportions of students from low socioeconomic backgrounds, often struggling with academic performance and school climate (OECD, 2016). To address these challenges, education policies can help balance schools’ socioeconomic composition, provide targeted support, and incentivise good teachers to work in disadvantaged schools.

Despite the introduction of numerous “equalising” policies in recent decades in Europe, persistent challenges remain as educational inequalities are still pervasive across and within the EU Member States (Erikson, 2020; European Commission, 2022b; 2022c; 2023a; European Commission/EACEA/Eurydice, 2020a; 2023; Hadjar et al., 2022). For instance, in 2022, 9.6% of all 18-24-year-olds in the EU (approximately 3.1 million) had left school without achieving upper secondary education, which is widely recognised as the minimum standard for educational attainment (European Commission, 2023a). Figure 1 depicts the equity levels⁴ across Europe (European Commission/EACEA/Eurydice, 2020a), which vary significantly, especially in secondary education. Equity is assessed using the achievement gap between high- and low-achieving students in primary and secondary education (inclusion dimension) and the impact of socioeconomic background on student achievement across primary and secondary education (fairness dimension). Larger achievement gaps tend to pair with more decisive parental background influence, meaning that when an education system is less able to minimise gaps among students, it also tends to allow extra-school resources to play a stronger role in shaping students’ performance.

⁴ The countries of the LINEup consortium are placed in three quadrants: In Spain there is a strong impact of SES but with a narrow achievement gap; in Germany, France and Portugal, SES’s impact is strong, but the achievement gap is wide. On the other hand, in Greece and Italy, the impact of SES is weak, but the achievement gap is wide.

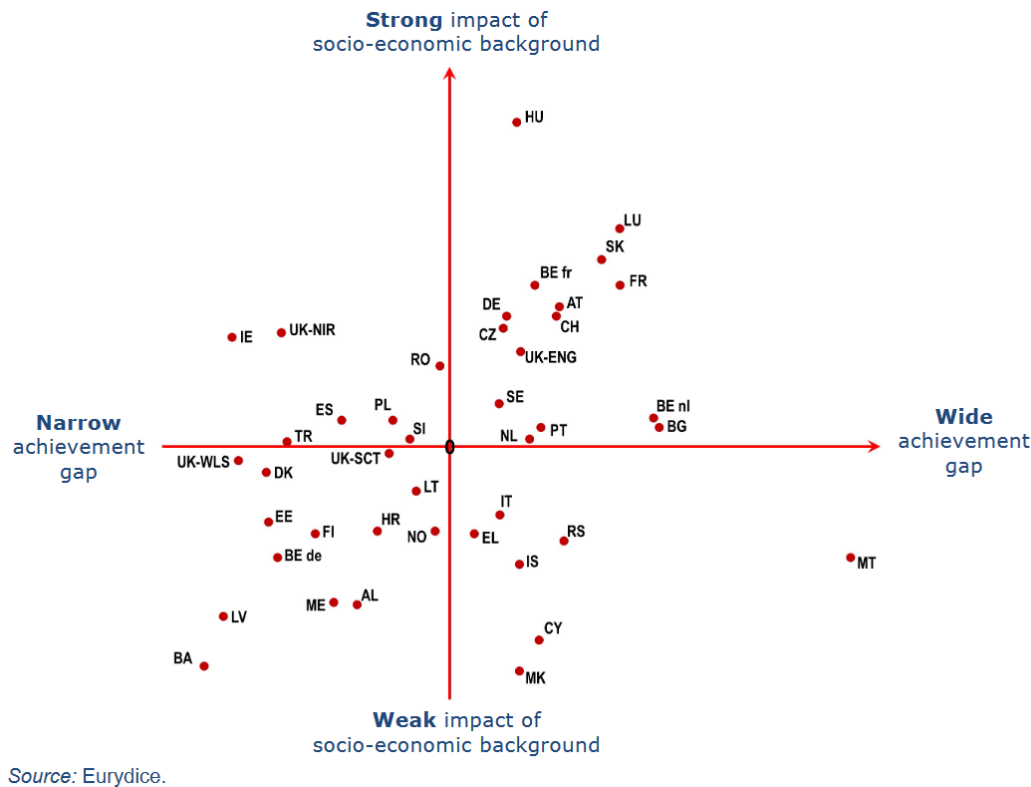


Figure 1. Levels of equity across the EU Member States

Source: European Commission, 2022c

Research consistently shows that socioeconomic background significantly influences children's participation in early childhood education, school choice, educational pathways, and learning outcomes at primary, secondary, and tertiary levels. For example, according to the Education and Training Monitor 2022 (European Commission, 2022a, p. 9), "students of low socioeconomic status are 5.6 times more likely to underachieve in school education than students of high socioeconomic status". A recent study (European Commission/EACEA/Eurydice, 2020a) confirms that socioeconomic disadvantage adversely affects educational outcomes across most European education systems. Students from low socioeconomic backgrounds often show lower motivation, leave education earlier, and attain lower qualifications while exhibiting more learning-related behavioural problems. These circumstances have been identified as fall-out factors that can negatively contribute to students' drop out of school (OECD, 2023b).

Academic achievement in basic skills

Academic achievement in school education is closely connected to acquiring basic skills, namely reading, mathematics, and science, as these foundational abilities are essential for personal development, employability, social inclusion, and active citizenship⁵. Proficiency in reading is fundamental for students to understand and engage with content across all subjects. Math skills are needed not only for excelling in math-related subjects but also for developing logical thinking and problem-solving abilities. Scientific literacy (including understanding basic biology, chemistry, and physics principles) fosters critical thinking and curiosity. Results indicate (e.g., Cabral-Gouveia et al., 2023) that targeted strategies, such as enhancing reading skills and implementing subject-specific

⁵ It is worth mentioning that changes in Europe's economy and societies and the rapid technological developments also drive a broader conceptualisation of basic skills at the policy level, including other key competences and skill sets such as digital competence (e.g., European Commission, 2023d).

interventions, are effective in improving the attainment of minorities and students with lower economic, social and cultural status (ESCS).

Skills development is considered a precondition for more sustainable, resilient and fair EU societies (European Commission, 2023c). However, widespread underachievement in basic skills remains a significant concern throughout the EU (European Commission, 2023a). As highlighted in the Council Recommendation on Pathways to School Success (European Commission, 2022c), the proportion of low achievers in Europe remains high: 22.5% in reading, 22.9% in mathematics, and 22.3% in science, significantly above the EU-level target of 15%. The underachievement gap in basic skills has reached 37 percentage points in all European countries (European Commission, 2024). For example, low performance in mathematics is more frequent among students with disadvantaged socioeconomic backgrounds than among their socioeconomically advantaged peers in all EU countries in 2022 (European Commission, 2024).

Academic underachievement, low school engagement and early school leaving cannot be attributed to a single cause or factor. These issues are complex and multi-faceted, with numerous interrelated drivers. Early school leaving is typically the culmination of gradual disengagement from education, rooted in poor academic performance, resulting from a combination of interdependent individual, family-related, educational, social, and economic factors, which could create cumulative disadvantages (European Commission & PPMI, 2022). Individuals at risk are usually those with lower socioeconomic status, facing multiple disadvantages, and affected by a complex interplay of different factors. Among these factors, certain features of education systems - such as limited access to quality early childhood education, early tracking, segregation, and grade repetition - can exacerbate cumulative disadvantages (European Commission & PPMI, 2022). On the other hand, evidence reveals that inclusive education systems benefit students from disadvantaged backgrounds, improving their performance, while students from more advantaged backgrounds perform well regardless of the system's inclusivity. In Holtmann's words (2016, p. 61), "there is no conflict between equality of opportunity and excellence in education. In contrast, excellence can be improved through equality of opportunity without hindering advantaged students or top performers".

Attention to educational inequalities has significantly increased after the COVID-19 pandemic (Langthaler & Malik, 2023). Research highlights that the pandemic and the educational solutions put in place to ensure continuity of education intensified educational inequalities, widening existing gaps and increasing learning losses and dropouts among students from weak socioeconomic groups (Carretero et al., 2021; Langthaler & Malik, 2023; Patrinos et al., 2022) and increased gender-based inequalities (Moulin & Soncin, 2023).

The rationale for identifying and analysing longitudinal data

Identifying the predictors of educational inequalities is a significant challenge for education systems globally (e.g., OECD, 2018), while there is a pressing need for evidence-based policies to address educational inequalities and underachievement in basic skills. Despite this need, such evidence-based approaches are not yet common across European education and training systems. Utilising available data and investing in methodologically robust experimentations and evaluations are critical for effective, equitable, and efficient policies and interventions. In this context, developing a standardised framework for policy evaluation would be highly beneficial. It would enhance understanding evaluation methods and identify effective policies across EU Member States (European Commission, 2022b). On the other hand, implementing a large number of experiments in education, such as Randomised Control Trials (RCTs), to learn beyond results from single studies with limited external validity would require time and resources. Hence, it is still necessary to attend to the causality issue resorting to observational studies. In this context longitudinal data are a

promising second best to gather evidence based on robust associations while designing and implementing experiments to get stronger causal evidence.

Over the past three decades, social sciences have increasingly implemented longitudinal and repeated cross-sectional research to assess causal mechanisms and relationships of educational inequalities (Saw et al., 2018; Sheppard-Jones et al., 2018; Ulferts et al., 2019), together with an expansion of achievement testing (Betebenner & Linn, 2009). In particular, repeated cross-sectional analyses are among the most common approaches to studying educational inequalities over time. This type of studies collect data about the same or similar information from a different sample of participants at each time point, enabling comparisons over time (e.g., Rafferty et al., 2015). On the other hand, purely longitudinal studies rely on continuous measures to follow the same individuals or groups of people over extended periods, often spanning years or decades (Caruana et al., 2015). Longitudinal data also allow for the control of any unobserved heterogeneity, potentially biasing the estimates at the level of the clustering data (in the LINEup context, mainly at the student's level). Both approaches can collect large-scale data across schools and student cohorts using fixed indicators that facilitate temporal comparisons.

When studying dynamic concepts linked to educational inequalities, longitudinal and repeated cross-sectional data are essential to understanding individuals' development, school performance, and learning outcomes (Anders et al., 2013; Anders et al., 2012; White & Arzi, 2005). By gathering information from the same people over an extended period, researchers can explore heterogeneity in the evolution of different phenomena and determine the causal relationship between specific predictors and the growth trajectory over time (Singer & Willett, 2003). The analyses of such data also facilitate the identification of trends and help understand the interplay between individual-, family-, school- and system-level factors. Furthermore, addressing the multifaceted nature of educational inequality necessitates moving beyond well-studied but less evolving factors, such as students' socioeconomic background, and exploring the role played by more dynamic and malleable factors, such as school engagement and well-being. These factors, which emerge as key predictors of academic achievement, represent flexible areas where schools can more easily intervene to influence learning outcomes positively (Garcia et al., 2020).

Several countries and international organisations have been actively gathering different types of data to monitor and evaluate students' performance. Additionally, international assessments like the OECD's Programme for International Student Assessment (PISA) provide valuable insights into students' learning outcomes and allow for cross-country comparisons. However, most of the collected data by these organisations do not have a longitudinal nature. The European Union Statistics on Income and Living Conditions (EU-SILC)⁶ is among the few EU studies offering longitudinal data on inequalities across multiple countries, although for a relatively brief period. At the national level, the situation varies significantly among countries. Some EU countries have established systematic efforts to collect longitudinal data nationwide. Others gather such data for specific age groups, often through national tests, while in some countries, longitudinal data collection is fragmented, isolated, or absent.

In the context of the LINEup project and the systematic review presented in this report, we analysed studies with a longitudinal research design on inequalities in primary and secondary education in several European countries. Studies with repeated cross-sectional design were included as they provide comparable data on factors influencing school performance and engagement over time,

⁶ <https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions>

topics at the centre of the LINEup project, and also from those countries where longitudinal data is unavailable.

3.2 Objectives and research questions

As highlighted in the previous section, data on academic achievement are crucial for monitoring the quality and equity of education, especially when they are longitudinal. The LINEup project aims to contribute to this effort by mapping and analysing existing longitudinal data at primary and secondary school education levels to provide evidence on educational inequalities and effective compensatory interventions.

More specifically, this systematic review informs the LINEup project and research by collecting, describing, and analysing studies on educational inequalities with a longitudinal and/or repeated cross-sectional research design at primary and secondary school education levels. In addition, this deliverable aims to provide a comprehensive overview of the existing literature on the topic, with a description of the analytical methods usually implemented and the main factors/predictors identified in determining educational inequalities, focusing on students' school performance and engagement.

This systematic literature review aims to answer the following research questions (RQ):

RQ1. What are the studies with a longitudinal or repeated cross-sectional research design on inequalities in primary and secondary school education in the countries covered by LINEup? What are the datasets they are based on?

RQ2. Which analytical methods and techniques⁷ are used in the identified studies to assess inequalities in primary and secondary school education through longitudinal and repeated cross-sectional data?

RQ3. Which variables are identified as factors/predictors⁸ of educational inequalities in the analysed studies?

To achieve its objectives, the systematic review incorporates (i) leading works from mainstream academic literature (peer-reviewed journal articles and conference papers, edited book chapters), and (ii) influential grey literature such as key policy reports and white papers, books, and online content, impacting and shaping the educational inequalities infosphere. Therefore, the systematic review includes a wide range of viewpoints, positions, and experiences and provides a comprehensive summary of current research as well as policy and practice developments.

The systematic review is expected to contribute to Work Package 3 (WP3) of the LINEup study, which aims to identify and map existing longitudinal (or repeated cross-sectional) datasets from the 32 European countries covered by the project⁹ (see Figure 2). The predictors of educational inequalities identified through this systematic review for answering RQ3 can also offer valuable insights for designing the guide and protocols for the interviews and focus groups of LINEup case

⁷ In this review, methods refer to the overarching strategies employed by researchers to answer their research question(s) and, consequently, the methodology chosen. Techniques refer to the data collection instruments and/or to the type of analysis done on the collected data.

⁸ In this review, we use the term "factor" when describing the relationship between two or more variables - hence factors *associated* with an outcome of interest. The term "predictor" is used when a variable reliably predicts an outcome - hence predictors *have an impact* on the outcome of interest. Studies with a longitudinal or repeated cross-sectional design are useful in understanding what factors are predictors of educational inequalities.

⁹ EU Member States (AT, BE, BG, HR, CY, CZ, DK, EE, FI, FR, DE, GR, HU, IE, IT, LV, LT, LU, MT, NL, PL, PT, RO, SK, SI, ES, SE), European Economic Area Associated Countries (Iceland, Liechtenstein and Norway), Switzerland and the United Kingdom.

studies (WP4 and 5), which will cover the different elements that influence students' school engagement and positive learning outcomes.



Figure 2. The 32 European countries covered by the LINEup project

Finally, the publications collected and analysed for the systematic review will remain a valuable source of knowledge throughout the project's lifetime, and that is why the LINEup partners regard it as a living infrastructure that will be continuously updated.

4. Review methodology

Between February and June 2024, the LINEup research team conducted a systematic review of studies on educational inequalities with a longitudinal and/or repeated cross-sectional research design in primary and secondary school education. Following the UNESCO's Institute for Statistics (2012) International Standard Classification of Education (ISCED), the systematic review covers the following school education levels: ISCED 1 (Primary education), ISCED 2 (Lower-secondary education), and ISCED 3 (Upper-secondary general education and Upper-secondary initial vocational education and training - IVET). The review was scoping and exploratory in nature, focusing on the breadth of coverage of the relevant literature (Paré et al., 2015).

The research team identified, screened, and analysed in depth 157 publications published from 1995 to 2024. To do so, the research team utilised the Scopus scientific literature database to locate the relevant academic literature (e.g., peer-reviewed journal articles, conference papers, edited book chapters, etc.) reporting studies from the 32 countries covered by the project. In addition, the research team searched international and national databases (e.g., Google Scholar, the Greek National Archive of PhD theses, etc.) to identify relevant grey literature (e.g. project reports, theses, and policy documents), which are an additional important source of evidence.

The systematic review was documented using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) reporting items and workflow steps (Identification, Screening, Inclusion), increasing the dependability and reliability of the collected data (Page et al., 2021). More specifically, the 27 items of the PRISMA 2020 checklist¹⁰ were considered throughout the systematic review process.

4.1 Search and identification strategy and open data approach

The first task for conducting a systematic review of academic and grey literature was to compile a comprehensive list of keywords based on the LINEup project objectives and research activities. These keywords were the basis for developing the search terms by adding synonyms and alternative terms¹¹. Then, the search terms were transformed into search strings using Boolean operators (e.g., AND, AND NOT, PRE/0 and OR), field codes (e.g., TITLE-ABS-KEY, PUBYEAR) and wild cards (e.g., asterisks and quotation marks) for identifying as many relevant publications as possible. The search terms were applied to publications' titles, abstracts, and keywords to ensure the best precision and relevance of the search results. The complete list of keywords, search terms and search strings is presented in Table 1.

Table 1. Keywords, search terms and search strings

Keywords	Search terms	Search strings
Educational inequality	education/ educational inequality/ inequity, equality/ equity	S#1 (education*) AND (inequalit* OR inequit* OR equit* OR equalit*)
Learning (under) achievement	learning/ academic/ educational outcome/ achievement/ attainment/ performance	S#2 (learning OR academic OR education* OR school PRE/0 outcome OR achievement* OR attainment OR performance OR results OR success)
	early leaving/ leavers, dropout, learning/ academic/ educational low	S#3 (early PRE/0 leaving OR leavers) OR (learning OR academic OR education* PRE/0 underachievement OR underperformance) OR

¹⁰ <https://www.prisma-statement.org/prisma-2020-checklist>

¹¹ For instance, for the keyword *education inequality*, the search terms included education, educational, inequality, inequity, equality and equity.

	achieving/ underachievement /underperformance, low socioeconomic status/ underprivileged/ marginalised	(low PRE/0 socioeconomic OR SES) OR (dropout* OR underprivileged OR marginali*) OR (school OR academic PRE/0 “drop out*” OR dropout*) OR (school OR academic PRE/0 failure)
School engagement	school engagement/ relatedness/ connectedness	S#4 (school OR academic OR student PRE/0 engagement) OR (relatedness OR connectedness)
Basic skills	basic skills, numeracy/ maths/ mathematics, reading literacy/ language skills, science/ STEM/ scientific literacy	S#5 (basic PRE/0 skills) OR (numeracy OR math* OR mathematics OR science OR STEM OR literacy OR language OR reading) OR (reading OR scien* OR math* PRE/0 literac*)
Education level	primary/ elementary, compulsory, lower/ upper secondary, vocational/ VET school/ level/ education	S#6 (lower PRE/0 education) OR (primary PRE/0 education OR level OR school) OR (elementary PRE/0 education OR school) OR (upper PRE/0 secondary) OR (secondary PRE/0 education OR level OR school) OR (vocational) OR (VET PRE/0 education OR school) OR (“high school” OR high- school) AND NOT (higher PRE/0 education) OR (tertiary PRE/0 education) OR (“post-secondary”) OR (university)
Longitudinal data	Longitudinal data/panel data/cross-sectional data/ time series data/ research/ survey/ study/ analysis/ cohort study/ design/ methodology/ outcome/ academic performance	S#7 (longitudinal OR panel PRE/0 data OR research* OR surve* OR stud* OR analysis OR “cohort study” OR design OR metho* OR outcome OR “academic performance”)
Repeated cross-sectional data	Cross-sectional/time series data/ research/ survey/ study/ analysis/ design/ methodology	S#8 (“repeated cross-sectio*” OR “repeated cross sectio*” OR “time series” PRE/0 data OR research* OR surve* OR stud* OR analysis OR design OR metho*)

Two complementary identification streams, compliant with the PRISMA 2020 Statement (Page et al., 2021), were performed for this systematic review.

Stream 1: Identification of relevant peer-reviewed academic publications in the Scopus database published after 1990 through the search strings presented in Table 1.

Stream 2: Identification of academic and grey literature, using adaptations of the search strings presented in Table 1, through:

- Searching in Google Scholar for relevant academic and grey literature;
- Searching the repositories of international organisations such as the European Commission, OECD, UNESCO, and the World Bank for grey literature, as Google Scholar is useful for finding such literature, but, as suggested by Haddaway et al. (2015), it should not be the only source searched;
- Performing citation mining, namely examining the bibliographies of relevant literature reviews and highly cited publications reporting results from studies on educational inequalities;

- Building on the LINEup research team's and Advisory Board members' in-depth knowledge of the literature on educational inequalities.

The rationale for searching mainly Scopus and Google Scholar is that they are comprehensive academic and grey literature databases. Scopus covers 330 disciplines including 94+ million records from 7,000 publishers meticulously reviewed and selected by an independent Content Selection and Advisory Board. According to a 2019 study (Gusenbauer, 2019), Google Scholar is the most comprehensive academic search engine, with 389 million records, while Haddaway and colleagues (2015, p. 1) state that "the majority of the literature identified using Web of Science was also found using Google Scholar".

The LINEup consortium fully supports the principles and actions of open data and open science by committing to making transparent data and other scientific deliverables available for monitoring and reuse purposes. The systematic review presented in this report followed an open data approach by creating a Zotero library for conducting and documenting the whole process of identifying, collecting, screening, and analysing relevant publications. Zotero is an open-source reference management tool that allows users to collect, organise, and cite various publications. LINEup's research team decided to use Zotero reference management tool instead of EndNote for the following reasons: (i) Zotero and EndNote are two of the most popular and very comparable tools¹², so the choice between them depends on specific needs and preferences, (ii) as open-source software that can be installed across platforms (Windows, MacOS, Linux), Zotero is more appropriate to facilitate the LINEup's open data approach, as more education stakeholders could access and reuse the LINEup's Zotero library, and (ii) by installing Zotero, the team avoided delays in the systematic review due to the administrative processes for purchasing the necessary EndNote licences by LINEup research organisations.

The University of Piraeus, the lead partner of the work package connected to the review (WP2), created and hosted the Zotero library¹³ and gave the LINEup research team access. The LINEup Zotero library is structured in several folders and subfolders, and references were tagged throughout the identification and screening process. The LINEup Zotero library will be a living infrastructure throughout the project's lifespan to be utilised not only for WP2 but also for the subsequent WPs, especially WP3, WP4, and WP5. The library will be hosted by the end of the project¹⁴ in the EU Open Repository for EU-funded Research in Zenodo¹⁵ in a format that allows access via other reference management software, such as Mendeley and EndNote. In this way, the publications collected and analysed in the context of LINEup can become valuable references for future studies, particularly for researchers and policymakers interested in using longitudinal data to study educational inequalities in Europe.

¹² See, for instance, at <https://paperpile.com/r/endnote-vs-zotero/#endnote-vs-zotero-which-is-better>

¹³ A typical Zotero library entry includes, among other information, the title, author(s), year of publication, abstract, keywords, tags (labels), and research notes. Therefore, the Zotero library allows the structured comparison of different sources, permitting the identification of major findings, emerging patterns, and missing or inadequate elements that require further investigation.

¹⁴ Access to the Zotero library can be granted before the end of the project upon request to the project coordinator and/or corresponding author of this systematic review.

¹⁵ <https://zenodo.org/communities/eu/>

4.2 Screening and inclusion process

LINEup's research team involved in the systematic review comprises ten researchers from the University of Piraeus and the consortium's research organisations¹⁶. Four researchers of the University of Piraeus, WP2 leader, screened and analysed in depth the publications in English, consisting of most of the identified literature. Furthermore, six researchers from the partner research organisations screened and analysed the publications in their languages (i.e., French, German, Greek, Italian, Spanish, and Portuguese).

The screening and inclusion process was organised in three steps, presented in the sections below. The inclusion/exclusion criteria were set before starting the screening in Steps 1 and 2 to ensure the best possible credibility of the review process. Special measures were taken to ensure that the researchers involved had a shared understanding of the screening and analysis process (see Section 4.3). Only peer-reviewed publications presenting study(ies) with a longitudinal or cross-sectional research design were considered for the academic literature, excluding editorials, commentaries, opinion pieces, etc. For the grey literature, only publications with a longitudinal or cross-sectional research design that included methodology and results sections were considered.

Step 1 – title-abstract-keywords screening

As discussed in Section 2.1, all publications identified through Streams 1 and 2 were stored in a dedicated Zotero library. Due to the high volume of identified publications (N= 1399), the screening was allocated to the ten researchers involved in WP2. The screening at Step 1 was performed by reading the title, abstract, and keywords for the academic literature and the title and executive summary of the grey literature. The five exclusion criteria used for screening the publications in Step 1 are presented in

Table 2. Each publication was tagged in Zotero, indicating promotion to step 2 or the reason for exclusion. The exclusion criteria were applied in the order presented in

Table 2. In other words, if one publication did not meet inclusion criterion 1, the researchers who screened it did not examine the other four criteria, and the publication was excluded from Step 2. For the publications the researchers had doubts about, the instruction was to mark them with a specific Tag (For_discussion). Two senior researchers from the University of Piraeus double-checked these publications and decided whether to include them or not for Step 2 screening.

Table 2. Step 1 exclusion criteria

Step 1 Exclusion criteria Screening of title, abstract and keywords	
1	It is not a study with a longitudinal or repeated cross-sectional research design
2	The study does not focus on the education levels targeted by LINEup (ISCED 1, 2 and 3)
3	The study is not devoted to the key topics targeted by LINEup, i.e., on educational inequalities with a focus on academic achievement/performance and/or school engagement
4	The study was published before 1990
5	The study is published in a language not covered by the LINEup project, namely EN or DE, EL, ES, FR, IT, PT

¹⁶ University of Piraeus (Piraeus - WP2 leader), Fondazione per la Scuola della Compagnia di San Paolo (FpS – LINEup project coordinator), Center for Planning and Economic Research (KEPE), Università Degli Studi di Macerata (UNIMC), Karlsruhe University of Education (PHKA), Institut National d'Etudes Demographiques (INED), Universidad Pompeu Fabra (UPF), and Universidade de Tras-os-Montes e Alto Douro (UTAD).

Step 2 – full-text screening

At this step, the full text of 843 potential publications for in-depth analysis at Step 3 was retrieved in the Zotero library and screened by applying the seven inclusion/exclusion criteria presented in Table 3. The exclusion criteria were applied in the order presented in Table 3 and tagged accordingly in Zotero. The screening at Step 2 was performed by reading the full text focusing on the publication's methodology and results sections for identifying and recording longitudinal or repeated cross-sectional datasets (RQ1), methods and techniques used to collect and analyse such data (RQ2), and factors/predictors of educational inequalities (RQ3). Like in Step 1, for the publications that the researchers had doubts about, the final decision was taken by two senior researchers of the University of Piraeus.

Table 3. Step 2 inclusion and exclusion criteria

Step 2 exclusion criteria	
Screening the full text, focusing on the publication's methodology section	
1	The publication is not written in English, French, German, Greek, Italian, Portuguese, or Spanish
2	Publication is four or fewer pages, and/or it does not include a methodology and results section
3	The publication reports results from a study conducted in a country that is not covered by LINEup
4	It is not a study with a longitudinal or repeated cross-sectional research design ¹⁷
5	The study does not focus on the education levels targeted by LINEup
6	It is not devoted to the skills/topics targeted by LINEup, i.e., on educational inequalities with a focus on academic achievement/performance and/or school engagement
7	The methodology reported in the study is of low quality

Step 3 - inclusion and in-depth analysis

After the Step 2 screening process, 157 publications were selected for in-depth analysis through a review matrix. The review matrix approach is a well-established method for conducting an in-depth comparative analysis of the selected publications to extract relevant information and insights to answer this systematic review's three research questions. The structure of the review matrix is presented in Table 6, and the PRISMA 2020 flow diagram is depicted in Figure 3. Figure 3. PRISMA 2020 flow diagram

¹⁷ We excluded from the in-depth analysis the publications based on randomised control trials with only a pre- and post-test.

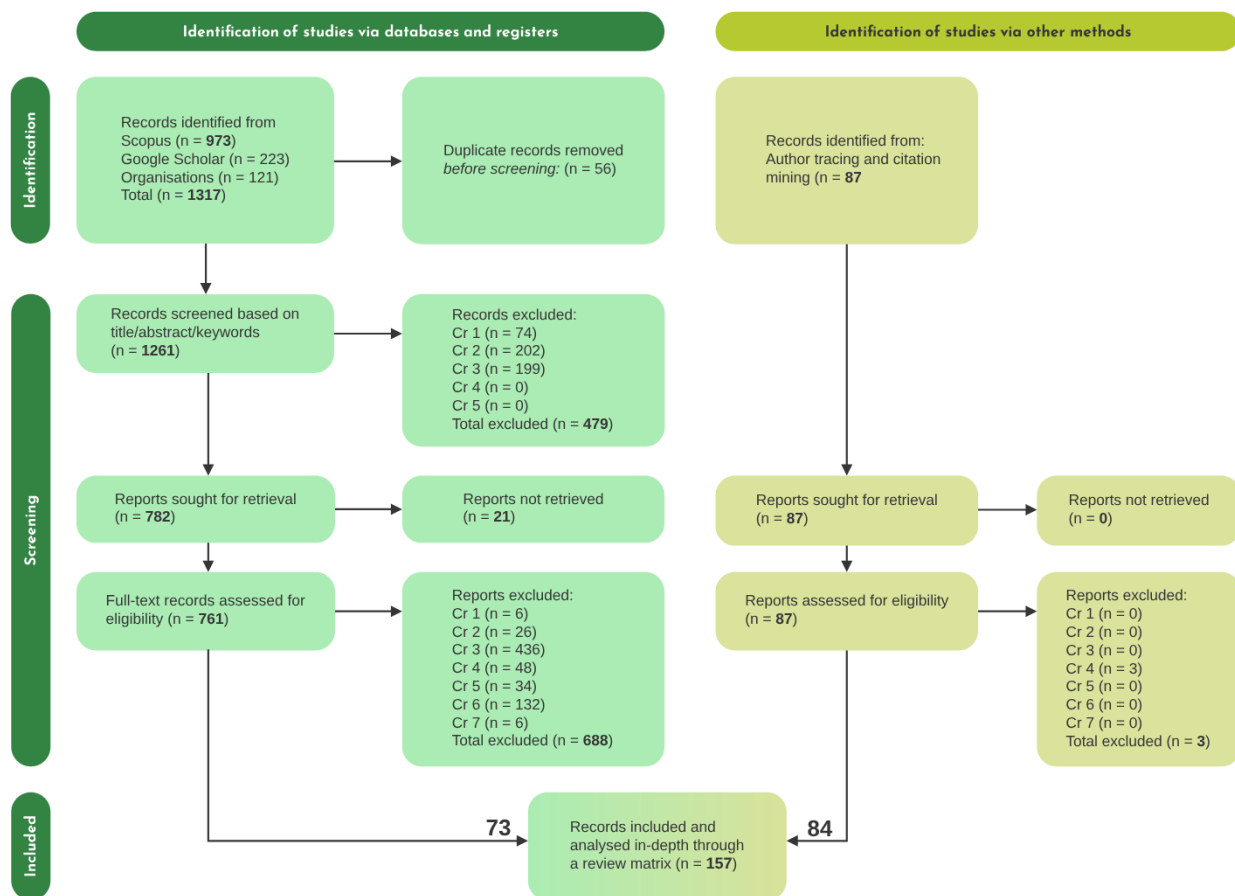


Figure 3. PRISMA 2020 flow diagram

Source: Adapted from Page et al., 2021

4.3 Inter-rater reliability

Systematic reviews are inherently resource-intensive, and multiple critical decisions are made at various stages, including determining the scope and focus of the review, selecting search terms, setting inclusion and exclusion criteria, and ultimately coding and analysing the selected publications. Discrepancies and differing viewpoints among team members must be effectively resolved (before and during the process) to achieve the best possible inter-rater reliability (e.g., Belur et al., 2021; Cohen et al., 2007).

The ten researchers who participated in the screening process in Step 1, Step 2, and the in-depth analysis through the review matrix in Step 3 had diverse experiences and backgrounds (education sciences, special education, social sciences, econometrics). No automation tools were used in the screening process. The quality assurance strategy of LINEup's systematic review included Inter-Rater Reliability (IRR) exercises in each of the three steps of screening and analysis presented above. The IRR exercises ensured that the involved researchers labelled and analysed the literature homogeneously and comparably.

In addition, the following actions¹⁸ were taken to ensure that all researchers had adequate knowledge of the methodology and tools used throughout the process of identifying, screening, and analysing the selected publications:

- A **concept note** was drafted by this report's first author explaining the systematic review process, complemented by detailed guidelines for the screening process (including examples) and the tagging of the publications in Zotero. The guidelines also included detailed instructions for analysing the selected publications through the review matrix;
- **Three webinars** were organised from March to May 2024 to present the main functions of Zotero and PRISMA statement processes to all researchers involved and discuss the results of the IRR exercises of Steps 1, 2, and 3;
- **Ad hoc meetings** were organised between the senior researcher leading WP2 and research partners to answer questions and explain processes.

In Step 1, 40 publications were selected randomly (see the complete list in Table 4) from the 1399 academic and grey literature identified through Streams 1 and 2 and screened by all researchers involved. The raters were asked to perform independently two rounds of evaluation of the 40 publications using the inclusion/exclusion criteria presented in Table 1. In the first round, they had to use 0 for the publications to be excluded, 1 for the ones to be included in Step 2 and 2 for the ones they had doubts about. Raters provided their ratings independently through an Excel file. Following the approach described by Belur and colleagues (2021), after this first round of coding, there was an open discussion between the coding team members, during which it was possible to clarify the criteria for inclusion/exclusion with the WP2 leader.

Table 4. Publications analysed by all researchers in Steps 1, 2 and 3

	Step 1 – Title, Abstract Keywords	Step 2 – Full text	Step 3 – Review matrix
1	Aguilar-Mediavilla et al., 2019	Ahearn, 2021	Arenas & Gortazar, 2024
2	Alexander et al., 2018	Allen et al., 2024	European Commission & PPMI, 2022
3	Alhadabi, 2021	Augustine, 2017	Ferraro & Pöder, 2018
4	Ansel et al., 2022	Austin, 2020	Niittylahti et al., 2023
5	Bayley et al., 2023	Baum & Cilliers, 2018	Widlund et al., 2021
6	Becker & Klein, 2021	Berger et al., 2021	
7	Broberg et al., 2023	Birdthistle et al., 2009	
8	Bumpus et al., 2020	Borgonovi & Ferrara, 2023	
9	Chaparro-Narváez et al., 2023	Brinbaum & Lutz, 2017	
10	Elsaesser et al., 2020	Bush et al., 1997	
11	Everett et al., 2023	Callahan & Shifrer, 2016	
12	Fagioli, 2014	Chang et al., 2022	
13	Fortin et al., 2013	Chen et al., 2023	
14	Galla et al., 2014	Chin, 2021	
15	Hakkarainen et al., 2015	Compton-Lilly, 2020	
16	Hallinan & Kubitschek, 2012	Corboz et al., 2019	
17	Haugan et al., 2019	Curran, 2017	
18	Heerde et al., 2020	DiLeo et al., 2022	
19	Hillmert et al., 2017	Duchesne et al., 2019	

¹⁸ All documents and recordings listed here were made available through BaseCamp, LINEup's project management platform, for easy retrieval and use.

20	Kamps et al., 2000	Engels et al., 2016	
21	Liber et al., 2022	European Commission, 2022c	
22	Lloyd et al., 2017	European Commission/ EACEA/Eurydice, 2023	
23	Maulana et al., 2015	Felner et al., 1994	
24	Merriam & Yang, 1996	Franco et al., 2008	
25	Mittleman, 2022	Gaxiola Romero et al., 2022	
26	Neel & Fuligni, 2013	Gölz & Wohlkinger, 2019	
27	Niittylahti et al., 2023	Guo et al., 2015	
28	Reyes & Domina, 2017	Haywood & Pienaar, 2021	
29	Schneider et al., 2024	Holas & Huston, 2012	
30	Shifrer, 2023	Jabbari & Johnson, 2022	
31	Singh, 2013		
32	Smyth & Privalko, 2023		
33	Su et al., 2021		
34	Terrier et al., 2021		
35	Timmermans et al., 2018		
36	Usinger, 2013		
37	Wuthrich et al., 2021		
38	Yang et al., 2018		
39	Zendarski et al., 2016		
40	Zhang et al., 2019		

Krippendorff's Alpha was employed to assess the inter-rater reliability of the rating scheme (Krippendorff, 2019). This statistical measure is particularly suited for studies with multiple raters. The aggregated ratings were input into the web-based statistical package K-Alpha Calculator (Marzi et al., 2024). The analysis provided a reliability coefficient for the coding scheme, indicating the extent of agreement among raters beyond chance. The resulting Krippendorff's Alpha coefficient is 0.823, above the threshold for a satisfactory level of this coefficient, which is 0.80, as suggested by Krippendorff (2019, see Table 5).

Table 5. Krippendorff's Alpha values and the related strength of agreement

Source: (Krippendorff, 2019, p. 356)

Alpha value	Strength of agreement
1	perfect agreement among raters
≥ 0.80	satisfactory level of agreement, indicating a reliable rating
0.67 - 0.79	moderate agreement; thus, outcomes should be interpreted with concern
< 0.67	poor agreement among rater
0	no agreement among raters than what would be expected by chance
< 0	systematic disagreement among raters

In Step 2, the same two-round process was followed for screening the full text of 30 publications, which were selected randomly and screened by all researchers (see Table 4). The resulting Krippendorff's Alpha coefficient is 0.852, which indicates a satisfactory level of agreement and a reliable rating.

To identify possible inconsistencies in Step 3, all researchers analysed five publications at the beginning of the process (see Table 4), which again were selected randomly. The analysis results

were presented and compared in a dedicated 1.5-hour team meeting. Possible misunderstandings on specific matrix fields were discussed, and the WP2 lead researcher provided clarifications.

4.4 Data extraction and synthesis

The review matrix approach allows for a structured comparison of the analysed publications by examining the matrix horizontally (where each row contains a publication) and vertically (where each column contains the relevant dimensions analysed). In these matrices, examining a row offers a summary of the key elements of a bibliographical reference, while analysing a column facilitates comparing how various sources address a specific aspect. This approach is extremely useful for effectively highlighting significant findings, emerging patterns, and underexplored elements. Table 6 shows the structure of the review matrix and the information collected in each field for both academic and grey literature.

Table 6. Review matrix structure and fields' description

Field	Type [answer options]	Description
Full reference* ¹⁹	Text box	The complete reference, in APA style 7th edition, as provided by Zotero reference management software, where all the collected literature is stored and organised.
Language*	Drop-down [EN, DE, EL, ES, FR, IT, PT]	The drop-down menu includes English, French, German, Greek, Italian, Portuguese, and Spanish, the seven languages covered in this systematic literature review.
Publication type*	Drop-down [Journal paper, Book chapter, Book, Report, Thesis, Unpublished document/Thesis]	In this drop-down menu, the type of bibliographical reference is selected.
Geographical coverage*	Drop-down [Cross-country, National, Regional, Local]	The geographical coverage of studies is listed in this drop-down menu, helping to identify where the research was conducted. When the study or the initiative refers to students from one or more schools in the same city, it is considered <i>Local</i> . When students from the same region/district are involved, it is marked as <i>Regional</i> . Similarly, when the study subjects come from all over the country, the <i>National</i> option is selected and the <i>Cross-country</i> when subjects from different countries are involved.
Country*	Drop-down [The two-letter code of the 32 countries covered by LINEup, plus the option Various]	Through this drop-down menu, the two-letter code of the country where the study was conducted is selected. The option Various is selected when the study covers more than one country.
Demographic of participant*	Text box	In this field, the review team briefly describe the demographic characteristics of participants in the study/-ies presented in the specific publication. For instance, "Students of public lower secondary schools from different regions of Swedish-speaking areas of Finland."
Total number of participants*	Text box	The overall number of participants in the study/-ies presented in this specific publication is documented in this field. Also, when available, the number of participants per wave.

¹⁹ Fields marked with an asterisk are mandatory.

Definitions of key terms	Text box	In this field, the review team copy/paste any definitions provided in the specific publication for one or more LINEup key terms (e.g., school engagement).
Dataset #1 title and link*	Text box	This is the first of the four fields that capture insights for the first research question of the literature report presented in this report. Here, the research team members add the title and the link to the dataset reported in the publication. For the studies with more than one dataset, the researchers added extra columns to document their title/link, type, timeframe and short description.
RQ1 – Dataset #1 type*	Drop down [Longitudinal, Repeated cross-sectional, Other]	In this drop-down menu, the type of dataset is selected. In the case of the <i>Other</i> option, more information is provided in the <i>Notes</i> field.
RQ1 – Dataset #1 timeframe	Text box	In this field, the duration of data collection, the number of waves and their frequency are described.
RQ1 – Dataset #1 short description*	Text box	Here, the researcher team members provide a brief description of the dataset. As most of the information is covered in distinct fields, here, it refers mainly to the purpose and focus of the dataset.
RQ2 – Methods*	Text box	This field is used to document insights related to RQ2. The aim is to document which specific method(s) was used to collect and analyse the data presented in the specific publication.
RQ3 – Variables*	Text box	Here, the research team members document the variables identified as factors of educational inequalities in the specific publication.
Other insights	Text box	Any other useful insights or relevant information that do not fit the previous fields are documented here, such as theoretical frameworks, innovative methodological approaches, implications for policy and practice etc.
Notes	Text box	When the research team members select the option “Other” in some of the previous fields, they provide here any additional information and clarification. Also, they provide any other notes that can be useful for the next steps of the LINEup project, such as the mapping of the datasets and the fieldwork in selected schools.

5. Results

This section provides an overview of the analysed studies and describes the systematic review results according to its three research questions.

5.1 Overview of analysed studies

The LINEup research team conducted an in-depth analysis of 157 publications through the review matrix. This section presents the distribution of collected and analysed publications by type, year of publication, language, research design, geographical coverage and education level.

Overall, the body of relevant literature includes 129 academic (82,1%) and 28 grey (17.8 %) literature documents. A wide variety and range of sources were detected: for the academic literature, 129 peer-reviewed journal papers and three book chapters; for the grey literature, 19 reports, four theses and two books.

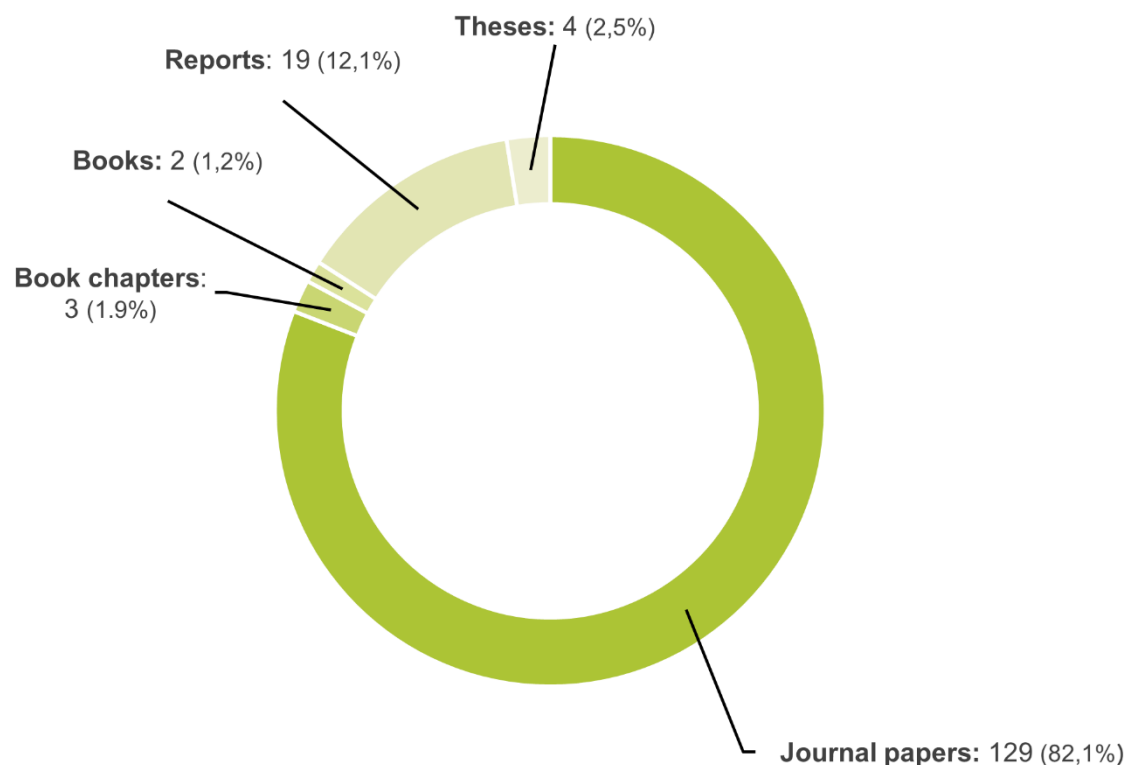


Figure 4. Distribution of analysed literature by type

Figure 5 depicts the publications' year: approximately two-thirds (110 publications, 70%) are from the last decade (2015-2024), while most of the analysed publications (24) were published in 2023. This could reveal that interest in the topic or the availability of studies with longitudinal and/or repeated cross-sectional design has grown recently.

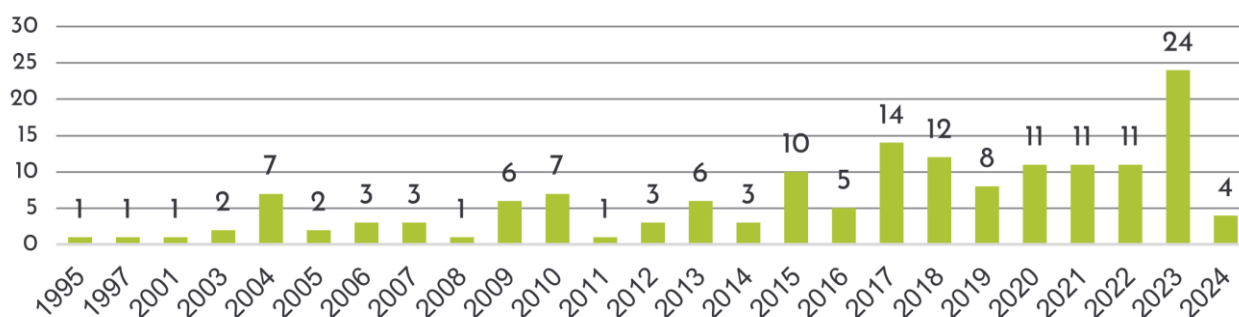


Figure 5. Distribution of analysed literature by year of publication

As stated in Section 4.2, the LINEup research team searched for relevant publications in English and the languages covered by the LINEup consortium, namely French, German, Greek, Italian, Portuguese, and Spanish. As expected, most of the publications identified, included, and analysed through the review matrix were written in English (94 out of 157 publications or 60%), followed by French (30 publications, 19%) and German (21 publications, 13%). The overall distribution of the publications in terms of language is presented in Figure 6.

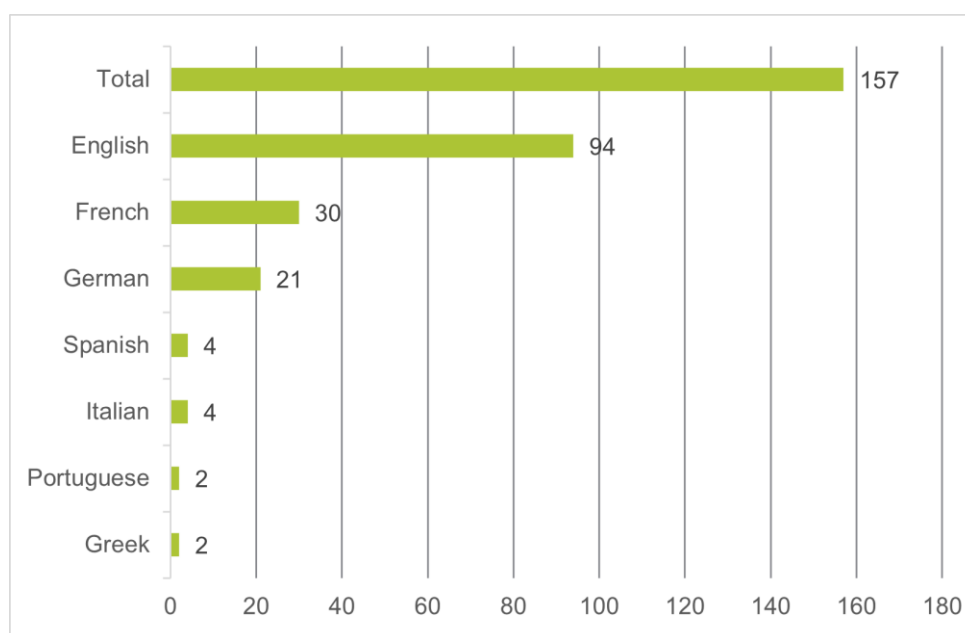


Figure 6. Distribution of analysed literature by language

Overall, relevant studies from 16 countries were identified through the review process (see Figure 7). Almost one out of four studies (38 publications, 24%) refers to Germany, followed by France (28 publications, 18%) and Italy (21 publications, 14%). Finally, 27 publications (16%) present studies where data was collected in more than one of the 32 countries covered by LINEup.

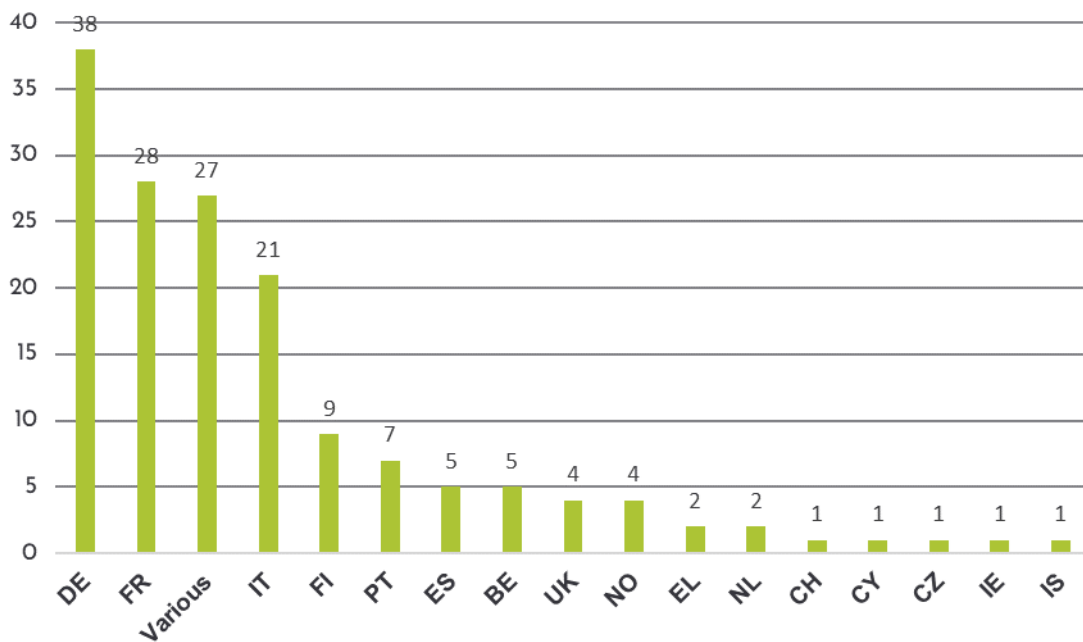


Figure 7. Distribution of analysed literature by geographical coverage

Figure 8 depicts the geographical scope of the studies, with almost half of them (46%) collecting data at the national level, one out of four (24%) at the regional, and the rest at the cross-country (16%) and local level (14%).

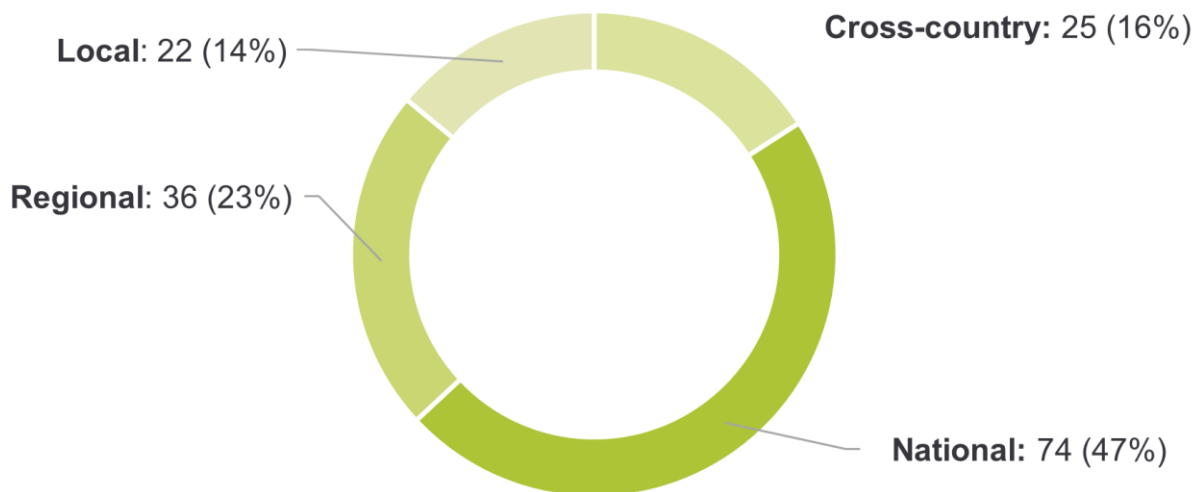


Figure 8. Datasets with local, regional, national and international scope

As shown in Figure 9, 129 studies (82%) had a longitudinal research design and 25 (16%) a repeated cross-sectional research design, while only three (2%) followed a different design²⁰.

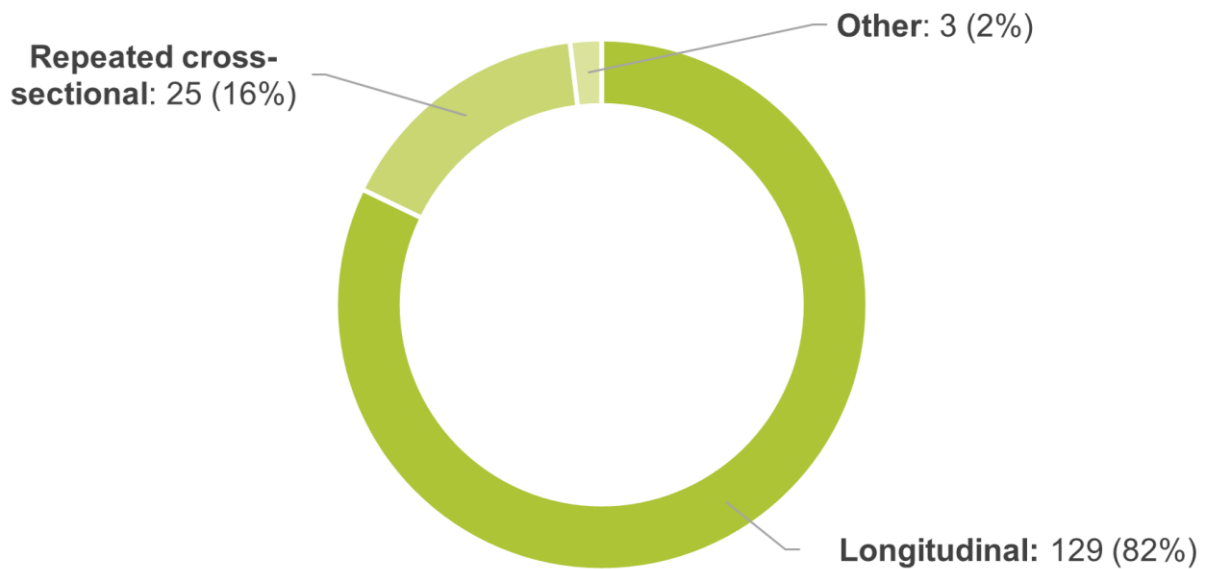


Figure 9. Distribution of analysed literature by research design

²⁰ Namely, two studies based on longitudinal randomised control trials and one conceptual paper were included because they met the inclusion criteria presented in Section 2.2.

5.2RQ1: The mapping of existing datasets from studies with a longitudinal or repeated cross-sectional research design

To answer RQ1, the selected publications were analysed to identify datasets in the 32 countries covered by the LINEup project. The criteria adopted for this systematic review (presented in detail in Section 4.2) led to the inclusion of studies with a longitudinal or repeated cross-sectional research design that collected and analysed longitudinal data, i.e., data that provide information at different points in time (at least more than two) for the same reference unit, e.g., individual, school, region, etc. As depicted in Figure 10, the in-depth analysis of the 157 publications through the review matrix identified 77 datasets, 69 (90%) longitudinal and eight (10%) repeated cross-sectional ones.

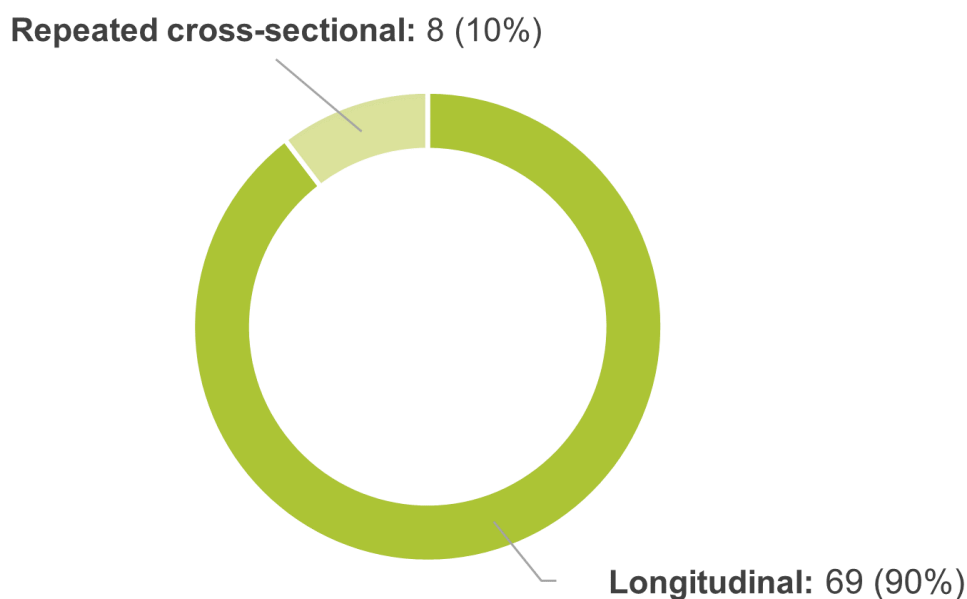


Figure 10. The distribution of the 77 datasets identified by the research design

Geographical coverage

The geographical scope of longitudinal and repeated cross-sectional research is extensive, encompassing cross-country, national, regional, and local levels. Some European countries have been active in collecting longitudinal or repeated cross-sectional data to monitor and track students' and schools' performance, while others have not. Although most datasets are derived from national and, in some cases, cross-country samples, the systematic review also identified datasets from regional and local studies, which focus on the unique characteristics of a specific local population and the implementation of targeted measures by local governments, administrative authorities, institutions, and other organisations.

As shown in

Table 7, the systematic review identified 69 longitudinal datasets from 16 out of the 32 countries covered by LINEup and two repeated cross-sectional datasets. Seven cross-country datasets (six repeated cross-sectional and one longitudinal) were identified, with data from different countries. Further information for each dataset, such as the timeframe, the number and demographic characteristics of participants, are provided in Appendix A.

Table 7. Datasets identified per type and country

Country	Longitudinal	Repeated cross-sectional	Total
DE	21		21
FI	9		9
IT	5	1	6
BE	4		4
PT	4		4
ES	4		4
UK	5		5
FR	2		2
NO	5		5
EL	2		2
CY	1		1
CZ	1		1
CH	1		1
IS	1		1
IE	1		1
NL	2	1	3
Cross-country	1	6	7
Total	69	8	77

One country with widespread longitudinal data is **Germany**, where 21 different datasets were identified. The one from the *National Educational Panel Study* (NEPS - Skopek & Passaretta, 2021; Passaretta et al., 2022; Wohlfinger & Ditton, 2023), a large-scale, multi-cohort study, includes data about psychological, sociological, economic, and educational variables of educational processes and competence development for a large, representative sample of children, adolescents, and adults at the national level. Other datasets are derived from smaller samples, like *Educational Processes, Competence Development and Selection Decisions in Preschool and School Age Project* (BiKS-8-14), which used a sample of 922 students to investigate the influence of school and home environment on differential academic competence developments depending on their choice of school track in Bavaria and Hesse Betters (Pfost et al., 2010, 2018). In addition, the systematic review identified eight datasets at the local level in Germany, such as in Berlin and Hamburg, and eight at the regional level. Some examples are the dataset from the *Study of Initial Achievement Levels and Academic Growth in Secondary Schools in the City of Hamburg* (LAU) (Caro & Lehmann, 2009; Lehmann et al., 2004) that gathered information on the learning progress and experiences of secondary school students in Hamburg and the dataset from the *BERLIN study* (Albrecht et al., 2018), which includes student data of educational pathways to evaluate the 2010/11 structural reform of the secondary school system in Berlin.

Finland is another country that makes wide use of longitudinal data and research. The systematic review identified nine longitudinal datasets in Finland. For example, the dataset from the *Adolescents' Well-being and Learning in Future Society project* (FRAM - Widlund et al., 2021) includes data at the national level and focuses on students' academic well-being, achievement and educational pathways. The dataset of the Longitudinal Anonymised Study on Student Engagement, Truancy, and Cynicism (Virtanen et al., 2021) includes data at the regional level about student engagement, truancy, and cynicism following students from kindergarten to the end of lower

secondary school. The dataset from the *Growing Mind* project (Salmela-Aro et al., 2021) includes data at the local level (in Helsinki) about the social impact and challenges of digitalisation on the social, personal and institutional levels. The *Staying on Track of Learning* project's dataset (Hakkarainen et al., 2015) offers data from a mid-sized Finnish city for the learning track of Finnish adolescents. The *Bridging the Gaps* (GAPS) project provides a dataset on youth development needs, practices and school context (Salmela-Aro et al., 2021).

In **Italy**, the *Italian National Institute for the Evaluation of the Education System* (INVALSI) offers repeated cross-sectional population data for almost 1.5 million Italian students (e.g., Borgonovi & Ferrara, 2023; Di Tommaso et al., 2024). Starting from the academic year 2012/2013, it allows to follow individual students through their educational careers thanks to a unique identification code for each student entering the Italian education system. Through these codes, it is possible to construct longitudinal designs following specific cohorts of students in specific grades. This dataset allows researchers to examine differences in students' reading, mathematics and language achievement. The dataset also includes micro-data that are useful for studying inequalities' evolution by gender and socioeconomic conditions (Passaretta and Skopek, 2018; Borgonovi & Ferrara, 2023). In addition to the INVALSI dataset, the studies identified in the systematic review for Italy derive data from (i) the *Anagrafe Nazionale degli Studenti* (Argentin et al., 2017; Salza, 2022) and (ii) the survey from *Istituto Assistenza Ragazzi Dotati - IARD* (Guetto & Vergolini, 2017), which aimed to examine track changes and developments over time of youth attitudes in Italy. Some identified studies use data coming from smaller longitudinal surveys (Asquini & Sabella, 2018; Di Tommaso et al., 2024; Grazia, 2022). The first examines students' learning gains in the second class of lower secondary schools in the Roman area (Asquini & Sabella, 2018). The second focuses on the influence of an intervention called the MATL program on reducing the gender gap in maths in 3rd grade (Di Tommaso et al., 2024). The third examines the changes in students' perceptions of school climate, school engagement's multiple dimensions and burnout (Grazia, 2022).

Datasets from studies with a longitudinal research design are pretty widespread in Flanders, the Dutch-speaking northern region of **Belgium** and they are developed to examine students' developmental trajectories. The review identified four longitudinal datasets. The dataset from *Schoolloopbanen in het basisonderwijs* (SiBO - Belfi et al., 2016; Verhaeghe et al., 2018) offers insights into the inter-individual differences in students' developmental trajectories throughout primary education until the first year of secondary in Flanders. The dataset from the *Longitudinal Project in Secondary School* (LOSO project) includes data on student achievement and non-cognitive outcomes (Van de Gaer et al., 2009a). Furthermore, the *Loopbanen in het Secundair Onderwijs* (LiSO) project (Dockx et al., 2020) also collected data during the six grades of secondary school about the trajectory of students. Finally, the *Studying Transactions in Adolescence: Testing Genes in Interaction with Environments* (STRATEGIES) project's dataset (Engels et al., 2017) could be used to investigate individual and contextual predictors of adolescents' behavioural development.

Four datasets were identified from **Portugal**. One of these includes data about students from the Gypsy²¹ community and their enrolment in primary school (Rosário et al., 2017). The larger of the other three datasets is the one from the *Portuguese Longitudinal Study* on school engagement, based on a representative sample of adolescents in Portugal. This dataset includes data on the changes in student engagement over time, including its correlates and predictors. It can also be used to examine interactions between academic performance and student engagement, the effect of

²¹ LINEup's research team acknowledges the controversial nature of the term "gypsy," which is increasingly recognised as a racial slur. We have chosen to use it here because the referenced publications employ this term, reflecting on it based on the participants' preferences (Rosália et al., 2017, pp. 554–555) or using it "to encompass both Romany Gypsies and Travellers of Irish descent" (Derrington, 2007, p. 357).

school characteristics on student engagement (Moreira & Lee, 2020), the effect of maternal education on student engagement over time (Rodrigues, 2023), or the effect of school retention on student engagement over time (Santos, 2023). This dataset can offer insights into the dynamics underlying the development of student engagement with school by comparing predictors of students' engagement with school in times of "normal" societal conditions and in times of especially challenging ones, such as confinement during the COVID-19 pandemic (De Faria et al., 2023). The other two datasets are derived from studies focused on 13-14-year-old students' engagement (Lemos et al., 2020) and parents' perspective of students from the 2nd to 4th grade regarding their relationship with the educational context (Ribeiro et al., 2023).

Four longitudinal datasets have been identified in **Spain** at the local and regional levels (Arenas & Gortazar, 2024; Marchesi et al., 2004; Mercader et al., 2017; Merino et al., 2020). At the local level, one dataset comes from the Merino et al. (2020) longitudinal survey with students in the 4th year of secondary education in Barcelona. The dataset includes data on students' expectations in their last year of compulsory education regarding the path they choose after completing this level, particularly between academic and professional tracks and the motivations of those who have chosen the vocational training option. The dataset from Marchesi et al. (2004), a four-year longitudinal research study, includes data on students' progress in language, mathematics, social sciences, and natural science throughout secondary education in the region of Madrid. At the regional level, the Evaluaciones de Diagnostico dataset in the Basque Country (Arenas & Gortazar, 2024) includes data from primary and secondary students in the Basque Country through competency-based assessments in Mathematics, Language (Basque, Spanish and English), Science and "learning skills". Finally, local data was collected from two Spanish provinces about a set of motivational variables on academic performance in mathematics by 180 pupils from pre-primary education to 2nd grade of primary school (Mercader et al., 2017).

The review identified four datasets from the **United Kingdom**. One of them, which comes from the *Science Aspirations and Career Choice* (ASPIRES) project, is focused on science aspirations (DeWitt et al., 2014a) as a variable of students' achievement. The other two datasets include data on students' tracks since their early years. The Avon Longitudinal Study of Parents and Children (ALSPAC study) collected data from students from Avon and their mothers since their pregnancy (Paget et al., 2018), while the School Matters study follows a sample of students from junior school to the end of compulsory schooling (Sandsør et al., 2023). Another includes data about Gypsy traveller students and the pull and push factors that affect Gypsy traveller students' engagement and retention in secondary school (Derrington, 2007). Finally, a comprehensive report analysed the evolution of socioeconomic status and migration-related inequalities across several European countries, including the United Kingdom, using longitudinal data from the Millennium Cohort Study (MCS) (Passaretta & Skopek, 2018). The MCS is a nationally representative birth cohort study that tracks children born in the UK between 2000 and 2001. It includes participants from England, Northern Ireland, Scotland, and Wales, employing a stratified sampling design. Over seven waves of data collection, spanning from 2001 to 2018, the MCS gathered extensive longitudinal data through home interviews with parents and their partners, cognitive, physical, and health assessments of the children, teacher surveys (when the children were in school), and direct interviews with the children themselves.

One of Europe's largest and longest-running longitudinal studies is the PANEL study from the statistical service of the Department of Evaluation, Foresight and Performance of the Ministry of National Education in **France** (DEPP) (e.g., Caille, 2014), which was carried out for almost 50 years (from 1973 to 2021) at the national level. This dataset includes massive data on French students'

tracks from elementary to post-secondary school. It measures equity by analysing family backgrounds and school characteristics, highlighting social disparities since 1973.

In **Norway**, the datasets from four longitudinal surveys have been identified (Eriksen et al., 2023; e.g., Haugan et al., 2019; Ribeiro et al., 2022; Sandsør et al., 2023). More specifically, Eriksen et al. (2023) collected data from students in lower secondary schools to examine individual changes in students' academic engagement, social competencies and classroom relationships. The dataset by Sandsør et al. (2023) provides information about the changes in gaps over time and achievement patterns across 5th, 8th and 10th grades. Haugan (2019) examined the factors predicting students' intentions to leave school. Finally, Ribeiro analysed language development across the first years of children's lives relying on longitudinal datasets from the Behavior Outlook Norwegian Developmental Study (BONDS; Naerde et al., 2014) and the Norwegian Mother, Father and Child Cohort Study (MoBa; Magnus et al., 2006). The BONDS study includes three cohorts of children born in 2006, 2007, and 2008. Cognitive, social, and behavioural development data was collected from 6 months through second grade using various data collection methods. The MoBa is a population-based pregnancy cohort study including information on demographics, health, lifestyle, and child development (including language development) from the 17th weeks of gestation until eight years of age.

In the **Netherlands**, the systematic review identified three longitudinal datasets (Passaretta & Skopek, 2018; Passaretta et al., 2022; Poorthuis et al., 2015), which measured students' emotional and behavioural engagement during the transition to secondary school. Passaretta & Skopek (2018) and Passaretta and colleagues (2022) utilised data from the COOL (Cohort Study Educational Careers of 5/18-year-olds) and Pre-COOL studies, which include a range of competence tests as well as information on family background. These datasets enabled the researchers to examine the evolution of socioeconomic and migration-related inequalities from ages 2 to 14. Data collection for the COOL study was conducted triennially between 2007–2008 and 2013–2014, covering the age range of 7 to 14 years. In contrast, data from the Pre-COOL study covered the earlier period, ages 2 to 6. In the same country, the review identified one cross-sectional dataset from the PRIMA project (Gijsberts & van der Ploeg, 2016) conducted from 1988 to 2005, collecting data about the achievements and school careers of almost 60,000 primary school students.

The systematic review identified two datasets in Greece and one per country in Cyprus, Czechia, Iceland, Ireland, and Switzerland. The dataset from **Greece** is derived from the *Athena Studies of Resilient Adaptation* project (AStRA - Motti-Stefanidi et al., 2015) that investigated immigrant early adolescents' adaptation in the middle school context in Athens. The other dataset comes from *Papadopoulou* (Papadopoulou, 2016), who collected data about the differential school effectiveness concerning students' gender, origin and socioeconomic background in the 1st and 2nd grades of primary school. In **Cyprus**, the identified dataset is derived from a three-year longitudinal study that provided data about the effect of teacher effectiveness and home learning environment on primary and secondary students' achievement gains (Demosthenous, 2019). The dataset from **Czechia** (Straková et al., 2016) is from the *Czech Longitudinal Study in Education* that focused on socioeconomic and demographic factors of students in 5th grade transitioning to lower secondary schools. In **Iceland**, the identified dataset is derived from a qualitative study with a longitudinal research design (Widlund et al., 2023) investigating the multifaceted parenting practices during adolescence and their influence on educational status through student engagement. The *Growing Up study* (GUI) in **Ireland** provides a dataset on children's cognitive and educational development and their families' socioeconomic, demographic and cultural characteristics (Sprong & Skopek, 2022). Finally, in **Switzerland**, the dataset developed by Helbling et al. (2019a) includes information on the association of social inequalities and academic performance during compulsory education,

considering disparities in students' social backgrounds and social deprivation of school attendance areas.

Comparative studies with samples from various countries have yielded solid evidence of students' performance and the variables that cause inequalities in education. For instance, data from the *Programme for International Student Assessment* (PISA) (e.g., OECD, 2023a) are used in 21 out of the 157 analysed studies. PISA follows a repeated cross-sectional research design and provides insights into the skills and knowledge of 15-year-old students in mathematics, reading and science. Eighty-one countries and economies participated in the 2022 assessment, which also tested students' financial literacy, creative thinking, global competence and collaborative problem-solving (OECD, 2023a). *Progress in International Reading Literacy Study* (PIRLS) (Volante et al., 2022) and *Trends in International Mathematics and Science Study* (TIMSS) (OECD, 2015) are large-scale, competency-based international assessments. These repeated cross-sectional datasets provide data on fourth-grade students' reading abilities and fourth and eighth-grade students' mathematics and science knowledge, respectively. Databases based on these international assessments offer the possibility to derive results regarding competencies in basic skills for a large number of students and facilitate comparisons across countries. Other cross-country databases identified through the systematic review come from the *Eurydice Network* (e.g., European Commission/EACEA/Eurydice, 2023), *EUROSTAT Regional yearbook 2009 and 2010* (Ballas et al., 2010) and *OECD Income Distribution Database* (Daniele, 2021). Although they do not focus on evaluating basic skills, they provide significant information and data about the characteristics of students, schools, and countries that influence academic performance. Finally, the longitudinal dataset *International Study of City of Youth* (ISCY) (García Gracia & Sanchez Gelabert, 2020; Kindt et al., 2023) includes data about the school systems, the experiences and outcomes of different groups of high school students in Spain and Norway.

Data collection methods

Various data collection methods, mainly quantitative but also qualitative, have been used to create the identified datasets: standardised competence-based assessments and tests, (self-report) surveys with a longitudinal design, administrative data collected through education and training systems and interviews. Considering the strengths and weaknesses of these data collection methods, some of the identified studies use a combination – e.g., a mixed-methods approach depending on the subject under investigation.

The standardised competence-based assessments and tests focus mainly on basic skills, namely literacy, numeracy and science, to measure students' achievement and other educational aspects. For example, PISA (e.g., OECD, 2023a), TIMSS (e.g., Strello et al., 2021), and PIRLS (e.g., Contini & Cugnata, 2020; Volante et al., 2022) also examine through assessments the mathematics, science and literacy competence, respectively. Also, studies at national and local levels follow a competency-based assessment approach to collect data. For instance, the ELEMENT study (e.g., Baumert et al., 2012a; Paetsch et al., 2016) in Germany collects longitudinal data through students' assessments in reading and mathematics. These assessments included items from the *International Association for the Evaluation of Educational Achievement's* (IEA) *Progress in International Reading Literacy Study* (PIRLS) for students in elementary school, for the measurement of reading skills, and mathematics test based on the standard contents of the Grades 4 to 6 curriculum (Baumert et al., 2012).

Surveys are mainly used to investigate students' perspectives, such as their school engagement as a factor of educational inequalities²². For instance, using self-report data, the Portuguese Longitudinal Study on Student Engagement (e.g., Moreira & Lee, 2020) examines students' cognitive engagement trajectories from 7th to 11th grade. The *Loopbanen in het Secundair Onderwijs* (LiSO) project (Dockx et al., 2020) also collected and analysed self-report data on the trajectory of secondary school students in Flanders (Belgium).

The systematic review identified administrative data collected by education authorities as another crucial source of information for examining factors of educational inequalities. For example, Sandsør (2023) used administrative data from Statistics Norway to examine changes in gaps over time and students' achievement patterns across grades. Administrative data often complements data collected from assessments, surveys or other methods. One example of a dataset that integrated survey data from students and their families with administrative information is the PANEL study from DEPP of the Ministry of National Education in France (e.g., Ben Ali & Vourc'h, 2015; Brinbaum & Kieffer, 2009) that collects data about French students' characteristics, their families and their cognitive and conative skills.

In some studies, quantitative data from longitudinal or repeated cross-sectional studies has been combined with qualitative data from interviews, which target mainly students as, for instance, the *International Study of City of Youth* (ISCY), a longitudinal study of 10th-grade students in cities worldwide on students' journeys through school and beyond (e.g., García Gracia & Sanchez Gelabert, 2020). Interviews have also been used to collect additional information from parents or teachers. For example, Ribeiro (2023) conducted a longitudinal study that included semi-structured interviews with parents to explore issues such as the child's characteristics and relationships, teachers' educational practices, and parents' educational practices and relationships with the school.

Combining more than one data collection method is often selected as the most appropriate way to investigate different factors of educational inequalities. Several studies (e.g., Ditton et al., 2019; Stanat et al., 2010) combine standardised competency-based assessments and tests with surveys delivering questionnaires to measure psychological, sociological, economic and educational variables. INVALSI in Italy (e.g. Borgonovi & Ferrara, 2023) collects information about students' performance in 2nd, 5th, 8th, 10th and 13th grades through standardised tests in reading, mathematics, and English. Moreover, starting from 5th grade, test scores can be linked with data from surveys with students and, for a smaller random subsample, with data regarding teachers. Another example is the German NEPS, which combines comprehensive competency-based assessment over a large observation window with interviews involving parents, teachers and school principals (e.g., Skopek & Passaretta, 2021).

Furthermore, in some studies, interviews are also combined with other methods. For instance, Niittylahti et al. (2023) conducted a mixed-methods research with a survey and interviews (once a year for three academic years) to examine the school engagement of vocational students. Similarly, DeWitt et al. (2014a) conducted the ASPIRES, a 5-year longitudinal mixed-methods study, to investigate students' interest in science and scientific careers and track changes. They conducted interviews and surveys to collect students' background data, such as ethnicity, gender, parental occupation, and information about students' and their families' aspirations and interest in science.

²² Emphasising the importance of the student's cognitive-affective processing of reality for understanding educational processes and outcomes, the students' engagement with school captures the subjective experience of connection with school context and experiences (Moreira et al., 2018). Student engagement is a dynamic and multidimensional phenomenon that emerges from the interaction among different domains of experience, including emotional, cognitive and behavioural indicators (De Faria et al., 2023).

Timeframe and sample

The repeated collection of data about the factors that affect student achievement, school engagement and inequalities in education, in general, started at the beginning of the 1960s. The oldest dataset identified through the systematic review comes from the INED survey (Broccolichi & Sinthon, 2011; Ichou & Vallet, 2012) that collected data about these educational issues, following a cohort for one decade from 1962 to 1972.

Some longitudinal or repeated cross-sectional datasets in European countries collect data regularly for a specific period. One is the PANEL study from DEPP in France (e.g., Farges & Monso, 2024), in which French students tracked for 8 to 17 years from 1973 to 2021. Also, the NEPS (e.g. Skopek & Passaretta, 2021; Wohlkinger & Ditton, 2023) provides longitudinal data on educational processes and competence development for a large, representative sample of children, adolescents and adults in Germany since 2008. In addition, the repeated collection of data from the same cohort in longitudinal studies, like the IARD survey in Italy (Guetto & Vergolini, 2017), and from similar cohorts in repeated cross-sectional studies, such as the PRIMA project that run for more than 15 years (Gijsberts & van der Ploeg, 2016), can provide relevant information. Indeed, following up on the same or similar cohort of students for such a prolonged duration can offer important information and contribute to identifying the variables and factors affecting inequalities over time.

Several studies with longitudinal and repeated cross-sectional research designs aim to identify the variables influencing students' achievement in basic skills and their school engagement, providing data collected over periods ranging from 8 to 14 years. This extended duration allows tracking a cohort of students throughout their education and their transitions between educational levels, thereby highlighting the variables that impact their academic trajectories. Analysis of findings across European countries indicates that, except for two studies lasting 6 and 7 years, such as the Evaluaciones de Diagnostico that collected data from 2015 to 2021 (Arenas & Gortazar, 2024), and Portuguese Longitudinal study on student engagement (e.g., Moreira & Lee, 2020) that collected data from 2013 to 2020, nearly half of the identified longitudinal and repeated cross-sectional datasets were implemented for five or fewer years. For example, the ASPIRES collected data between 2009 and 2013 (DeWitt et al., 2014), and the *Assessment of Student Achievements in German and English as a Foreign Language* (DESI) provides data for one year, from 2003 to 2004 (Klieme, 2006).

In some cases, such as in DESI (Klieme, 2006), the analysis is based on one-year data, although the dataset includes data from several years. For instance, the OECD Income Distribution Database (IDD) offers data on levels and trends in income inequality and poverty. It is updated regularly, two to three times per year (OECD, 2024c), offering rich and comparable data.

It is worth mentioning that at least one identified dataset is collected with a repeated cross-sectional design (at the end of 2nd, 5th, 8th, 10th and 13th grades) but switched to a longitudinal study at the individual level. This is the case of the Italian INVALSI data: a collegial decision from the Italian Ministry of Education in 2014 allowed the introduction of a unique student identifier (the so-called SIDI code) in the collected data, allowing the construction of longitudinal data following students from the academic year 2012-2013 at the micro level throughout different data collection points. INVALSI is an excellent example of how a change at policy and technical levels supported a switch from a repeated cross-sectional assessment of students to a longitudinal data collection approach to better support the evaluation (i) of students' learning outcomes (from the beginning of primary school to the end of secondary education) and (ii) of the education system, as a whole.

The specific timeframe and duration were not specified in the retrieved articles for 19 datasets identified through the systematic review but will be investigated in the next WP. Also, it is likely that

this systematic review did not discover all publications referring to each of the 77 datasets identified and analysed. For the older ones, related publications may have occurred before the period covered by the systematic review presented in this report (i.e., 1990-2014). For the more recent datasets, related publications may be in the pipeline.

In studies with longitudinal or repeated cross-sectional research design, the frequency of data collection, the so-called waves, is an essential factor for their utility. International cross-sectional studies that collect data through assessments typically have a periodicity. The PISA assessment (e.g., OECD, 2023a) has been conducted every three years since 2000, and TIMSS (OECD, 2015) every four years since 1995. On the other hand, PIRLS (e.g., Volante et al., 2022) is run every five years to measure reading achievement at the fourth-grade level since 2001.

The datasets identified through the literature encompass a variety of participants from primary and secondary education, spanning a wide range of sizes, ages, grades and demographic characteristics. Most of these studies collect data from large samples, ranging from several thousand, such as the ELEMENT study with a sample of 3,169 participants (Baumert et al., 2012a; Paetsch et al., 2016) to 1.5 million students, as in assessments like INVALSI (e.g., Borgonovi & Ferrara, 2023). Conversely, only a few studies collect data from small samples, namely fewer than 500 participants (e.g., Lemos et al., 2020).

Furthermore, it is observed that datasets derived from assessments and tests of basic skills often provide data from larger samples. For instance, the *Assessment of Student Achievements in German and English as a Foreign Language* (DESI) collected data from almost 11,000 9th-grade students (Klieme, 2006). In contrast, self-report data collected through surveys, which gather students' or other education stakeholders' perspectives and opinions, typically employ more restricted samples. For instance, the *Teach! The Role of Teachers' Beliefs and Instructional Practices for Students' Beliefs and Academic Outcomes* (TEACH study) collected data through surveys with 959 students and 50 teachers to examine the longitudinal relationships between teachers' cognitive and motivational beliefs and instructional quality and students' cognitive and motivational development at the end of secondary school (Hettinger et al., 2023).

Although ages and grades vary according to each country's educational system, methodological information from analysed publications allows for a reasonably accurate estimation of the school level attended by the sample in each dataset. The number of identified datasets concerning primary and secondary education students is quite similar, with 41 and 45 datasets, respectively. Notably, 21 of these datasets also include data collected during the transition from one educational level to another, signalling the relevance of transition between levels in shaping inequalities when school choices typically occur. For example, the *Evaluaciones de Diagnostico* (Arenas & Gortazar, 2024) collects longitudinal data from students transitioning from primary to secondary school. This aspect provides a wealth of information about the variables and factors that influence students' achievement in basic skills and their school engagement at each educational level and how these factors are affected by (or also affect) the transition between education levels. This comprehensive dataset allows for a deeper understanding of educational dynamics and the impact of transitional phases on student performance and engagement (Bécares & Priest, 2015; European Commission, 2023b).

Although the majority of the identified datasets are sampled according to age or grade, some collect data targeting individuals with specific characteristics, such as immigrant background or belonging to an ethnic minority. These datasets provide valuable insights into the variables and factors that affect these student populations' educational trajectories, achievement and school engagement. Two of the datasets utilised data from Gypsy students in primary (Rosário et al., 2017) and secondary school (Derrington, 2007), while the *Social Integration of Migrant Children - Uncovering Family and*

School Factors Promoting Resilience (SIMCUR) study was focused on Turkish immigrants between 9 and 15 years old in Germany (Demir & Leyendecker, 2018). Several studies (e.g., Bécares & Priest, 2015; European Commission, 2023b) have stressed that the ethnic, national, linguistic, or religious characteristics of some groups of students are crucial factors underneath educational inequalities. Investigating these factors over time through longitudinal or repeated cross-sectional datasets can provide valuable insights for policy and practice.

Only three identified datasets focus on or include students in initial vocational education and training (IVET). These are the longitudinal surveys conducted by Niittylahti et al. (2023), the NEPS (Holtmann & Solga, 2023), and the INVALSI data. Although IVET studies are integral to many educational systems and serve almost half of the upper-secondary students across the EU²³, usually the ones with lower parental background, a notable scarcity of datasets and studies dedicated to this target group limits the evidence for the factors that affect their academic achievement and educational trajectories.

Some datasets focus on students and their teachers, like the TEACH study that used data from students of 9th to 10th grade and secondary school mathematics teachers in order to examine the longitudinal relationships between teachers' cognitive and motivational beliefs, instructional quality, and students' cognitive and motivational development at the end of secondary school.

Sixteen of the identified datasets include information collected from teachers and/or students' parents. For instance, a study conducted by Sandsør et al. (2023) with longitudinal research design collects data from 5th to 10th-grade students and their parents or guardians to examine changes in gaps over time and within-cohorts achievement patterns across grades. Also, Rosário et al. (2017) collected data from a sample of Gypsy families for a four-year longitudinal study, and Paget (2018), in the Avon Longitudinal Study of Parents and Children (ALSPAC study), collected data through surveys from students and their mothers since they were pregnant until children were seven years old.

In some studies, the collection of data from both parents and teachers is considered the most appropriate method for a holistic investigation of factors of educational inequalities. For example, the Kids' Outcomes and Long-term Abilities (KOALA-S) project (Ditton et al., 2019; Ditton & Krüsken, 2009), which used surveys for teachers and parents combined with assessments of students' performance in maths and German language. Also, the OECD's PISA (e.g., OECD, 2023a) used surveys to collect data not only from students but also from teachers and parents.

5.3RQ2: Methods and techniques used to assess inequalities over time

This section discusses the statistical methods most frequently used in the 157 studies analysed through the review matrix. The terms methods and techniques refer to practices that rest on certain theoretical assumptions and allow the researcher to identify and measure the correlation between variables (i.e., their relationship) and the *ceteris paribus*²⁴ effect of the independent variables on the dependent variable.

²³ According to Eurostat data, "In 2021, 2.0 % of pupils in lower secondary education across the EU followed vocational programmes, with this share reaching 48.7 % for upper secondary education" (<https://ec.europa.eu/eurostat/statistics-explained/index.php?oldid=578213>).

²⁴ This Latin phrase is generally used for saying 'all other things being constant'. It is particularly crucial in the study of cause and effect relationships between two variables such that other relevant factors influencing these are assumed to be constant by the assumption of Ceteris Paribus. Source: [The Economics Times](#).

To properly answer the research questions set in each study, suitable methods are used, namely descriptive statistics and inference, mainly based on causal analysis²⁵. On the one hand, descriptive statistical methods are used to provide a comprehensive overview of the data and, hence, to better understand the main parameters of the data at hand and to provide information about statistical associations emerging in the data. Through that process, the researcher(s) can make informed decisions on which methods are more suitable for further analysis. On the other hand, inferential statistics allow the researcher(s) to isolate and quantify the effect of an independent variable, going beyond the bivariate associations and taking into account the specific contribution of an independent variable on a dependent one (in our case, educational outcomes). For example, the academic performance of students, keeping everything else constant (e.g., area of residence, gender, etc.).

The choice of the specific statistical method relies on the research questions of each study, the processes the researcher wishes to explore, the underlying technical or theoretical assumptions²⁶, and the restrictions posed by the nature of the data²⁷ (primarily being longitudinal or repeated cross-sectional). Researchers often choose different methods of analysis based on the value attached to each of the above factors or implement the same analyses through multiple methods to test the sensitivity of their results to the different assumptions of the method, which is usually known as a robustness check.

Considering the above, the systematic review identified 54 statistical and causal analysis methods in the 157 studies analysed. Several studies use more than one analysis method for reasons already discussed (e.g., Hübner et al., 2019), while others use different methods to study the same topic, such as Derrington (2007) and Caro and Lehmann (2009). Table 8.8 presents the number of methods used per publication. Eleven of the analysed studies (7.2%) use no quantitative analysis. For example, Volante et al. (2022) studied how the results of cross-national achievement tests impacted education policies and used no quantitative analysis to draw their conclusions. Moreover, studies that provide cross-country comparisons often do not include any statistical analysis, such as the ones by the OECD (Farges & Monso, 2024) and the European Commission (2023b).

Table 8.8 Number of methods per study

	Frequency	Share in %
0	11	7.0
1	72	45.9
2	51	32.5
3	16	10.2
4	5	3.2
5	1	0.6
6	1	0.6
Total	157	100

The most common approach is to use a single analysis method, as nearly half of the studies (46.1%) do. Examples of this research design can be found in the works of Klieme (2006), Broccolichi and Sinthron (2011) and Ferraro and Pöder (2018) within the German, French, and English contexts, respectively. The second most popular choice is to employ two analysis methods, with one in three studies (32.2%) following this approach. For instance, Baumert et al. (2012) utilize two

²⁵ Causal analysis refers to advanced statistical analysis, which aims to identify the causal relationship between two variables. The most well-known technique used is Ordinary Least Squares (OLS) regression. Causal analysis has different names depending on the discipline, i.e. in economics it is called econometrics, in psychology it is called psychometrics, etc.

²⁶ For example, assuming a specific behaviour for the residuals, i.e., the part of the variability of the dependent variable that the independent variables cannot explain.

²⁷ For example, the dependent variable may be continuous, binary (e.g., logit), ordinal, truncated, etc.

complementary quantitative methods to analyse multilevel data. Similarly, DeWitt et al. (2014) apply different methods to explore distinct research questions—one focusing on primary education and the other on secondary education students. Hippe et al. (2018a) also employ a decomposition technique to enhance their analysis and interpret regional differences within countries based on PISA test scores, while Triventi et al. (2021) combine methods to address methodological challenges and improve the robustness of their findings.

One in every ten studies uses three quantitative analysis methods (9.9%). For example, Van de Gaer et al. (2009) base their analysis on three distinct quantitative methods of analysis to address different research questions and ensure the methodological soundness of their findings. Their research examines gender differences in the development of language achievements and school engagement among secondary school students. Brinbaum and Kieffer (2009) also address multiple research questions, e.g., how secondary school students of migrant origin differ from natives considering educational achievements at the beginning and by the end of secondary education, academic orientation and diplomas obtained, and employing various methods. The remaining studies that use more than three analysis methods account for just over 3% of the total, with only five studies falling into this category. Notably, a single study (Farges & Monso, 2024) employs five distinct quantitative methods to explore the differences between boarding school students and non-boarders, investigating how individual characteristics influence these differences. Finally, Dimosthenous (Demosthenous, 2019) uses six quantitative methods to address the various research questions of her doctoral research on the short- and long-term effect of teacher effectiveness and home learning environment on students' learning outcomes in mathematics.

Even though many statistical and econometric analysis methods are used in the literature reviewed²⁸, the report focuses here on the ten most common, i.e., used by at least six studies, with one exception discussed in the end. They are presented in

Figure 11, ranging from the most frequently used to the least frequently used. The Linear Regression Analysis (LiRA) is used in one-fourth of the studies reviewed, corresponding to 42 publications. LiRA is used to examine the relationships between multiple independent variables and a single dependent variable by accommodating several predictors simultaneously, allowing researchers to measure the net association between each independent variable of interest and the outcome variable (or, less frequently, to assess how different factors collectively influence an outcome of interest). For instance, Brinbaum and Kieffer (2009) employ the LiRA combined with other quantitative methods to predict the score of standardised maths and French language tests depending on ethnic origin, socio-cultural variables, and various students' characteristics. Borgonovi and Ferrara (2023) and Contini and Cugnata (2020) use LiRA to explore how family-background variables influenced students' achievements in reading and mathematics during the COVID-19 pandemic. Moreover, using the same method, Albrecht et al. (2018) concluded that students' performance-related features predicted a change in school track, while no secondary effects from the socioeconomic background were observed once differences in academic performance were accounted for.

²⁸ The complete list and a short description of each can be found in Appendix B.

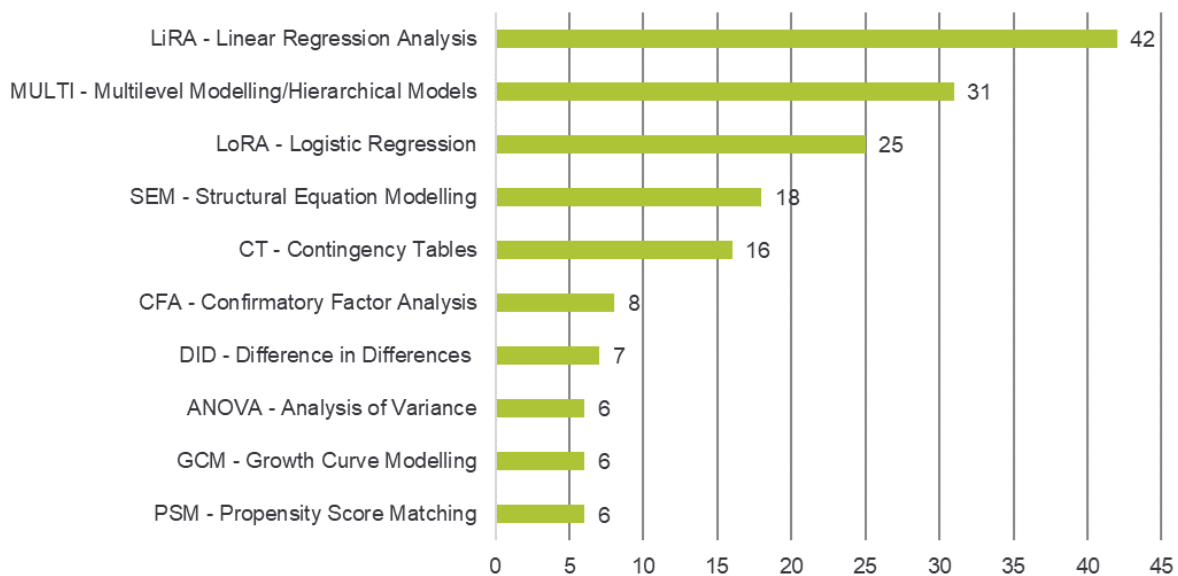


Figure 11. Top-ten statistical methods derived from the review

The second most common analysis method is Multilevel Modelling (MULTI), also known as hierarchical modelling. This method is used in one out of five studies reviewed, which is not surprising, as it is highly appropriate to analyse data with a nested or hierarchical structure, such as the education ones. For example, a dataset with a hierarchical structure consists of students nested in classrooms nested in schools. This allows the researcher to explore relationships at different levels of aggregation, such as individuals within groups, i.e., students attending the same school, while accounting for dependencies and variations across those levels. For instance, Caro and Lehmann (2009) use multilevel modelling to study how students' socioeconomic background affects their reading and maths performance and predicts their future achievements. The research question is similar in Helbling et al. (2019) with longitudinal data from Switzerland. Moreira and Lee (2020) follow a different path by focusing on testing students' cognitive engagement at two different points in time. Burger (2019) uses multilevel modelling to verify that the effect of socioeconomic status on student achievement is stronger in more segregated education systems, even after controlling for alternative system-level determinants of social inequality in student achievement.

The third most frequently used quantitative method is Logistic Regression Analysis (LoRA), used in approximately one out of six studies reviewed (around 16%). LoRA is a generalization of linear regression designed to handle situations where the dependent variable is not continuous but, instead, takes on discrete values, such as 0 and 1 (representing two possible outcomes). LoRA can be applied in various forms: binomial, for binary dependent variables; multinomial, when the dependent variable represents unordered categories (e.g., degree major); and ordered, for outcomes that can be meaningfully ranked (e.g., levels of education completed). For instance, Mikus et al. (2021) utilize binary logistic regression to investigate the incidence of parental concerted cultivation activities and their impact on students' cognitive skills. Similarly, Kindt et al. (2023) apply both multinomial and binomial logistic regression to model occupational aspirations and educational tracks, investigating how various independent variables influence these outcomes. Conversely, Fougère et al. (2017) examine the impact of the presence of students from migrant backgrounds on overall educational outcomes within a class, finding that, unlike ethnic and social segregation, this factor has a limited effect.

Two statistical techniques are used 16 and 18 times, which means that almost one out of ten analysed studies tend to employ them. The first is Contingency Tables (CT), and the second is Structural Equation Modelling (SEM).

Contingency Tables (CT) are used to explore relationships between two or more variables (but limited in number) and belong to descriptive analyses. The method is based on a matrix (table) that displays the frequency distribution of specific variables (typically two), and it is used to explore descriptively the relationship between categorical variables, enabling the analysis of patterns and interactions within the data. Each cell in the table usually represents a frequency, while shares by row or column are useful to compute, providing additional information. Only two studies use CT as the only statistical technique: Cosnefroy and Rocher (2004) and Broccolichi and Sinthon (2011). Cosnefroy and Rocher examine the incidences of grade repetition and how they relate to lower academic achievements later in school life. On the other hand, Broccolichi and Sinthon explore how parents' occupations and levels of education impact the rate of admission to non-vocational education. Compared to LiRE or LoRA, the limit of this technique is that the association provided is not robust and can be interpreted causally only in limited circumstances.

Structural Equation Modelling (SEM) tests and estimates causal relationships by simultaneously investigating a set of associations among variables considered in the model and assessing to what extent the researcher's hypothesis fits the observed data. SEM encompasses, as special cases, multiple regression analysis, factor analysis, and path analysis, enabling researchers to explore complex relationships among observed and latent variables simultaneously. In this case, some studies rely solely on SEM to answer the research questions they set. For example, Blondal and Adalbjarnardottir (2014) explore the effect of parenting practices on dropout rates in upper secondary education, while Poorthuis et al. (2015) study how grades shape students' school engagement. On the other hand, Lazarides and Rubach (2017) use both SEM and FIML (Full-Information Maximum Likelihood), i.e., an estimator used to handle missing observations, to examine the relationship between student-perceived teaching for meaning, support for autonomy, and competence in maths, and students' achievement goal orientations and engagement in maths. Moreover, Sprong and Skopek (2023) use SEM and Path Analysis to explore how achievement gaps in the country's host language among students with migrant backgrounds evolve during primary school, revealing that these gaps were already present before formal schooling began.

A recent (in the EU) trend in social sciences is evaluating programmes, measures and policies by focusing on groups' experiences, either by design (i.e., by conducting an experiment) or by taking advantage of naturally occurring (i.e., random) exposure of individuals to different conditions. Even though such practices are still relatively rare in education and training, they all may be categorised under the label "counterfactual impact evaluation" and rely on defining and comparing a subsample, e.g., of students who have received a treatment vs. another subsample that did not receive it, used as a control group. Difference-in-Differences (DiD) is a typical example, and it is used in seven of the studies reviewed. This technique compares the changes in outcomes over time between a group exposed to a treatment and a control group, effectively controlling for confounding variables and unobserved factors. For example, Lavrijsen and Nicaise (2015) rely on DiD to investigate the effect of social origin on educational attainment using different groups of students in 33 countries. It is important to note that in this systematic review, the LINEup research team only included studies employing experimental or quasi-experimental designs that collected data beyond the standard pre- and post-test measures.

Apart from the quantitative methods presented above, some studies used qualitative methods or a mixed-method approach that combines quantitative and qualitative methodologies. For instance, semi-structured interviews were used for data collection and were analysed through content

(Niittytahti et al., 2023) or thematic analysis (Ribeiro et al., 2023). The former study investigates the evolution of vocational students' engagement during their studies and the factors driving it while identifying three different profiles of student engagement: immediate, nascent, and indeterminate. The latter study analyses qualitative data using the thematic analysis approach in a deductive manner and at a semantic level to explore the facilitators of and obstacles to school engagement amongst children exhibiting significant problems at school. At the same time, it employs multilevel correlation analysis to perform quantitative analysis and identify individual, family and school predictors of children's school engagement.

None of the methods and techniques presented in this review is preferable or superior to the others. Given that the data and research questions allow for multiple methods to be used, the choice depends on the researchers' expertise, background and preferences. Also, in many studies, using multiple methods is a way to test further, expand and verify their findings, which is a widespread research approach.

5.4RQ3: Variables identified as factors and predictors of educational inequalities

This section presents the results from analysing through the review matrix presented above the variables identified in the 157 publications as factors or predictors of educational inequalities²⁹.

Research in the sociology and economics of education has mainly focused on the individual factors affecting students' educational achievement and attainment, such as students' gender, social origin, and migratory background. In the literature, these factors producing differences in students' learning outcomes have been interpreted as sources of 'primary' and 'secondary' effects: students' characteristics directly influence their educational achievement and are also connected to students' and parents' choices at turning points in education careers, beyond their performances (Boudon, 1974; OECD, 2024a). A more recent strand of research has then introduced the concept of 'tertiary effects' (Jackson, 2013; Schneider, 2014; Esser, 2016) to refer to the role that school's community members, and in particular teachers, can play through their expectations, evaluations and suggestions towards students with different backgrounds. In fact, inequalities can also be reinforced and reproduced by a complex set of micro-mechanisms at play within the school context and between school players (teachers and school leaders) and families (Argentin & Pavolini, 2020; Passaretta & Skopek, 2021). Moreover, as explained in Section 1, specific policies and characteristics of the education system also contribute to shaping educational inequalities. For instance, standardisation is often associated with gender equality, stratification is related to high ethnic inequality, and between-school stratification is related to higher socioeconomic inequality (Zapfe & Gross, 2021). Other important examples at the system level producing noteworthy differences and inequalities include, among others, the level of schools' autonomy and public expenditure on education.

Many variables linked to educational inequalities were scrutinised and analysed within this theoretical framework. Unsurprisingly, the research team identified 70 variables through the systematic review. Appendix C lists the analysed publications from which each of the 70 variables was derived.

Considering the literature on inequalities in education and the research findings of the publications analysed in the systematic review, the 70 identified variables have been grouped into four clusters and ten sub-clusters to create a conceptual model (see Figure 12 and Table 9) that will be fine-tuned in the next WPs of the LINEup project:

- **Student cluster** variables linked to individual characteristics and attributes;
- **Family cluster** variables linked to the family and home environment;
- **Teacher cluster** variables linked to teachers' characteristics, attributes and practices;
- **School and system cluster** variables linked to policies, environment and organisation at the school and/or system level.

For illustrative purposes, the variables of each cluster are then grouped into the sub-clusters presented in Figure 12 and described in Table 9. As shown in Figure 12, several variables refer to more than one level (student, family, teacher, school and system), and they are interrelated and interdependent by nature.

²⁹ As stated in Footnote 8, we use the term "factor" when describing the relationship between two or more variables and the term "predictor" when a variable reliably predicts an outcome.

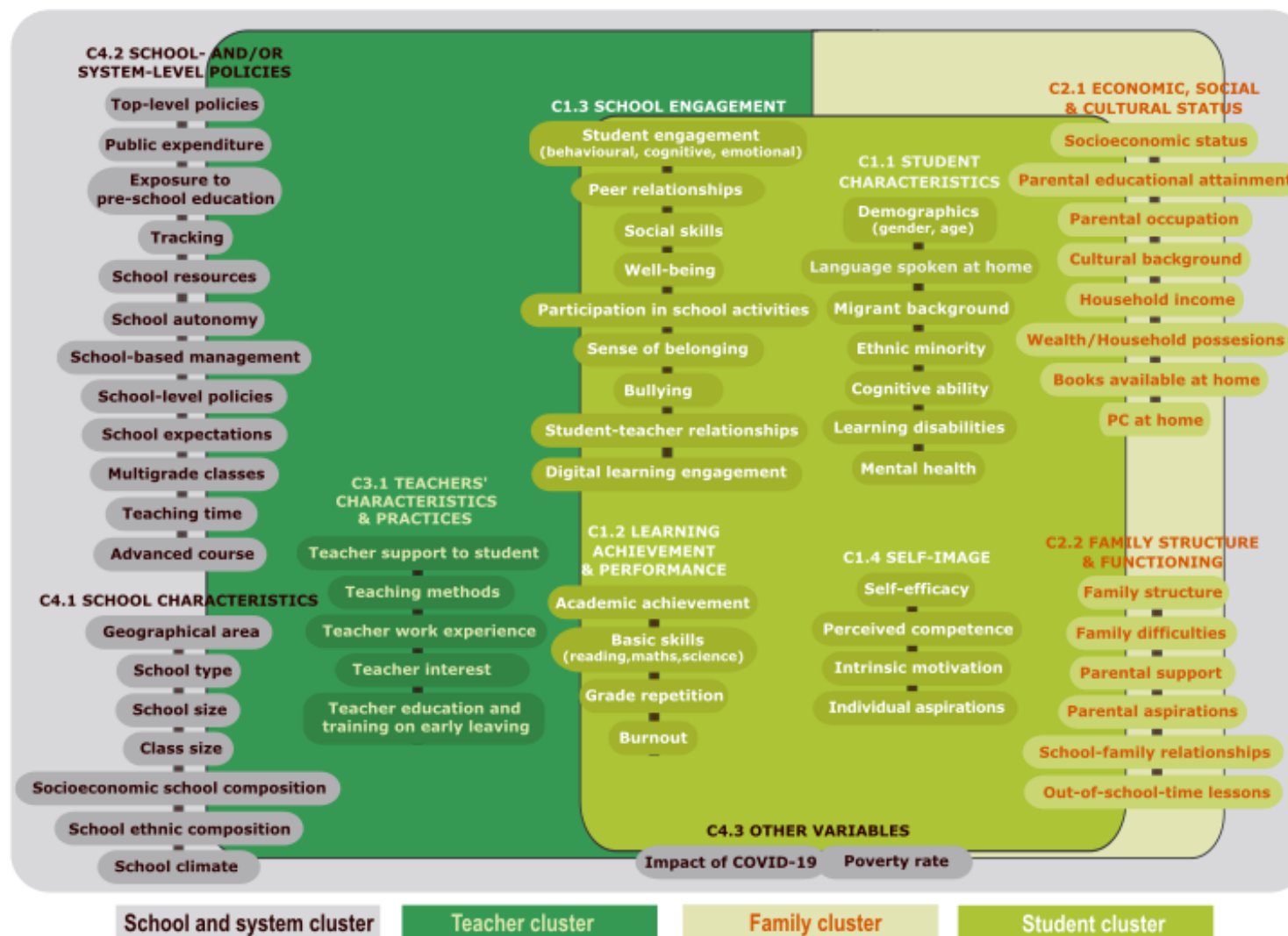


Figure 12. LINEup conceptual model: general overview

Table 9. LINEup's conceptual model: clusters, sub-clusters and variables

Clusters	Sub-clusters	Variables	Definitions
Student (C1)	Student characteristics (C1.1)	Gender	Gender refers to the characteristics of women, men, girls and boys that are socially constructed. This includes norms, behaviours and roles associated with being a woman, man, girl or boy, as well as relationships with each other. As a social construct, gender varies from society to society and can change over time. Source: World Health Organisation, 2022
		Age	The age of a student is calculated as the difference between the year and month of testing and the year and month of the student's birth. Source: OECD, 2018
		Language spoken at home	Main language spoken in the home environment and acquired as a first language. Source: UNESCO, 2006
		Migrant background	A person who is outside the territory of the State of which they are nationals or citizens and who has resided in a foreign country for more than one year irrespective of the causes, voluntary or involuntary, and the means, regular or irregular, used to migrate. Source: European Commission Migration and Home Affairs
		Ethnic minority	A group numerically inferior to the rest of the population of a State and/or in a non-dominant position, whose members possess ethnic differing from those of the rest of the population and show, if only implicitly, a sense of solidarity, directed towards preserving their culture, traditions, religion or language. Source: UNEVOC
		Cognitive ability	Having to do with the ability to think and reason. This includes the ability to concentrate, remember things, process information, learn, speak, and understand. Source: Scientific Committees
		Learning disabilities	A number of disorders which may affect the acquisition, organization, retention, understanding or use of verbal or nonverbal information. These disorders affect learning in individuals who otherwise demonstrate at least average abilities essential for thinking and/or reasoning. As such, learning disabilities are distinct from global intellectual deficiency. Source: Learning Disabilities Association of Canada
		Mental health	Mental health is a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community. Source: World Health Organisation
	Learning achievement & performance (C1.2)	Academic achievement	Academic achievement represents performance outcomes that indicate the extent to which a person has accomplished specific goals that were the focus of activities in instructional environments, specifically in school, college, and university. Source: Steinmayr et al., 2014
		Math skills	Individual's capacity to reason mathematically and to formulate, employ, and interpret mathematics to solve problems in a variety of real-world contexts. Source: OECD, 2023

		Reading skills	Individual's capacity to understand, use, evaluate, reflect on, and engage with texts in order to achieve one's goals, develop one's knowledge and potential, and participate in society. Source: OECD, 2023
		Science skills	The scientific knowledge to identify questions, acquire new knowledge, explain scientific phenomena, and draw evidence-based conclusions about science-related issues. Source: OECD
		Grade repetition	Students with poor academic performance who repeat the same grade for an additional year. Source: Salza, 2022
		Burnout	It can be defined as a school-related syndrome including exhaustion, negative cynical attitude toward school and feelings of inadequacy as a student. Source: Salmela-Aro et al., 2021a
	School engagement (C1.3)	Student engagement	Student or school engagement can be understood as a developmental process comprised of student thoughts, feelings, beliefs, and behaviors in relation to the schooling context and his or her lifelong learning trajectory. There is emerging consensus on a definition of student engagement that includes behavioral, emotional/psychological, and, more recently, cognitive components. Source: Furlong & Rebelez-Ernst, 2014
		Emotional engagement	Emotional engagement describes student's positive emotions and attitudes towards teachers, classmates, and school in general. Source: Dockx et al., 2020
		Behavioural engagement	The level of active involvement and positive attitudes about learning activities is described as behavioral school engagement. Source: Dockx et al., 2020
		Cognitive engagement	Students' interest and performance in school's academic challenges and emotional engagement, which is seen in students' connectedness and affective reactions with their peers, teachers and school environment in general. Source: Blondal & Adalbjarnardottir, 2014
		Peer relationships	The quality of interactions and relationships with fellow students. Source: Niittylahti et al., 2023
		Social skills	A set of learned abilities that enable an individual to interact competently and appropriately in a given social context. The most commonly identified social skills in Western cultures include assertiveness, coping, communication and friendship-making skills, interpersonal problem-solving, and the ability to regulate one's cognitions, feelings, and behavior. Source: APA Dictionary of Psychology
		Well-being	The psychological, cognitive, social and physical functioning and capabilities that students need to develop their potential, learn and play creatively and therefore live a happy and fulfilling life. Pupils who experience well-being can build and enjoy positive relationships with others and feel belonging to their school community. Source: Adapted from European Commission, European Education Area
		Participation in school activities	Active engagement in class activities, discussions, and tasks, contributing to a deeper understanding of the course material and enhancing learning outcomes. Source: O'Connor, 2013
		Sense of belonging	Students' sense of belonging at school is the extent to which students feel accepted by and connected to their peers, and part of the school community. A sense of belonging gives students feelings of security,

			identity and community which, in turn, support academic, psychological and social development. Source: OECD, 2018
		Bullying	Physical, verbal and relational behaviours, which involve one party having the intention to repeatedly hurt or harm another, within an uneven power relationship where the victim is unable to defend him/herself. Source: European Commission & PPMI, 2022
		Student-teacher relationships	Teachers' and students' aggregated and ongoing perceptions of one another, affect toward each other, and interactions over time; these perceptions are stored in memory and guide future interactions with the other party. Source: Brinkworth et al., 2018
		Digital learning engagement	The out-of-school learning component that reflects informally emerging socio-digital participation. The gap hypothesis proposes that students who prefer learning with digital technologies outside of school are less engaged in traditional school. Source: Hietajärvi et al., 2020
	Self-image (C1.4)	Self-efficacy	The extent to which students believe they have the ability to engage in learning activities and deal with tasks, especially in an adverse situation. It impacts multiple student academic performance, such as math score or math problem-solving ability, reading score, and English learning for foreigners. Source: Adapted from Jin et al., 2023
		Perceived competence	Perceived competence refers to students' sense of what they can do and how good they are at different tasks. Source: Xiang & Lee, 1998
		Intrinsic motivation	The undertaking of tasks and activities for their inherent value, includes affective components, such as enjoyment and cognitive components, such as the willingness to do an activity for its inherent satisfaction. Source: Lazarides & Rubach, 2017
		Individual aspirations	The long-term goals that act as drivers of success and school attainment. Source: Ditton et al., 2019
Family (C2)	Economic, social & cultural status (C2.1)	Socioeconomic status (ESCS)	Socioeconomic status is a measure of students' access to family resources (financial capital, social capital, cultural capital and human capital) and the social position of the student's family/household. Source: OECD, 2019
		Parental educational attainment (ESCS)	Part of the main socioeconomic status parameters refers to the highest level of education attained by a student's parents or guardians. Source: Authors' elaboration
		Parental occupation (ESCS)	Parental occupation is one of the main socioeconomic status parameters. It refers to the job or profession held by a person's parents or guardians. Source: Authors' elaboration
		Cultural background (ESCS)	The set of distinctive spiritual, material, intellectual and emotional features of a society or a social group encompassing, in addition to art and literature, lifestyles, ways of living together, value systems, traditions and beliefs. Source: European Commission Migration and Home Affairs

		Household income (ESCS)	It is one of the SES components indicative of a standard of living and life chances household members experience through sharing goods and services. Source: Adapted from Duncan et al., 2002
		Wealth/ Household possessions (ESCS)	The definition of wealth, or net worth, for micro statistics on household wealth is the value of all the assets owned by a household less the value of all its liabilities at a particular point in time. Source: OECD, 2013
		Books available at home (ESCS)	The number of books at home therefore seems to capture unique aspects of a family's SES that are key in explaining students' academic achievement in general and their language development in particular. Source: Heppt et al., 2022
		PC at home (ESCS)	The number of personal computers (PCs) in working order that a student has access to at home. Source: Authors' elaboration
	Family structure & functioning (C2.2)	Family structure	People related by marriage, birth, consanguinity or legal adoption, who share a common kitchen and financial resources on a regular basis. Source: Sharma, 2013
		Family difficulties	Family difficulties are often an underlying source of students' distress, giving rise to a variety of issues that they may have to deal with. The difficulties may involve on-going conflicts, disruptions and/or crisis both within the family and between the student and family members. Source: University of Galway
		Parental support (to student)	Parental involvement in school activities, their contact with the school and their communication with their child about what's happening in the school environment. Source: Blondal & Adalbjarnardottir, 2014
		Parental aspirations	Parental aspirations refer to their ambitions for their child's education. Source: Trinidad, 2019 Academic success and school-leaving qualifications desired from parents for their children. Source: Ditton et al., 2019
		School-family relationship	Family-school partnerships are collaborative relationships and activities involving school staff, parents and other family members of students at a school. Effective partnerships are based on mutual trust and respect, and shared responsibility for the education of the children and young people at the school. Source: Australian Government, 2008
		Out-of-school-time lessons	Lessons only in subjects that students learn at school, that they spend extra time learning outside of normal school hours. The lessons might be held at their school, home or somewhere else. Source: OECD, 2011
Teacher (C3)	Teachers' characteristics & practices (C3.1)	Teacher support (to student)	Teachers' ability to foster interactions with students and between the students, by paying attention to students' difficulties, students' emotions and opinions, and by supporting them socially and emotionally, in order to create a warm and respectful classroom climate. Source: Hettinger et al., 2023
		Teaching methods	Approaches used by educators to facilitate learning. Source: Niittylahti et al., 2023
		Teacher work experience	Years of teaching work experience. Source: Authors' elaboration

		Teacher interest	The interest of the teachers in their job. Source: Authors' elaboration
		Teacher education and training on early leaving	Education and training opportunities that can enhance teachers' capacity to address issues related to early leaving in education and training, such as teaching a diverse range of learners and promoting inclusive approaches, teaching in multilingual and multicultural settings, promoting a positive school climate and awareness of learners' social and emotional development. Source: European Commission/EACEA/Eurydice, 2023
School & education system (C4)	School characteristics (C4.1)	Geographical area	The area where the school is located (e.g., urban or rural), where the student lives, and/or the distance between them. Source: Authors' elaboration
		School type	Schools vary in funding (e.g., public, private), size (small, medium, big), area (e.g., rural, urban), and focus (e.g., general, vocational), catering to different needs and preferences. Options include public, charter, private, magnet, virtual/online, international, alternative, whole-day, and vocational schools. Source: Authors' elaboration
		School size	School size refers to the total number of pupils enrolled regardless of the grade. Source: IIEP Learning Portal
		Class size	Class size refers to the number of students in a given course or classroom, specifically either (1) the number of students being taught by individual teachers in a course or classroom or (2) the average number of students being taught by teachers in a school, district, or education system. The term may also extend to the number of students participating in learning experiences that may not take place in a traditional classroom setting, or it may also refer to the total number of students in a particular grade level or "class" in a school (although this usage is less common in public education). Source: The Glossary of Education Reform
		Socioeconomic school composition	The percentage of low-, medium-, or high-socioeconomic backgrounds of students in a school. Source: Belfi et al., 2016
		School ethnic composition	The ethnic school concentration and the school's ethnic heterogeneity or diversity. Source: Agirdag et al., 2011
		School climate/culture	The term school culture generally refers to the beliefs, perceptions, relationships, attitudes, and written and unwritten rules that shape and influence every aspect of how a school functions, but the term also encompasses more concrete issues such as the physical and emotional safety of students, the orderliness of classrooms and public spaces, or the degree to which a school embraces and celebrates racial, ethnic, linguistic, or cultural diversity. Source: Glossary of Education Reform
	School- and/or system-level policies (C4.2)	Top-level policies/measures	Regulations, recommendations, actions (including monitoring and evaluation) and/or funding provided by top-level education authorities – that aim to reduce early leaving in education and training. Source: European Commission/EACEA/Eurydice, 2023

	Public expenditure in education	Total public finance devoted to education by local, regional and national governments, including municipalities. Household contributions are excluded. Source: UNESCO, 2006
	Exposure to preschool education	Programmes at the initial stage of organized instruction, primarily designed to introduce very young children, aged at least 3 years, to a school-type environment and provide a bridge between home and school. Various referred to as infant education, nursery education, pre-school education, kindergarten or early childhood education, such programmes are the more formal component of Early Childhood Care and Education. Upon completion of these programmes, children continue their education at ISCED 1 (primary education). Source: UNESCO Digital Library, 2007
	Tracking	Tracking refers to the practice of separating students into different educational tracks after primary school (e.g., academic or vocational) with differing curricula and cognitive demands. Source: Adapted from Benz et al., 2021
	School resources	School resources means any funds, facilities or resources (including equipment and consumables, use/supply of heat, light or power) of the school. Source: Law Insider
	School autonomy	School autonomy is defined as a school's right of self-government—encompassing the freedom to make independent decisions—on the responsibilities that have been decentralized to schools. Source: Neeleman, 2019
	School-based management	School-based management transfers decision-making authority and responsibility for school operations from central government to local stakeholders to better reflect local priorities and improve student outcomes. Source: (UNESCO Digital Library, 2017)
	School-level policies	Policies and procedures cover all aspects of school life. They can be written for a variety of audiences, depending on the subject, including students, parents, staff, and governors. Policies ensure that values are applied consistently, define clear expectations, and help provide a framework for employees and students alike. Source: High-Speed Training
	School expectations	Schools aspirations for students to maintain regular attendance, succeed academically, demonstrate respectful behaviour, develop personal and social skills, and contribute to the school community through involvement in activities and extracurriculars. Source: Authors' elaboration
	Multigrade classes	Several grades or divisions taught simultaneously in the same classroom by a single teacher. Source: IIEP Learning Portal
	Teaching time	The number of hours spent teaching a group or class of students according to the formal policy in the country. Source: OECD
	Advanced course	Classes that typically offer higher levels of academic rigor, a more challenging curriculum, and higher expectations than standard grade level courses. In middle school, these may be referred to as honors courses; at the high school level, the terms may include honors level, Advanced Placement, International Baccalaureate, and Dual Enrollment courses. Source: IGI Global

	Other variables (C4.3)	Impact of COVID-19 pandemic education	The COVID-19 pandemic affected educational systems across the world. At its peak, nearly 1.6 billion learners in more than 190 countries, or 94% of the world's student population, were impacted by educational institution closures resulting in learning losses. Source: Adapted from Donnelly & Patrinos, 2022
		Poverty rate	People whose disposable income, after taxes and transfers, is lower than the poverty threshold, set at 50% of the national median household income. Source: Daniele, 2021

Student cluster

Student cluster comprise 30 variables, categorised into four sub-clusters: **Student characteristics (C1.1)**, **Learning achievement and performance (C1.2)**, **School engagement (C1.3)**, and **Self-image (C1.4)**.

C1.1 - Student characteristics

Student characteristics is a prominent sub-cluster of educational inequalities variables identified through this review. In 53 of the publications analysed, **gender** is referred to as a key variable of educational inequalities (e.g., Berendes et al., 2018; Borgonovi & Ferrara, 2023; Brinbaum & Kieffer, 2009; Caille, 2004a). Several studies report differences in basic skills acquisition among students from different genders (e.g., Borgonovi & Ferrara, 2023; Costanzo & Desimoni, 2017; Demir & Leyendecker, 2018). According to some studies (European Commission & PPMI, 2022), boys are more likely to leave early from education and training than girls, and they underperform in many schooling outcomes, such as in tertiary degree attainment rate and average literacy skills. However, other studies (e.g., Contini et al., 2017) report that girls systematically underperform boys in mathematics, even without accounting for the impact of individual and family background characteristics. According to Sammons (1995), gender differences in academic achievement may change over time; in earlier years of education (3 to 6 years old), girls show better math achievement than boys. However, girls show better skill growth in grades 5-8 (10 to 13 years old), while boys show better in grades 9 and 10 (14 to 15 years old) (Lehmann et al., 2004). The gender gap in performance mirrors the gender gap in students' drive, motivation, and self-efficacy (OECD, 2013), which increases with children's age (Contini et al., 2017). Also, the gender gap is performance-based; it is smaller at the lowest percentiles of performance but bigger among the highest performance (Contini et al., 2017). Finally, according to Termes (2022), girls are more likely to take the academic track. The results are heterogeneous because different studies look at different outcomes at different school levels and countries.

Another important variable of educational inequalities, grouped under *student characteristics*, is the **students' age**, identified in 16 of the analysed publications (e.g., Caille, 2004a; Dockx et al., 2020; Verhaeghe et al., 2018). Although the relationship with age is weaker than the association with gender (UNESCO, 2006), age is a significant mediating factor. For example, the relationships between academic well-being and performance become more prominent during adolescence (Widlund et al., 2023). Previous research found a negative connection between age and academic performance in the classroom, where older students had lower educational achievement (e.g., Sammons, 1995; Lehmann et al., 2004). As a result, potential inequalities can be "magnified" at older ages because achievement and engagement are reduced for all. Grenet (2010) observed that the birth month also affects educational outcomes and educational trajectories, but not salaries or occupations, similarly to birth date (Caille & Rosenwald, 2006).

Research indicates (e.g., Arenas & Gortazar, 2024; Dockx et al., 2020) that **language spoken at home** is crucial to educational achievement. Felouzis (2003) reports that students whose native language is not their mother tongue have lower educational performance, while Helbling et al. (2019b) relate it to lower prior knowledge. Another variable of this sub-cluster is the **migrant background**, which research indicates that affects educational achievement in math and reading (Costanzo & Desimoni, 2017; Nagy et al., 2017; Passaretta & Skopek, 2018) and scientific literacy (Kähler et al., 2023; Passaretta & Skopek, 2018). Students with a migrant background are more vulnerable and struggle in most EU education systems. However, as reported by Herrera-Sosa et al. (2018), the gap is notably wider for first-generation immigrant students than for second-generation ones compared to native students). Research indicates that students with immigrant backgrounds

have a higher risk of lower school engagement, especially in middle school (Motti-Stefanidi et al., 2015), and a lower sense of belonging (OECD, 2003). Research also reveals that educational inequalities linked to migration background already exist before school enrolment and persist over primary schooling ((Kähler et al., 2023; Passaretta & Skopek, 2018) while possibly remaining even in Grade 9 (Salza, 2022). **Ethnic minority** membership is also reported as a predictor of greater educational vulnerability (European Commission, 2022c). According to Sammons (1995), ethnic background differences in educational achievement are already visible in years 3 to 6.

According to some studies (e.g., Gil-Hernández, 2021; Hübner et al., 2019), students with lower **cognitive ability** must cope with educational inequalities generally leading to lower academic performance than those with higher cognitive skills, who achieve better results with the same or less effort. **Learning disabilities** is another variable affecting educational performance (e.g., Di Tommaso et al., 2024; OECD, 2003; Paget et al., 2018). Ribeiro et al. (2023) report that students with learning disabilities face obstacles to school engagement, and a European Commission study (European Commission/EACEA/Eurydice, 2023) that they are at high risk of dropping out. According to UNESCO (2006), about 35% of dropout students have learning disabilities, and 2% of students with disability are dropouts. **Mental health** is also considered crucial in students' educational achievement (Dockx et al., 2020; Niittylahti et al., 2023; OECD, 2003). For instance, according to Paget et al. (2018), students' exclusion from school from 8 to 16 years is associated with mental health.

C1.2 - Learning achievement and performance

The second student sub-cluster, *learning achievement and performance*, includes important variables such as academic achievement and basic skills (i.e., reading, maths, and science). **Academic achievement** is an umbrella term referring to the student's level of success in meeting the objectives set during educational activities, especially within school, college, and university environments (Steinmayr et al., 2014). As derived from the systematic review, academic achievement, as the acquisition of basic skills, is not only an outcome variable in several studies but also a significant predictor of students' educational pathways and qualifications later on (e.g., Grelet, 2005; Passaretta et al. 2022; Stéfanou, 2017). The review reveals a strong connection between academic achievement, student engagement, and early leaving school (Lemos et al., 2020) since students who cannot incorporate prior knowledge into the school environment are more likely to feel disengaged (Hietajärvi et al., 2020). Confirming the strength of the association between academic achievement and student engagement, student academic achievement remained a strong predictor of student cognitive engagement, even after controlling for previous student cognitive engagement (Moreira & Lee, 2020). According to some scholars (Ben Ali & Vourc'h, 2015; Guimard et al., 2007; Passaretta et al., 2022), assessments at the 1st grade are also good predictors of school achievement in later grades. Also, according to Caille (2004a, 2014), students' knowledge level at the beginning of lower secondary education is related to better educational outcomes in later grades. Students' grades, as a proxy measure of academic achievement, can affect students' probability of school dropout in upper secondary education (Haugan et al., 2019; Sandsør et al., 2023), emotional and behavioural engagement (Lemos et al., 2020; Poorthuis et al., 2015), and further educational attainment (Ditton, 2013). In addition, Straková et al. (2016) report that students' academic performance predicts the probability of attending the academic track. Motti-Stefanidi et al. (2015) assert that achievement in school lessons reinforces students' interest and prevents school disengagement. Finally, Lemos et al. (2020) state that high grades, school engagement, and academic achievement are strongly connected.

The analysis of the 157 publications reveals that achievement in basic skills is strongly associated with academic achievement in general over time (Wohlking & Ditton, 2023). The most well-known

survey of academic achievement is the Programme for International Student Assessment (PISA), which measures 15-year-olds' ability to use their reading, mathematics, and science knowledge and skills to cope with life's challenges. **Reading** is a key factor in school performance predicting dropout in upper-secondary-level schools (Hakkarainen et al., 2015). Van de Gaer et al. (2009) report a positive correlation between language achievement and school engagement. Other studies show that students' reading comprehension at the end of third, fourth, and fifth grade (Verhaeghe et al., 2018) and reading performance in the ninth grade (Wohlkinger & Ditton, 2023) affect academic performance in later grades. Moreover, according to Paetsch et al. (2016), students' reading comprehension predicts their mathematical competence in fourth grade and their learning gains in mathematics from grades 4 to 6. Finally, some studies (Brinbaum & Kieffer, 2009; Robert-Bobée, 2013) show that the initial level of reading competence in secondary school is related to academic achievement, while the gap in performance of reading competence is wider in secondary school (Pfof et al., 2010).

Also, according to some of the analysed studies, **mathematics** achievement or numerical literacy is critical in predicting academic performance (Ben Ali & Vourc'h, 2015; Verhaeghe et al., 2018) or dropout (Holtmann & Solga, 2023). Other studies show that students' knowledge level in mathematics at the beginning of primary (Caille & Rosenwald, 2006) or secondary school (Brinbaum & Kieffer, 2009; Robert-Bobée, 2013) affects their academic outcomes in the subsequent grades. According to OECD (2013), the students who participate in additional support and tutoring in mathematics perform better and show increased drive, motivation, and more positive self-beliefs. Also, Widlund et al. (2023) found that cynicism and students' loss of interest in maths in school make them less engaged over time.

According to Wohlkinger and Ditton (2023), better academic performance in **science** at the beginning of secondary education is associated with higher student achievement. However, DeWitt et al. (2014) report that participation in science-related activities outside school has dropped from 6th to 8th year. Longitudinal studies also show that students' positive attitudes and aspirations in science are improved from 6th year (DeWitt et al., 2014a).

As stated above, in several analysed studies, **reading, mathematics and science are also treated as dependent variables** (e.g., Baumert et al., 2012). Some studies (e.g., Borgonovi & Ferrara, 2023; Hübner et al., 2019) report that reading and math performances are influenced by age, as are lower for secondary school students, and by gender – for instance, boys in primary school have lower performance in reading. In general, boys perform worse in reading, while girls perform worse in mathematics (European Commission/EACEA/Eurydice, 2010). Interestingly, Helbling et al. (2019) report that gender differences in math performance increase over time.

Moreover, research (e.g., Caille, 2004b) reveals that **grade repetition** in primary education or at the beginning of lower secondary education predicts educational achievement. In particular, some studies report a negative effect on students' academic achievement (e.g., European Commission, 2022c; Hübner et al., 2019) and school engagement over time (Sousa Monteiro Santos, 2023), while according to OECD (2013), it is correlated with lower performance. Some of the analysed studies report that even when performance remains the same for disadvantaged students, grade repetition affects them disproportionately (Salza, 2022), and the negative correlation between repetition and performance is stronger for the least advantaged social groups, widening the gap of educational inequalities (Contini & Salza, 2024). Moreover, research shows that students who have repeated a grade are less motivated, have lower ambitions (Cosnefroy & Rocher, 2004) and have greater dropout levels (European Commission, 2022c). Finally, according to Salza (2022), among students with similar poor performance, those with parents without a high school degree or with a migrant

background have a higher risk of grade repetition compared to students with tertiary-educated parents, especially in academic tracks and schools with a higher share of advantaged students.

Interestingly, the systematic review revealed that students with high levels of school engagement and academic achievement may be more likely to experience also depression and **burnout**, leading to lower levels of school engagement over time (Salmela-Aro, 2015) and educational performance (Widlund et al., 2023). These results are also confirmed through longitudinal data from Finland and Australia, showing the positive aspect of disengagement (Salmela-Aro, 2015). Adolescents who had an extra year between high school and university manage to catch up with those who went directly to university.

C1.3 – School engagement

The third sub-cluster of student cluster variables consists of the ones related to *school engagement*. It includes behavioural engagement, emotional engagement, cognitive engagement, sense of belonging, participation in school activities, peer relationships, social skills and mental health, well-being, burnout and digital school engagement. School engagement is a complex construct referring to the developmental process that involves a student's thoughts, feelings, beliefs, and behaviours regarding their educational experience and lifelong learning (Niittylahti et al., 2023). The student experience is influenced by four psychosocial mechanisms: academic self-efficacy, emotions, belonging, and well-being (Niittylahti et al., 2023). In some studies, the term engagement is generally used (e.g., Rautanen et al., 2022; Widlund et al., 2021), but the three engagement components are analysed separately in others (Engels et al., 2017; Poorthuis et al., 2015).

Research findings reveal that **school engagement** is associated with increased student willingness and ability to share studying support among peers (Rautanen et al., 2022), leading to better academic performance (Widlund et al., 2023). Virtanen and colleagues (2021) report that school engagement correlates to lower truancy levels in upper secondary education. In addition, according to Moreira and Lee (2020), schools with higher autonomy support have higher school engagement levels, and the decline in engagement over time is less pronounced. Eriksen et al. (2023) found decreased school engagement and classroom relationships in the first year of lower secondary school. Research also reveals that school engagement may decrease over time in primary and upper-secondary schools (Esteves Rodrigues, 2023; Sousa Monteiro Santos, 2023). Indeed, according to Esteves Rodrigues (2023), all school engagement dimensions appear to decrease in the first six years of schooling except cognitive engagement.

Research reveals (Virtanen et al., 2021) that students' **behavioural engagement** and connections with school as early as primary school can prevent adverse outcomes later in the student's education paths. Characteristics such as popularity are negatively associated with behavioural engagement (Engels et al., 2017). Grades affect both students' behavioural and **emotional engagement**. For instance, Poorthuis et al. (2015) report that the ranking within the classroom may affect the perception of students' ability compared to their classmates, affecting emotional engagement. Consistent with other studies worldwide, student engagement with school tends to decrease over time, especially over adolescence. According to Moreira and Lee (2020), the tendency for student engagement to decrease with the differentiation of adolescents' behavioural system is pervasive in the different engagement indicators, including **cognitive engagement**.

Some of the analysed studies (Engels et al., 2017; Eriksen et al., 2023) report that **peer relationships** impact students' learning outcomes and are regarded as another variable of students' school engagement. Other studies indicate that higher levels of cooperation between students (European Commission & PPMI, 2022) and higher quality of their interactions affects positively both educational achievement (Niittylahti et al., 2023) and attitude toward schoolwork (Virtanen et al., 2021). Research also shows that the impact of peer relationships is more substantial in primary

schools, especially among students with low achievement (Davezies, 2005). Finally, some studies (e.g., Demir & Leyendecker, 2018) report that peer support positively impacts school engagement in primary school but not in secondary. However, other researchers (Moreira & Lee, 2020) found that peer support for learning decreases the typical decline in student engagement over time.

Similarly, **social skills** are part of and linked with students' learning and educational achievement but are also strictly connected to their relationships in school and their levels of school engagement (Eriksen et al., 2023). Research shows that low sociability is associated with higher educational inequalities (Ribeiro et al., 2023). According to Salmela-Aro and colleagues (2021), students with higher socio-emotional skills have tools to overcome burnout and enhance school engagement.

Students' **well-being** is a crucial variable directly associated with engagement and achievement. Well-being at school is associated with better educational outcomes for students and creates more favourable conditions, especially for students in disadvantaged situations. In times of adversity, such as COVID-19 confinement, student engagement with the school was more dependent on an individual's subjective well-being than on regular school functioning (De Faria et al., 2023). In addition, it seems it increases over adolescence (Widlund et al., 2023). Family is crucial to students' well-being and educational achievement, and their positive attitudes toward school and high expectations positively affect students' motivation (European Commission, 2022c). Low students' well-being is considered a warning sign for their educational path (European Commission/EACEA/Eurydice, 2023).

Student **participation in school activities** also affects their school life. Students who have attended fewer classes seem to have poorer literacy skills (OECD, 2003). The research shows that Gypsy students who participated in an experimental group having a four-year everyday call for attending school had lower absenteeism, better school grades in mathematics, classroom behaviour and overall better school progression (Rosário et al., 2017). Higher levels of late school arrival and skipping classes are negatively correlated with performance in mathematics (OECD, 2013). Finally, Virtanen et al. (2021) state that unexcused absenteeism negatively correlates with educational achievement.

Another identified variable related to engagement is the **sense of belonging**, namely when students feel accepted by their peers and are part of the school community. PISA 2018 results show that students' sense of belonging at school is declining compared to results from previous PISA assessments (European Commission, 2022c). The analysed literature shows a negative relationship between students' sense of belonging and participation levels. Students' sense of belonging is unrelated to school participation or any of the measures of literacy skills at the individual level (OECD, 2003). Moreover, a low sense of belonging is still a warning sign for educational achievement (European Commission/EACEA/Eurydice, 2023).

The review results show that **bullying** negatively affects all student groups and age levels. According to several studies (e.g., European Commission, 2022c; European Commission/EACEA/Eurydice, 2023), higher levels of (cyber)bullying at school negatively impact student's health and academic achievement. Derrington (2007) reports that racist bullying affects students from minorities, such as Gypsies, with consequences for their school track as well. Other studies (e.g., European Commission/EACEA/Eurydice, 2023) reveal that victims of bullying are at higher risk of early leaving than those who have not experienced bullying.

Moreover, **student-teacher relationships**³⁰ may impact educational performance: having good relationships with teachers is associated with better students' emotional and behavioural engagement (Ribeiro et al., 2023). Specifically, according to Moreira and Lee (2020), teachers'

³⁰ Student-teacher relationships, like the school-family ones, are good examples of variables that belong to more than one cluster/sub-cluster.

support for student autonomy is a significant scaffold against decreased student engagement over time. Also, other researchers (e.g., Demosthenous, 2019) report that a good relationship between students and teachers impacts the goal orientation, structure and time management of the lesson, implementation of the learning objectives and interactions with the students and between them. The poor relationships between students and teachers can be a crucial factor associated with early leaving in primary school (Paget et al., 2018).

Finally, a specific form of engagement emerges from the review, the **digital learning engagement**, which can also foster school engagement - the more digital learning experiences students have, the better their schoolwork engagement. Digital practices and competences also help students build new connections for schoolwork. On the other hand, students with a strong preference for digital learning but who cannot experience that in school will be more disengaged (Hietajärvi et al., 2020).

C1.4 – Self-image

The fourth sub-cluster of student cluster variables consists of those grouped under the *self-image* label, incorporating student's personality traits that may play a crucial role in educational performance. **Self-efficacy** is students' belief in their ability to succeed in their studies, and it is another important variable in predicting academic achievement (Niittylahti et al., 2023). **Student-perceived competence** is one variable that indirectly affects educational achievement through its impact on aspirations, expectations of success and motivational characteristics (Ditton et al., 2019). Also, research shows (Ditton et al., 2019; European Commission, 2022c) that **intrinsic motivation** correlates positively with school performance.

Moreover, according to Ribeiro et al. (2023), students who do not discuss their problems and are characterised by a lack of intrinsic motivation derange their academic achievement and school engagement. Also, research shows that a lower level of interest in schoolwork and questioning its value drives unexcused absenteeism (Virtanen et al., 2021). Student **aspirations** is another of the 70 variables identified through the systematic review and is interrelated with self-efficacy. Some studies report that high aspiration levels can create exhaustion and feelings of inadequacy (Windlund et al., 2021). Research reveals that aspirations in science will be increased slightly from the 6th to 8th year (DeWitt et al., 2014). Also, according to Hippe et al. (2018), student aspirations about occupation affect their science attainment. The relationship between educational aspirations and outcomes may be less strong for students with immigrant backgrounds because of their higher probability of dropping out or being delayed in the last year of upper secondary education level (Kindt et al., 2023).

Family cluster

The family cluster has 14 variables, split into two sub-clusters: **economic, social and cultural status (C2.1)** and **family structure and functioning (C2.2)**.

C2.1 - Economic, social and cultural status

The *economic, social and cultural status (ESCS)*³¹ sub-cluster includes eight interlinked and interconnected variables. According to several studies (Costanzo & Desimoni, 2017; Lagravinese et al., 2020; Skopek & Passaretta, 2021), the **socioeconomic status** of a student's family is another essential factor that strongly affects their performance on basic skills. It is a central and well-studied predictor of educational inequalities in educational research (e.g., Arenas & Gortazar, 2024; Engels et al., 2017; Trebits et al., 2022; Skopek & Passaretta, 2021), and there are different ways of conceptualising it in the literature (Sirin, 2005). The systematic review identified studies that mention

³¹ This systematic review uses the general term Economic, Social and Cultural Status - ESCS (OECD, 2022). In OECD's PISA (2023), ESCS includes parents' highest level of education, parents' highest occupational status and home possessions. In our analysis, the ESCS cluster includes socioeconomic status (SES) in general, parental educational attainment, parental occupation, cultural background, household income, wealth, books and PCs available at home.

SES as one variable (e.g., Cretin, 2012; Ichou & Vallet, 2012), while in others, SES is measured as an index that includes parents' occupational status, parents' educational attainment and home possessions³² (Burger, 2019) and income³³ (Olczyk et al., 2021), or ESCS index (Hippe et al., 2018b).

Socioeconomic status is a fundamental predictor of educational performance (European Commission, 2010). In this analysis of 157 studies, in 57 studies, SES is considered a predictor of educational achievement. Students entering school face existing inequalities because of the gap between their SES backgrounds (Contini & Cugnata, 2020; Passaretta et al., 2022). SES is a prognostic factor of students' school pathways (class repetition, etc.) (Cayouette-Remblière & de Saint Pol, 2013) and their academic track and curriculum selection (Guetto & Vergolini, 2017). Some studies indicate that students from lower socioeconomic backgrounds start school with lower knowledge of language and math (Helbling et al., 2019; Skopek & Passaretta, 2021), have slower development in academic performance (European Commission & PPMI, 2022), and face a high risk of early leaving (European Commission/EACEA/Eurydice, 2023) as many of them help their families in the house or work to support them (OECD, 2013). The differences in attainment are already evident from the earlier years of education (3 to 6 years), persist later on, and only slightly increase in achievement tests at the end of primary and lower secondary school (Olczyk et al., 2021; Skopek & Passaretta, 2021). The effect of SES on students' performance is measurable at every educational level: from infant school, where students with higher SES have higher probabilities of entering primary school at a higher level of knowledge (Helbling et al., 2019b), to tertiary education, where advantaged students have higher probabilities to study in college than students with lower-SES backgrounds (Gil-Hernandez, 2021). Moreover, they perform better in a vocational programme in boarding schools, although there is no effect if they attend the 'general track' (Farges & Monso, 2024).

Similarly to ESCS, **parental educational attainment** (a specific component of ESCS) is reported (e.g., Engels et al., 2017; Verhaeghe et al., 2018) as decisive in educational success. Research indicates that parental educational attainment affects educational outcomes (educational pathways), academic track and curriculum selection (e.g., Guetto & Vergolini, 2017; Straková et al., 2016) as well as students' progress in their educational achievement (e.g., Ditton & Krüsken, 2009; Volante et al., 2022; Passaretta et al. 2022). According to Cayouette-Remblière and de Saint Pol (2013), a high level of parents' education attainment is a good predictor for a lower risk of grade repetition. Students whose parents have a lower level of education are less likely to display higher academic performances or progress further in education (European Commission & PPMI, 2022). Other studies (e.g., Argentin et al., 2017; Papadopoulou, 2016) stress that **parental occupation status** (another component of ESCS) also affects student achievement. The high occupational prestige of the father is also driving the educational success of the offspring (Ditton, 2013). Interestingly, as reported by Passaretta and Gil-Hernandez (2023), parental education and occupational status impact both the development of basic skills (like math or vocabulary) and the development of digital skills, both in childhood and adolescence.

Generally, **cultural background** is a significant predictor of educational achievement (European Commission & PPMI, 2022; European Commission, 2023b), as found in 18 analysed publications. Research reveals that cultural background affects students' performance in basic skills, reading and maths (Costanzo & Desimoni, 2017) and science (Lagravinese et al., 2020). Research also indicates that the cultural and social capital of the parental home affects children's reading performance at the end of elementary school (Schubert & Becker, 2010).

³² A construct consisting of items assessing family wealth, cultural possessions, educational resources, and number of books at home.

³³ Gross income, earnings, disposable household income.

In addition, owning a house, household income, wealth, books, and utilities at home are also part of ESCS and impact educational outcomes. Some analysed studies indicate that higher **household income** positively affects students' academic success (e.g., Olczyk et al., 2021; Verhaeghe et al., 2018) and achievement gains (Ditton & Krüsken, 2009). Sandsør et al. (2023) report that educational gaps due to household income correspond to about 3 to 4 months of school attendance. **Wealth** is also identified as a key determinant of educational achievement (Olczyk et al., 2021). PIRLS 2016 results reveal that children from families with more than 100 **books available at home** score 54 points higher than those with fewer than 100 books (e.g., Volante et al., 2022). Also, specific utilities such as **personal computers (PCs) at home** are another indicator of learning outcome (e.g., Marchesi et al., 2004; Papadopoulou, 2016), as access to better learning sources at home enhances educational achievement.

C2.2 - Family structure and functioning

Family structure, such as single-parent families, blended families, and the number of siblings, affect students' educational outcomes (e.g., Cretin, 2012; Ichou, 2013). However, **family difficulties** are often an underlying source of students' distress and lead to various issues they have to deal with, negatively impacting their educational outcomes (Robert-Bobée, 2013). Studies (e.g., Wohlkinger & Ditton, 2023; Demosthenous, 2019) show that **parental support** positively impacts students' academic performance. Other studies indicate that parental positive attitude increases students' positive attitude toward schoolwork (Virtanen et al., 2021), reducing school absenteeism (European Commission & PPMI, 2022) and drop-out risk (Haugan et al., 2019) and improving school engagement. In addition, high levels of acceptance, supervision, and psychological autonomy within the family are reported by Blondal and Adalbjarnardottir (2014) to impact secondary school completion positively. In contrast, Paget and colleagues (2018) found that less parental support for their children's writing and reading exercises can lead students to drop out when they are 16 years old. Other studies (e.g., European Commission & PPMI, 2022) indicate that parental support promotes students' school behaviour, social skills, and peer relations. Apart from parental support, the review reveals that **parental aspirations** also affect educational achievement (Grelet, 2005). According to OEC (2013), parents who expect their children to graduate from university and go on to professional work later empower them with perseverance, intrinsic motivation and self-confidence. Ditton et al. (2019) report that academic performance is affected by parents' expectations and how they perceive their children's abilities.

School-family relationships also affect students' educational performance. For instance, according to Ditton et al. (2019), middle-class parents have a closer relationship with the school than working-class parents.

Out-of-school-time lessons is another variable identified in the analysed literature as a factor of educational inequalities. This variable can also be categorised in other clusters/sub-clusters, but as often these lessons are held outside school it is listed under the family cluster. Families that prioritise education are supportive not only in their children's schooling but also in their extra-curricular activities. Research reveals that extra instructional time could affect students' educational success as might help students cope with inefficiencies of the school system (Hippe et al., 2018).

Teacher cluster

Students spend considerable time interacting with teachers in primary and secondary education. Therefore, **teacher cluster** variables are crucial predictors of educational inequalities. The review identified five teacher-level variables allocated in one sub-cluster: **teachers' characteristics and practices (C3.1)**.

C3.1 – Teachers' characteristics and practices

Haugan et al. (2019) state that **teachers' support** fosters greater student engagement and helps reduce truancy. According to Hettinger et al. (2023), sufficient teacher support predicts better average academic outcomes for students at the class level, while Lazarides and Rubach (2017) report that it enhances students' chances to achieve their academic goals and intrinsic motivation. Teachers' support has also been found to be relevant for students' motivations but to a different extent for boys and girls. For instance, teachers' support affects boys' intrinsic motivation when they do not have a specific goal orientation and helps them feel supported and in their need for achievement (Lazarides & Rubach, 2017). Virtanen et al. (2021) found that teachers' attitudes can affect students' positive attitudes toward schoolwork. Other studies show that teachers' behaviour evaluations (Guimard et al., 2007) and recommendations for school tracking significantly predict their future academic performance (Argentin et al., 2017).

The review also revealed that **teaching methods** affect students' academic achievement. Specific teaching methods, designed and based on student characteristics, like socioeconomic and migrant background, enhance students' performance. Moreover, as stated by Hippe et al. (2018), attending inquiry-based teaching positively impacts student performance. Other studies stress that teachers who provide adaptive instruction (Gehrer & Nusser, 2020) and who manage to connect learning tasks and students' everyday lives (Lazarides & Rubach, 2017) can enhance students' mathematics skills. Teachers' digital practices and competences may also ensure students' engagement and achievement (Hietajärvi et al., 2020). In addition, teaching methods, such as group work and discussions, impact maths and reading performance depending on the origin of the students and class size (DeVries et al., 2020). Research also reveals that **teacher work experience** also affects students' educational outcomes (Davezies, 2005), and **teacher's interest** in the course they teach improves learning outcomes (European Commission, 2022c).

Finally, according to European Commission/EACEA/Eurydice (2023), **teachers' education and training on early leaving**, such as teaching different learners in multilingual and multicultural settings, can promote more inclusive educational approaches, create a positive school climate, and enhance students' social and emotional development.

School and education system cluster

Teachers, students (and their families) do not operate in a vacuum. The review identified 21 variables of educational inequalities at the school and education system cluster that consists of three clusters: **school characteristics (C4.1)**, **school- and/or system-level policies (C4.2)** and **other variables (C4.3)**.

C4.1 – School characteristics

The **geographical area (location)** plays a significant role in school performance. Considering the European context, the educational opportunities and outcomes are differentiated across the member-states of the EU (e.g., Ballas et al., 2010; Ditton & Krüsken, 2009). Learning results and educational opportunities present significant disparities across and within EU countries but also across regions (Ballas et al., 2010). These results underline the role played by local contexts in shaping education outcomes. A strong example is the differences in performances of Italian students between the country's North and South, where higher academic achievement and performances are registered in the North (e.g., Ferraro & Pöder, 2018). For example, students' mathematics and reading scores are higher in schools located in the North than in the South of Italy (Costanzo & Desimoni, 2017).

Similarly, in Greece, geographic and regional aspects strongly impact educational inequalities (Ballas et al., 2010). Overall, school location correlates with students' school attainment and dropout rates, and the geographical context can also shape educational inequalities. For example, in Germany, the effects of students' socioeconomic background are higher in Bavaria than in Saxony (Ditton & Krüsken, 2009). Geography is also critical when we study the difference between urban

and rural areas (including remote areas such as small islands) regarding inequalities and academic achievement. Rural areas often face issues related to the quality of school education (due to attracting and recruiting teaching staff) and difficulties in accessing schools. Therefore, residents in urban areas have higher literacy levels than rural residents (UNESCO, 2006). However, a number of studies stress that within urban areas, it is possible to differentiate between advantaged and disadvantaged areas, the latter characterised by higher rates of dropping out of education and training (Di Tommaso et al., 2024; European Commission, 2022c).

The review provides indications that the **school type**, public or private, general or vocational, is an important determinant that can shape inequality in performance among students (Caille, 2001; Nagy et al., 2017; Oppedisano & Turati, 2015), especially in maths (Cayouette-Remblière, 2019). Moulin (2023) found that private school attendance has a large and significant effect on educational success (e.g., between 0.193 and 0.222 standard deviations higher on standardised tests of boys in 9th grade). According to Hippe et al. (2018), attendance of vocational upper secondary education (VET) affects students' science attainment, as they have lower scores than those in the general (academic) track. Belfi et al. (2016) report that **school size** also affects educational outcomes since this characteristic negatively impacts educational performance in low-SES schools compared to high-SES schools. Also, some of the analysed studies state that **class size** affects educational outcomes (Di Tommaso et al., 2024), as reducing the number of pupils in a classroom could improve their performance. It is important to notice that some schools, such as schools of educational priority zones (ZEP) aim to tackle primary and secondary students' educational inequalities (Caille, 2001), potentially reducing them.

Studies indicate that **school socioeconomic composition** can influence student achievement (DeVries et al., 2020; Verhaeghe et al., 2018). For instance, some studies report that schools with many students from low socioeconomic backgrounds register, on average, worse educational outcomes/achievement (European Commission, 2022c; OECD, 2003), especially in early elementary education (Helbling et al., 2019). Burger (2019) reports that social segregation, also strongly associated with socioeconomic status, affects student and school performance. The educational progression for mid-education level students who attend classes with the same socioeconomic composition is weak (Duru-Bellat & Mingat, 1997). According to Belfi et al. (2016), the average educational performance is higher in more homogenous schools with medium or high socioeconomic composition. They also state (ibid.) that math achievement is higher in more homogeneous schools regarding socioeconomic composition, especially where the percentage of students from advantaged backgrounds is higher. Kähler et al. (2023) found that classroom composition impacts scientific literacy and student achievement. Students who attend classes with a high number of children with low socioeconomic status do not have an increase in scientific literacy compared to those who attend classes with few students with low socioeconomic status. Finally, research indicates that **ethnic school composition**, namely schools with a higher proportion of ethnic minority students, impacts academic performance, negatively affecting students' mathematic achievement and development (Belfi et al., 2016; Verhaeghe et al., 2018).

Several studies stress that a positive **school climate** ensures educational achievement (European Commission, 2022c) and engagement (Grazia, 2022). On the opposite, when the school climate is characterised by negative experiences (like violence, bullying, or lack of support), research shows that students are at higher risk of early leaving. Consequently, a negative correlation exists between higher levels of school well-being and better mental health (European Commission/EACEA/Eurydice, 2023) and lower burnout levels (Grazia, 2022). Schubert and Becker (2010) report that schools with enhanced student support register better performances in reading literacy, contrary to schools with a strict disciplinary climate. However, research reveals that schools with disciplinary climates have higher levels of engagement (OECD, 2003). A negative school climate affects introverted students' academic achievement (Ribeiro et al., 2023). Moreover, other studies reveal that school climate affects reading performance (Schubert & Becker, 2010), while student

performance in science is also affected by the minutes of science teaching, inquiry-based teaching, and student expectation occupational status, which affect different levels of students' science attainment (Hippe et al., 2018).

C4.2 – School- and/or system-level policies

Most EU education systems have **top-level policies** and measures to support learners at risk of early leaving from education and training (ELET) (European Commission/EACEA/Eurydice, 2023). Some of these policies also include the availability of psychosocial services to support students' well-being and mental health (European Commission/EACEA/Eurydice, 2023).

Public expenditure on education is one of the system cluster variables that play a critical role in students' opportunities to achieve their learning potential. The economic situation and adequate public expenditure also affect access to Information and Communication Technology (ICT) resources at schools (OECD, 2003). Findings of Oppedisano and Turati (2015) indicate that Germany and Spain, where regional governments significantly influence the provision of education—not only in managing and running schools but also in education spending and funding—showed the highest reduction in inequality between 2000 and 2006. Conversely, inequality increased over the study period in France, Italy, and Greece, where education policies are almost entirely centralised, especially regarding spending and funding.

Several studies reveal that exposure to **preschool education** affects educational achievement (European Commission, 2022c; Olczyk et al., 2021) and positively impacts students' academic achievement (Herrera-Sosa et al., 2018). On the other hand, research shows that early **tracking** negatively affects educational equity because the gap in students' socioeconomic backgrounds increases since students with low socioeconomic backgrounds have more difficulties coping with limited access to academic resources, fewer learning opportunities outside school, and less support from their educational environment (e.g., Contini & Cugnata, 2020; Lavrijsen & Nicaise, 2015). Track recommendations from teachers may also shape and reinforce educational inequalities (Pfof et al., 2018). Barone et al. (2017) state that low-educated parents are more likely to believe that the academic path is more challenging to complete and provide fewer occupational opportunities, so they usually choose vocational education for their children, even though they have good academic performance.

School resources was identified as an issue of great importance for the understanding of educational inequalities. For instance, teachers' employment status, as an indicator of school quality, is one aspect of school resources that can impact inequalities, as well as teachers' turnover, which shapes effectiveness in multigrade classes (Barbetta et al., 2023).

The study by Arenas and Gortazar (2024) shows that **school autonomy** also affects students' outcomes, as it provides different human and financial resource management. For example, in Spain, public and private schools differ in their budgetary autonomy, as private schools have more freedom to manage their financial resources. In contrast, due to insufficient public funding, public schools seek alternative financing through voluntary parental co-payments. Also, there are differences in the student composition, as private schools have an increased percentage of students from higher socioeconomic backgrounds (Arenas & Gortazar, 2024).

School-based management is also identified (Herrera-Sosa et al., 2018) as affecting students' academic performance as these programs enable schools and communities to respond to students' needs. Similarly, according to Ferraro and Pöder (2018), specific **school-level policies**, such as publicly posted assessment policies, positively affect students' efficiency but not equity. Although studies claim that policies related to school autonomy may reduce students' efficiency,

decentralisation and autonomy promote the market mechanisms in education, giving more school choices that may ensure education for all and increase equity (Ferraro & Pöder, 2018). Research also shows that grade repetition policies can foster educational inequalities, as they appear to affect disadvantaged students.

According to OECD (2003), high **school expectations** are linked with higher school engagement, as high expectations for student success are positively related to students' engagement. Policies on **multigrade classes** also affect students' academic achievement. For instance, Barbetta and colleagues (2023) found that the duration a student attends a multigrade class and the teaching personnel allocated to these classes are variables that affect students' achievement. Also, according to Warwas et al. (2009), students who attend **advanced courses** have better educational outcomes.

The review also revealed that the more **teaching time** students have, the better their academic achievement will be. For instance, students who have more than four periods of mathematics (European Commission & PPMI, 2022) or more minutes of science teaching per week (Hippe et al., 2018) have better academic performance (Di Tommaso et al., 2024). Research also found that arriving late to school is associated with a 27-point lower score in mathematics while skipping classes or days of school has a 37-point lower score (OECD, 2013).

C4.3 – Other variables

The COVID-19 pandemic and poverty rate variables comprise the sub-cluster *other variables*.

The **COVID-19 pandemic** affected many aspects of economic and social life, including education. At its peak, almost 94% of the world's student population was impacted by school closures, which resulted in learning losses (Donnelly & Patrinos, 2022). More specifically, there seems to be an academic decline due to COVID-19 (Arenas & Gortazar, 2024; Salmela-Aro et al., 2021). For instance, according to Borgonovi and Ferrara (2022; 2023), mathematics and reading achievements have declined at the primary and secondary school levels of education during the pandemic in Italy. The COVID-19 pandemic fostered educational inequalities since students from socioeconomically disadvantaged families, who already had below-average school performance before the pandemic, were more negatively affected during the lockdowns (European Commission, 2022c). Also, in times of adversity, such as pandemic confinement and severe limitations to regular school functioning, student engagement with the school is more dependent on individual-level resources (a strong predictor of educational inequalities), such as subjective well-being and positive emotions (e.g., De Faria et al., 2023). Also, this can be relevant to other unexpected events such as fires / natural disasters or wars that cause similar school conditions.

Finally, the **poverty rate** is an essential, generic variable correlating with students' performance and education inequalities. For example, Daniele (2021) reports that scores in mathematics are negatively correlated with the regional poverty rate in Italy and Spain. Moreover, studies (e.g., Daniele, 2021; European Commission, 2022c) indicate that the poverty rate is related to school engagement for students from the poorest families.

6. Discussion

6.1 Limitations of the literature review

As with any systematic review, the one presented here has its limitations. First, the search for identifying relevant academic publications was limited to the Scopus database and Google Scholar. While these are comprehensive and widely-used databases, they do not cover every possible source of academic publications, and some relevant studies might have been missed. This constraint potentially introduces a publication bias, where relevant studies not indexed by these databases may have been excluded. To mitigate this issue, the research team conducted citation mining and built on team members' extensive experience and knowledge of the literature on educational inequalities to identify relevant literature not indexed in Scopus and Google Scholar.

Furthermore, although several combinations of the search strings were applied, if the authors of the publications that have been reviewed did not include these specific terms in their papers' title, abstracts, and keywords, the respective publications might have been excluded from this review. This reliance on specific search terms means that relevant studies using different terminology could have been overlooked, affecting the comprehensiveness of the review.

Another possible limitation can be attributed to the involvement of ten researchers in the screening and inclusion processes. Differences in interpretation and emphasis among the researchers could have influenced which studies were ultimately included, impacting the review's findings. On the other hand, the several measures taken to ensure the best possible inter-rater reliability, as described in Section 4.3, minimised the potential for human error and subjective judgment in the inclusion process. Also, the involvement of a big multicultural team of researchers with various backgrounds and expertise allowed for a more targeted approach for analysing in-depth 157 studies with diverse research designs (quantitative/qualitative/mixed-methods, longitudinal/repeated cross-sectional) and context (geographical coverage, publication language, etc.) in the time available.

Finally, the scope of the review was restricted to publications in English, French, German, Greek, Italian, Portuguese, and Spanish. Consequently, studies published in other languages were not considered, potentially leading to a language bias. This exclusion might have omitted valuable research contributions from non-English-speaking European countries, thus limiting the comprehensiveness of the review. However, according to some estimations (e.g., Ramírez-Castañeda, 2020), 98% of the scientific research is published in English. Therefore, the exclusion of relevant literature due to the language is expected to be very limited.

In conclusion, while the review presented in this report aimed to be thorough and systematic, these limitations highlight the inherent challenges in conducting such reviews. Recognising these limitations is crucial for interpreting the findings accurately and understanding the scope and applicability of the conclusions drawn from the reviewed literature. At the same time, it seems useful not to overestimate the impact of these limitations on the main results here provided, unlikely very far from the pursuit ones.

6.2 Synthesis of findings

This systematic review gives a comprehensive overview of the studies with a longitudinal or repeated cross-sectional research design on inequalities in primary and secondary education, which is useful to:

- Map existing longitudinal and repeated cross-sectional datasets (RQ1);
- Identify the methods and techniques used to analyse these datasets (RQ2);
- Identify and cluster the variables reported in academic and grey literature as factors or predictors of educational inequalities (RQ3).

Overall, the review confirmed that longitudinal and repeated cross-sectional data are valuable for investigating educational inequalities in students' performance/ qualifications and attitudes/daily experience. Repeated cross-sectional data, but even more individual longitudinal data, are valuable for understanding causal relationships among factors shaping education outcomes and related inequalities to designing evidence-based policy initiatives and compensatory interventions.

For **RQ1**, the systematic review highlights that (i) longitudinal and repeated cross-sectional data are widespread only in some European countries, and the data collection can happen through different means (e.g. standardised competency-based tests, surveys, etc.) and at different levels (national, regional and local); (ii) there is a growing body of literature and studies with a longitudinal or repeated cross-sectional research design; (iii) these studies are mainly quantitative, even though in few cases they are based on a mixed-method approach, (iv) the available studies differ significantly as some are based on significant larger dataset and/or timespan, compared with others.

For **RQ2**, the systematic review highlights a wide range of statistical and causal analysis methods and techniques that are chosen depending on the research questions of each study, the processes the researcher wishes to explore, the underlying technical or theoretical assumptions, the restrictions posed by the nature of the data, or by the type of data collected or available. The review also identified a few qualitative methods that complement the quantitative ones.

For **RQ3**, the systematic review confirms the complexity and multifaceted nature of inequalities in education, with a wide range of factors related to students, families, schools, teachers, and the (education) system. The variables identified through the systematic review are presented through a conceptual model that highlights how each of them plays an important role individually and in connection with others, making the design and implementation of effective interventions even more challenging.

The review results indicate that despite many policy initiatives to promote equity, conceived as fairness and inclusion, **educational inequalities remain a considerable challenge** across Europe. The analysis of 157 publications confirms the importance of the three core issues of educational inequalities (see Figure 13) identified by the European Commission's initiative Pathways to School Success (European Commission, 2022) - **school engagement, well-being, and academic achievement** - by confirming a strong connection between academic achievement, student engagement-well-being, and early school leaving since students who cannot incorporate prior knowledge into the school environment are more likely to feel disengaged.



Figure 13. The core issues of the European Commission's Pathways to School Success Initiative

Source: (European Commission, 2022c)

Academic achievement

The review found that longitudinal and repeated cross-sectional data are fundamental for understanding the dynamic phenomena of educational inequalities by exploring how early experiences, attitudes and results (and interventions) impact later outcomes. These studies show that educational inequalities often emerge early in a child's life and persist throughout their educational journey. For example, children from lower socioeconomic and disadvantaged cultural backgrounds start school with fewer cognitive and non-cognitive skills than their more privileged peers, and these initial gaps tend to persist or even grow over time. Repeated cross-sectional studies, which involve collecting data from different samples at multiple time points, provide more evidence about the persistence and evolution of these inequalities. Such studies confirm that despite efforts to increase access to quality education, there are still significant and widening gaps in academic achievement between students from different socioeconomic and cultural backgrounds.

As derived from several studies analysed in the context of this systematic review, the acquisition of basic skills is not only an outcome variable but also an important predictor of students' educational pathways and qualifications later on. Also, in several studies analysed in-depth, reading, mathematics and science are also treated as dependent variables as, for instance, they are influenced by age or gender.

Overall, the review shows **worrying trends** in acquiring reading, mathematics and science skills in European countries correlated with educational inequalities. Analyses relying on longitudinal data from several European countries show that a considerable proportion of students (at all education levels) are still not proficient in these key areas, which are fundamental for personal development, employability, and active citizenship. In particular, longitudinal studies show that the level of early **reading skills** is a strong predictor of later academic success: students struggling with reading in the early years of schooling will continue to struggle throughout their academic paths. Moreover, analyses conducted on repeated cross-sectional data from PIRLS assessments show persistent gaps in reading literacy across different socioeconomic groups, with students from lower ESCS underperforming all the time. In this regard, early interventions are crucial to support reading development and foster reading skills among students with different socioeconomic backgrounds.

Longitudinal findings show that foundational **mathematic skills** developed in primary school are key to success in more advanced maths taught in secondary school. However, repeated cross-sectional analyses of TIMSS data show that, on average, students in many European countries do not improve their maths performance later on, especially considering those from more disadvantaged backgrounds. On average, the proportion of students who are proficient in maths is well below the

EU target of 15%. **Science skills** are crucial for students' academic and professional development, providing a foundation for critical thinking, problem-solving, and innovation. However, educational disparities hinder the equitable acquisition of these skills, particularly in marginalised communities. Research shows that students from underprivileged backgrounds, including ethnic minorities and students with low ESCS, often have less access to advanced science curricula, laboratory experiences, and qualified STEM (science, technology, engineering, and mathematics) teachers.

School engagement

School engagement emerges as a critical factor in academic achievement and overall educational outcomes. The review shows that students who engage with their schoolwork, participate in extracurricular activities and connect to their school community are more likely to achieve better academic outcomes and less likely to drop out. The review also shows that several literature strands (from different disciplinary fields) focus on engagement, making it a multi-faceted concept that includes behavioural, emotional, and cognitive dimensions. All these factors interplay with ascriptive students' characteristics, contributing to their overall educational experience and shaping their learning outcomes and related inequalities. The review results indicate that behavioural and emotional school engagement decreases in primary education while, overall, student engagement with school tends to decrease over time, especially over adolescence. Some studies stress that behavioural engagement in primary education can positively affect their education paths.

Well-being

Students' well-being also emerged from the literature as essential for their school engagement and academic performance. A strong sense of belonging and well-being is linked to better educational outcomes and creates more supportive learning environments, particularly for disadvantaged students. Students' subjective well-being strongly influences their school engagement, especially in challenging periods, such as confinement due to COVID-19. Family functioning and support as well as school and teacher-related factors, could positively affect students' well-being. On the other hand, low levels of well-being often signal potential challenges in a student's academic path and are related to educational inequalities.

The essential role of teachers, families, schools and education systems

One original contribution of the systematic review of academic and grey literature presented in this report is the clustering of the 70 variables identified as factors or predictors of educational inequalities in primary and secondary education across Europe. The proposed conceptual model offers a comprehensive overview and an initial categorisation of the identified variables. Apart from the variables associated with individual students (especially those related to academic achievement, school engagement and well-being presented above), the model stresses the importance of the teacher-related variables and those referring to the role of family, school and system.

Teachers are highlighted in the analysed literature as important actors who can foster students' engagement with school and enhance their chances of achieving their potential. The teaching methods they employ, based on their work experience and interest, can positively affect not only students' engagement with school but also the acquisition of basic skills. Having to teach very often in multilingual and multicultural classrooms, teachers can promote inclusive educational approaches, enhancing students' social and emotional development. In this context, appropriate teachers' education and training on tackling early leaving and educational inequalities is essential.

The review also provided insights into the crucial role **families**, especially parents/carers, play in their children's school engagement and academic achievement. Family structure and economic, social and cultural background, and aspirations for children's education paths strongly influence their academic performance, school engagement and well-being.

Several school characteristics, such as the location, size, socioeconomic and ethnic composition as well as the school climate, were identified through the review as factors or predictors of educational inequalities. For instance, some studies report a correlation between school location with students' school attainment and dropout rates. Other studies indicate that, on average, a high number of students from low socioeconomic backgrounds and/or a high ratio of ethnic minority students are associated with low educational performance.

The systematic review highlights the role of **systemic factors** in perpetuating educational inequalities and shows that this is a research field less investigated in European literature. Educational policies, public expenditure on education, tracking and school resources are among the variables that could tackle or maintain educational inequalities. For instance, countries with more stratified education systems, where students are tracked into different educational pathways early on, are characterised by wider gaps in academic performance by socioeconomic and cultural status. On the contrary, countries with more inclusive education systems, where tracking is delayed and there is more support for disadvantaged students, are characterised by smaller gaps in students' performance.

6.3 Implications for policy, research and practice

The findings from this systematic review (77 datasets, 54 methods and techniques of data analysis and 70 variables as factors/predictors of inequalities) can have several implications for policymakers, researchers, educators and other educational stakeholders who want to promote equity and quality in education.

Implications for policy

The review provides insights into the need for educational policies to follow a **systemic and evidence-based approach** in addressing the multifaceted phenomenon of educational inequalities. Policy initiatives could address school segregation, discriminatory practices, and unequal access to education resources. Systemic reforms should aim to create an inclusive education system where all students can succeed. Given socioeconomic and cultural status's massive and long-lasting impact on educational outcomes, policies to reduce poverty and socioeconomic gaps should be part of education reforms. Initiatives such as providing financial support to low-income families, improving access to early childhood education and ensuring equitable funding for schools can help mitigate the effects of socioeconomic disadvantage.

The review revealed that **high-quality teaching** is essential for addressing educational inequalities. Policies should focus on recruiting and retaining good teachers, especially in disadvantaged areas. Updated professional development should be continuously provided to teachers. This would improve the development of teaching practices designed based on student characteristics, among which socioeconomic status and migrant background, to address students' diverse needs and to improve their performance.

The review also revealed a need to **pay more attention to students' "attitudes" and not only to their academic achievement**. Therefore, policy interventions at the school or system level must target not only students' performance but also the daily quality of their school experience to promote their school engagement as a key leverage for improving their well-being and education outcomes.

Finally, **monitoring and rigorously evaluating the short-, medium- and long-term effects of the related policies** is crucial so policymakers can develop better strategies to address achievement and engagement gaps at the local, regional, national and European levels. Using longitudinal and cross-sectional data for monitoring and evaluating interventions to tackle educational inequalities is crucial to ensure that policies deliver what they promise. As the collection and use of longitudinal and/or repeated cross-sectional data is not yet widespread across Europe, additional effort and

support at the policy level is needed. At the same time, counterfactual impact evaluations may benefit from or even produce reach and deep longitudinal data on student engagement and achievement.

Implications for research

The review findings highlight that longitudinal and repeated cross-sectional data can offer valuable insights into educational inequalities. Although the review identified and analysed in depth 157 related publications, it is evident that the available longitudinal or repeated cross-sectional datasets do not cover all European countries and/or all the variables that are predictors of educational inequalities. Therefore, there is a **need for intensifying the collection and analysis of longitudinal and repeated cross-sectional data** to monitor and understand the evolution of educational inequalities, their predictors, and the impact of related policies. The combination of various methods for collecting and analysing longitudinal or repeated cross-sectional data can be beneficial for a better understanding of the dynamic evolution of the multifaceted phenomenon of educational inequalities in primary and secondary education settings across Europe.

Implications for practice

The insights derived from the review indicate that schools should implement **strategies to increase student engagement**, as it is a key predictor of academic achievement. This may involve creating a supportive school environment and inclusive teaching practices. Schools should also provide access to support services, including counselling, mentoring and special education resources. Targeted support for students at risk of falling behind can help close the gap and create a more inclusive education environment. Moreover, it seems crucial to promote **extracurricular activities**, connecting schools, students and their community. As stated by OECD's Education GPS (OECD, 2024b), "Students need to be engaged, motivated, willing to learn new things and feel they can succeed; without those dispositions, they will be unable to translate their raw potential into high-level skills, no matter how intelligent and gifted they are, no matter how much effort and professionalism teachers put into their jobs, and no matter how many resources countries devote to education". In this same direction, parents need to be more involved in the education process, especially the ones with lower cultural resources. Schools and policymakers should develop programs to **encourage parental engagement**, provide resources for at-home learning support and build partnerships between schools and families. This approach could include parent education workshops and better communication between home and school.

7. Conclusions

This systematic literature review collected and screened 1399 publications of academic and grey literature across Europe, with the majority of them from the last decade. The review's focus was collecting and analysing studies with longitudinal or repeated cross-sectional research design. Through the in-depth analysis of 157 publications, the research team identified 77 longitudinal or cross-sectional datasets, 54 methods for analysing this data and 70 variables that can be predictors of educational inequalities. Furthermore, the variables were clustered and presented through a four-level conceptual model of four levels: student, family, school/teacher and system.

Although the identified datasets and their analysis provide valuable insights into the variables and predictors of educational inequalities, especially in countries with longstanding traditions in longitudinal studies (e.g., Germany, Finland and Italy), they cover only half of the 32 countries targeted by the LINEup project³⁴. Therefore, there is a need for increasing the collection and analysis of longitudinal and cross-sectional data across Europe. Also, the systematic review revealed a plethora of methods used to analyse this data, providing insights into various factors that affect educational inequalities. These findings are key to informing policies, research and practices to reduce educational inequalities and improve academic achievement in reading, mathematics and science.

The systematic review presented in this report provided a broad and complex picture of the evolution of educational inequalities. The analysis confirmed that educational inequalities are deeply rooted in our society and emerge early in a child's education path. Children from lower socioeconomic and cultural backgrounds start school with more obstacles to the acquisition of cognitive and non-cognitive skills than their more advantaged peers. Longitudinal studies show that these gaps are persistent and cumulative and may grow as students progress in their educational paths. Analysis of repeated cross-sectional data confirms these findings, showing that the performance difference among students from different socioeconomic backgrounds is evident all over Europe. Despite many European policy initiatives to reduce these inequalities, the gaps in students' performances are still non-negligible, and their consequences are severe for many students from disadvantaged backgrounds.

Beyond the usual variables well known in the literature investigating education inequalities, school engagement emerged as an essential and multidimensional factor in predicting academic achievement and overall educational outcomes. Longitudinal studies show that students who are engaged with their schoolwork, participate in extracurricular activities, and feel connected to their school perform better academically and are less likely to drop out.

Many European countries struggle to improve education performance in basic skills, especially among students from disadvantaged backgrounds. Academic achievement in basic skills is key to personal development, employability, and active citizenship. Reading literacy is a strong predictor of later academic success. Students who struggle with reading in the early years will continue to struggle throughout their school career, so early interventions to support reading development are crucial. Similarly, foundational numeracy skills learned in primary school are essential for success in more advanced mathematical concepts taught in secondary school. However, many European countries struggle to improve mathematics performance, especially among students from disadvantaged backgrounds. Scientific literacy is also a significant challenge - many European students lack basic scientific literacy, which hinders them from engaging with scientific concepts and pursuing careers in STEM fields.

³⁴ The number of studies is closely linked to the availability of data. For instance, the INVALSI dataset in Italy became longitudinal recently, and sufficient time is needed for relevant studies to be published.

System-level factors also play an essential role in the persistence of these gaps. Educational policies, school funding and operating mechanisms contribute to the inequalities. Countries with more stratified education systems where students are tracked into different educational pathways early have more significant academic performance gaps. On the other hand, countries with more inclusive education systems with delayed tracking and more support given to disadvantaged students have smaller performance gaps. This shows the importance of system-level factors in shaping educational outcomes and the need for policies that promote inclusivity and equity. The review also provided insights into the importance of the variables clustered under school, teacher and family labels, which also affect or predict educational inequalities and their evolution over time.

7.1 Next steps

While the analysis of the longitudinal and repeated cross-sectional studies gave us a good insight into the evolution of educational inequalities in Europe, more research is needed to cover all aspects and factors of these disparities and how they emerge and develop over time. The **systematic literature review** presented in this document is the **first research output of the LINEup project**.

The LINEup research team will build on the systematic review findings by mapping and analysing datasets with longitudinal and repeated cross-sectional designs. This **desk research** will collect, access, analyse and summarise existing data that allows assessing educational inequalities over time across 32 European countries, focusing on Southern and Western Europe. This will involve identifying and gathering relevant longitudinal and cross-sectional datasets, conducting detailed analysis to understand trends and disparities in educational outcomes, and assessing the comparability and harmonisation of different databases.

Furthermore, the LINEup research team will conduct **data-driven qualitative research** to investigate the implementation and impact of compensatory measures in selected schools in Germany, France, Italy, Greece, Spain and Portugal. The fieldwork will complement the desk research and look into schools' strategies and activities to keep students engaged, meet their needs, and reduce inequalities. This part of the research activities will help to deepen our understanding of educational inequalities and inform policy and intervention development.

The desk research and fieldwork will provide valuable insights for **policy, research and practice recommendations** and finetuning and validating the conceptual model presented in Section 3.4.

By combining longitudinal data analysis with practical fieldwork insights, the LINEup project wants to influence education systems across the EU to develop evidence-based policies, targeted interventions and comprehensive support systems for promoting all students' school engagement, academic achievement and personal development.

8. References³⁵

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³⁵ The references analysed in depth through the review matrix are listed in bold.

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9. Appendices

9.1 Appendix A: Datasets identified through the in-depth analysis

	Longitudinal datasets/studies	Publication(s) included in the review	Data collection	Country	Geographical coverage	Timeframe	Participants	Demographics
1	LiSO - Loopbanen in het Secundair Onderwijs	1 study: Dockx et al., 2020	<i>School engagement measures for assessing the level of effort and involvement</i>	Belgium	Regional (Flanders)	2013-2017	N=5.417	Students in secondary education
2	LOSO - Longitudinal Project in Secondary School	1 study: Van de Gaer et al., 2009	Competency-based assessments in mathematics and language & <i>non-cognitive outcomes</i>	Belgium	Regional (Flanders)	1990-1999	N=2.270	Students from 7th to 12th grade
3	SiBO - Schoolloopbanen in het basisonderwijs	2 studies: Verhaeghe et al., 2018; Belfi et al., 2016	Mathematics achievement data. Dutch language skills	Belgium	Regional (Flanders)	2002-2011	N=3.619 up to N=6.000	Students from 5 to 12 years old
4	STRATEGIES project - Studying Transactions in Adolescence: Testing Genes in Interaction with Environments	1 study: Engels et al., 2017	Surveys	Belgium	Regional (Flanders)	Unspecified	Nw1=1.116, Nw2=987, Nw3=886	Students from 7th to 11th grade
5	Quantitative study with a longitudinal design	1 study: Dimosthenous, 2018	Mixed method (competency-based assessments in mathematics & surveys for parents & observation of teaching practices for teachers)	Cyprus	Local (Nicosia)	2013-2016	N=1.444	Students in primary schools
6	Czech Longitudinal Study in Education	1 study: Straková et al., 2016	Data from PIRLS and TIMSS	Czech	National	2010-2012	N=3679	11-year-old students
7	GAPS - Bridging the Gaps	1 study: Salmela-Aro et al., 2021	Surveys	Finland	Local (Helsinki)	2019-2023	Unspecified	High school students born in 1997

8	Longitudinal study	1 study: Widlund et al., 2023	Mixed method (competency-based assessments in mathematics & surveys)	Finland	Regional (different regions of Swedish-speaking areas of Finland)	2016-2019	N=1.131	Students from 7th to 9th grade
9	Three-wave longitudinal survey	1 study: Rautanen et al., 2022	Surveys	Finland	National	2017-2019	Nw1=2.401 Nw2=2.003	10-year-old students
10	FRAM - Adolescents' well-being and learning in the future society	1 study: Widlund et al., 2021	Surveys	Finland	Regional (different regions of Swedish-speaking areas of Finland)	2016-2019	N=1.131	Students in lower secondary schools
11	Growing Mind (GM)	1 study: Salmela-Aro et al., 2021	Surveys	Finland	Local (Helsinki)	2018-2020	N= 2.755	Students from 5th to 8th grade
12	Longitudinal Anonymised Study on Student Engagement, Truancy, and Cynicism	1 study: Virtanen et al., 2021	Surveys	Finland	Regional (4 Finnish municipalities)	No information available	N=1.853	Students from kindergarten to the end of lower secondary school
13	Longitudinal study	1 study: Hietajärvi et al., 2020	Surveys	Finland	Local (Helsinki)	No information available	N=1.705	Students from 9th to 12th grade
14	Longitudinal study	1 study: Niittylahti et al., 2023	Mixed method (surveys and interviews)	Finland	Regional	No information available	N=12	IVET students of 16-17 years old
15	Staying on Track of Learning	1 study: Hakkarainen et al., 2015	Competency-based assessments in mathematics & language	Finland	Local (a midsized Finnish city)	2004-2009	N=595	Students in grade 9
16	PANEL from the statistical service of the Department of Evaluation, Foresight and Performance (DEPP)	29 studies: Ben Ali & Vouc'h, 2015; Brinbaum & Kieffer, 2010; Broccolichi & Sinthon, 2011; Caille, 2001; Caille,	Mixed method (surveys & competency-based assessments in	France	National	1973-2011	N=9.000 up to N=37.500	Students from primary to high school

		2004a; Caille, 2004b; Caille, 2014; Caille & Rosenwald, 2006; Cayouette-Remblière & De Saint Pol, 2013; Cayouette-Remblière & Moulin, 2019; Cebolla Boado, 2008; Cosnefroy & Rocher, 2004; Cretin, 2012; Davaillon & Nauze-Fichet, 2004; Davezies, 2005; Duru-Bellat & Mingat, 1997; Farges & Monso, 2024; Fougère et al., 2017; Fougère et al., 2017; Grelet, 2005; Grenet, 2010; Guimard et al., 2007; Ichou, 2013; Ichou, 2015; Robert-Bobée, 2013; Stéfanou, 2017; Tavan, 2004; Monso et al., 2019; Ichou & Vallet, 2012	mathematics & language)					
17	Scolarité file of the Bordeaux academy	1 study: Felouzis, 2003	Administrative data	France	Regional	2000-2001	N=10.357 up to N=28.426	Students from 6th grade to 9th grade
18	BERLIN study	1 study: Albrecht, et al., 2018	Mixed methods (competency-based assessments & surveys & interviews)	Germany	Local (Berlin)	2010-2018	Nw1= 754 Nw2= 1470	Students from 6th grade until the end of secondary school, teachers & parents
19	BiKS - Educational Processes, Competence Development, and Selection Decisions in Preschool and School Age	2 studies: Pfof et al., 2010; Pfof et al., 2018	Mixed method (competency-based assessments & semi-standardized observations)	Germany	Regional (Bavaria and Hesse)	2005-2019	N=922	Students from 3rd to 7th grade, parents, educators & teachers
20	DESI - Assessment of Student Achievements in	1 study: Klieme, 2006	Competency-based assessments in	Germany	National	2003-2004	N=11.000	Students in 9th grade

	German and English as a Foreign Language		German and English language					
21	ELEMENT - Survey for reading and mathematics literacy. Developments in Grades 4 to 6 in Berlin	1 study: Paetsch et al., 2016	Competency-based assessments in reading and mathematics	Germany	Local (Berlin)	2003-2005	N=3,169	Students from 4th to 6th grade
22	EVES - Evaluation eines Vorschultrainings zur Prävention von Schriftspracherwerbsproblemen sowie Verlauf und Entwicklung des Schriftspracherwerbs in der Grundschule	1 study: Roos & Schöler, 2009	Competency-based assessments in language skills	Germany	Local (Heidelberg)	2001-2006	N=1.520	Students in primary school
23	KESS - Skills and Attitudes of School Children	1 study: Stanat et al., 2010	Competency-based assessments in German, Mathematics, Social Studies/Science, and English/surveys with students, parents, teachers, and school principals	Germany	Local (Hamburg)	2003-2005	N=10.447	Students in 4th grade
24	KOALA-S - Kids' Outcomes and Long-term Abilities study	2 studies: Ditton et al., 2019; Ditton & Krüsken, 2009	Mixed method (competency-based assessments & surveys)	Germany	Regional- (Bavaria and Saxony)	No information available	N=1.247	Students in 2nd, 3rd and 4th-grade and their parents and teachers, when they were in 5th and 6th grade
25	LAU - Aspects of Learning Background and Learning Development	2 studies: Caro & Lehmann, 2009; Lehmann et al., 2004	Competency-based assessments	Germany	Local (Hamburg)	1996-2005	Nw1=12.959 Nw2=56.411	Students from 5th to 11th grade

26	Longitudinal study	1 study: Bonefeld et al., 2017	Competency-based assessments	Germany	Regional	No information available	N=1.487	Students from 5th to 6th grade
27	Longitudinal study	1 study: Ditton, 2013	Competency-based assessments in German and mathematics/ information about familial, regional and school-related conditions	Germany	Regional (Bavaria and Saxony)	2005-2007	N=1.453	Students from 2nd to 4th grade, their parents and teachers
28	Longitudinal study	1 study: Duzy, 2013	Competency-based assessments	Germany	National	No information available	N=393	Students from the end of kindergarten to 2nd grade
29	Longitudinal study	1 study: Nett et al., 2022	Mixed method (Surveys & interviews)	Germany	Regional (Bavaria)	2019-2020	N=225	Students from 3rd to 4th grade
30	Longitudinal study	1 study: Trebits et al., 2022	Surveys	Germany	National	No information available	N=39	Students in regular or immersion primary schools
31	Longitudinal study	1 study: Warwas et al., 2009	Comparisons of means in test results	Germany	Local (Lower-Saxony)	2006-2007	N=11.000	Students in 11th grade
32	MOVE - Motivation and learning in mathematics	1 study: Lazarides & Rubach, 2017	Surveys	Germany	Local (Berlin)	No information available	N=746	Students from 9th to 10th grade
33	National Educational Panel Study (NEPS)	14 studies: Wohlkinger & Ditton, 2023; DeVries et al., 2020; Gil-Hernández, 2021; Herrmann et al., 2022; Holtmann & Solga, 2023; Hübner et al., 2019; Mikus et al., 2021; Kähler, 2023; Nachbauer, 2023; Gehrler & Nusser, 2020; Passaretta et	Mixed method (competency-based assessments, surveys, interviews & administrative data)	Germany	National	2008-2017	N=342 up to N=2.000	Children from 4-5 years old to upper secondary schools. Include VET students in 9th grade, parents, and other care

		al., 2022; Skopek & Passaretta, 2021; Passaretta & Skopek, 2018; Passaretta & Gil-Hernández, 2023						takers, teachers & educators
34	One-year longitudinal study	1 study: Fischer & Rustemeyer, 2007	Mixed method (competency-based assessments & surveys)	Germany	Regional (Rhineland-Palatine)	No information available	N=618	Students from 5th to 6th grade
35	SIMCUR - Social Integration of Migrant Children - Uncovering Family and School Factors Promoting Resilience	1 study: Demir & Leyendecker, 2018	Surveys	Germany	Local (Ruhr)	2009-2014	Nw1=216 Nw2=161	Turkish immigrant students from 9 to 15 years old
36	StEG - Study on the Development of All-Day Schools	1 study: Fischer et al., 2009	Mixed method (competency-based assessments, interviews & surveys)	Germany	National	2005-2009	N=5.656	Students in 5th to 7th grade, teachers, parents, educational staff, and partners collaborating with schools
37	TEACH - Teach! The Role of Teachers' Beliefs and Instructional Practices for Students' Beliefs and Academic Outcomes	1 study: Hettinger et al., 2023	Surveys	Germany	Regional (Berlin and Brandenburg)	2019-2020	N=959 students N=50 teachers	Students of 9th to 10th grade and secondary school mathematics teachers
38	TRAIN - Tradition and Innovation: Developmental processes at non-academic track secondary schools in Baden-Wuerttemberg and Saxony	1 study: Berendes et al., 2018	Mixed method (competency-based assessments, interviews & surveys)	Germany	Regional (Baden-Wuerttemberg)	2008-2012	N=2.505	Students in grades 5th to 8th

39	AstRA - Athena Studies of Resilient Adaptation project	1 study: Motti-Stefanidi et al., 2015	Surveys	Greece	Local (Athens)	No information available	N=1057	Immigrant students from 13 to 15 years old
40	Quantitative study with a longitudinal design	1 study: Papadopoulou, 2016	Mixed method (surveys for teachers and parents and competency-based assessments in mathematics and reading)	Greece	Regional	2013-2014	N=626 students N=483 parents N=51 teachers	Students in primary schools, their teachers and parents
41	Reykjavik Adolescent Risk-Taking Longitudinal Study	1 study: Blondal & Adalbjarnardottir, 2014	Surveys	Iceland	Local (Reykjavik)	1994-2002	N=835	Adolescents in compulsory schools
42	GUI - National longitudinal study of children in Ireland, Growing Up in Ireland study	1 study: Sprong & Skopek, 2023	Mixed method (competency-based assessments in mathematics and reading and teacher measures)	Ireland	National	No information available	N=7.577	9-year-old students
43	Anagrafe Nazionale degli Studenti	3 studies: Argentin, et al., 2017; Salza, 2022; Piano di valutazione 2014-2020	Administrative data & data from INVALSI	Italy	National	2010-ongoing	Nw1=140,000 Nw2=27.410	Students from 8th to 9th grade
44	IARD survey from Individuazione Assistenza Ragazzi Dotati (IARD) Institute	1 study: Guetto & Vergolini, 2017	Surveys	Italy	National	1983-2004	Unspecified	Students from 15 to 34 years old
45	One-year longitudinal study	1 study: Di Tommaso et al., 2024	Randomised Control Trials	Italy	Local (Turin)	2018-2019	N= 1,044	Students in 3 rd grade
46	Quantitative study with a longitudinal design	1 study: Grazia, 2022	Surveys	Italy	Regional (Northern Italy)	2019-2020	N=243	Students in 6th to 7th grade
47	Survey on the Development of Language Skills of Students with Special Educational Needs	1 study: Asquini & Sabella, 2018	Survey	Italy	Local (Roma)	No information available	N=767	Students in 7th grade

48	Longitudinal study	1 study: Poorthuis et al., 2015	Surveys about students' emotional and behavioural engagement	Netherlands	Local	No information available	N=438	Students from 11 to 14 years old
49	COOL- Cohort Research on Educational Careers in The Netherlands	2 studies: Passaretta et al., 2022; Passaretta & Skopek, 2018	Competency-based assessments	Netherlands	National	2007-2014	N= 7,075 & students from around 400 schools	Children from 2 to 14 years old
50	BONDS- Behavior Outlook Norwegian Developmental Study	2 studies: Passaretta & Skopek, 2018; Ribeiro, 2023	Mixed method (interviews & surveys)	Norway	National	2006-2014	N=1.150	Children from 0 to 8 years old and their parents
51	MoBa- Norwegian Mother and Child Cohort Study	2 studies: Passaretta & Skopek, 2018; Ribeiro, 2023	Surveys	Norway	National	1999-2018	N=100.000	Children from 0 to 8 years old and their parents
52	One-year longitudinal study	1 study: Eriksen et al., 2023	Surveys	Norway	Regional (large municipality in eastern Norway)	2018-2019	N=1.205	Students in 8th grade
53	Quantitative study with a longitudinal design	1 study: Haugan et al., 2019	Surveys	Norway	Regional (Trøndelag)	2015-2017	N=1.695	Students in upper secondary schools
54	Longitudinal study using data from Statistics Norway	1 study: Sandsør et al., 2023	Competency-based assessments in Mathematics and language and administrative data	Norway	National	2007-2018	N=1.103.081	Students of 5th to 10th grade and their parents/guardians
55	Four-year longitudinal study	1 study: Rosário et al., 2017	Randomised Control Trials	Portugal	Local (a city in Northern Portugal)	2010-2014	N=30	Gypsy families with children preparing to enter the first year of elementary school

56	Longitudinal mixed-methods study	1 study: Ribeiro et al., 2023	Mixed method (surveys with students and semi-structured interviews with parents)	Portugal	Regional	2018-2019	N=369 students/N=17 parents	Students in 2nd, 3rd and 4th grade
57	Longitudinal study	1 study: Lemos et al., 2020	Student control beliefs, teacher-reported student engagement, and student academic achievement	Portugal	Regional	No information available	N=391	13 to 14-years-old students
58	Portuguese longitudinal study on school engagement	4 studies: De Faria et al., 2023; Moreira & Lee, 2020; Rodrigues, 2023; Santos, 2023	Surveys	Portugal	National	2013-2020	N=241 up to N=33.107	Students in 8th grade
59	Evaluaciones de Diagnostico	1 study: Arenas & Gortazar, 2024	Competency-based assessments in Mathematics and language	Spain	Regional (Basque Country)	2015-2021	N=41.476	Students in primary and secondary education
60	Longitudinal study	1 study: Marchesi et al., 2004	Surveys	Spain	Local (Madrid)	1996-1997	N=1.668	Students in primary and lower secondary education
61	Longitudinal study	1 study: Mercader et al., 2017	Mixed method (competency-based in mathematics & surveys)	Spain	Local (two Spanish provinces)	No information available	N=180	Students from 5 years old to 2nd grade
62	Longitudinal study	1 study: Merino et al., 2020	Surveys	Spain	Local (Barcelona)	2013-2017	N=2.056	Students during the fourth-year compulsory secondary education
63	ISCY - International Study of City of Youth	3 studies: Kindt et al., 2023; García Gracia & Sánchez Gelabert, 2020	Surveys	Spain and Norway	Cross-coutry (Barcelona & Bergen)	2014-2017	Nw1=1.702 Nw2=2.056	Students from 10th to 12th grade

64	Longitudinal survey	1 study: Helbling et al., 2019	Competency-based assessments	Switzerland	Local (Zurich)	No information available	N=2.043	Students in primary and secondary education
65	MCS- Millennium Cohort Study	2 studies: Passaretta et al., 2022; Passaretta & Skopek, 2018	Mixed method (interviews & surveys)	United Kingdom	National	2000-2015	N= 19,243	Children from birth to 15 years old, their parents and teachers
66	ALSPAC - Avon Longitudinal Study of Parents and Children	1 study: Paget, 2018	Parents' reports and students' self-reports	United Kingdom	Regional (Avon)	No information available	N= 14,541	Pregnant women expected to deliver between April 1991, and December 1992
67	ASPIRES - The Science Aspirations and Career Choice project	1 study: DeWitt et al., 2014	Mixed method (interviews & surveys)	United Kingdom	National	2009-2013	Nw1=9,319 Nw2=5,634	Students from 6th to 8th grade
68	Quantitative study with a longitudinal design	1 study: Derrington, 2007	Interviews	United Kingdom	National	2000-2005	N=44	11 to 16 years old Gypsy traveller students, their parents and teachers
69	School Matters	1 study: Sammons, 1995	Competency-based assessments	United Kingdom	National	1985-1994	N=1.000	Students from junior school to the end of compulsory schooling

	Repeated cross-sectional datasets/studies	Publication(s) included in the review	Data collection	Country	Geographical coverage	Timeframe	Participants	Demographics
1	PISA - Programme for International Student Assessment	21 studies: Contini & Cugnata, 2020; Daniele, 2021; European Commission,	Mixed method (competency-based)	Cross-country	Cross-country	2000-2022	N=31.073 up to N=510.000	15-year-old students,

		2022c; European Commission & PPMI, 2022; Ferraro & Pöder, 2018; Herrera-Sosa et al., 2018; Hippe et al., 2018; Lagravinese et al., 2020; Lavrijsen & Nicaise, 2015; Nagy et al., 2017; OECD, 2003; OECD, 2013; OECD, 2015; OECD, 2023a; Oppedisano & Turati, 2015; Schubert & Becker, 2010; Volante, et al., 2022; Burger, 2019; Olczyk et al., 2021; Pensiero et al., 2019; Strello et al., 2021	assessments & surveys & administrative data)					parents and teachers
2	PIRLS - Progress in International Reading Literacy Study	4 studies: Contini & Cugnata, 2020; Lavrijsen & Nicaise, 2015; Schubert & Becker, 2010; Volante et al., 2022	Competency-based assessments in reading literacy	Cross-country	Cross-country	2001-2006	N=8.997 up to N=171.486	Students from 9 to 15 years old
3	TIMSS - Trends in International Mathematics and Science Study	2 studies: OECD, 2015; Strello et al., 2021	Competency-based assessments in mathematics and science	Cross-country	Cross-country	1995-2023	No information available	Students in 4th to 8th grade
4	EUROSTAT - Regional yearbook 2009 and 2010	1 study: Ballas et al., 2010	Administrative data	Cross-country	Cross-country	1997-1998	No information available	Students in primary, lower secondary education, upper secondary and post-secondary non-tertiary education (aged 15 to 24 years old)

5	Data collected by the Eurydice Network ³⁶ on structural indicators of early leaving from education and training	1 study: European Commission/EACEA/Eurydice, 2010; 2023	Administrative data	Cross-country	Cross-country	No information available	No information available	Unspecified
6	OECD Income Distribution Database	1 study: Daniele, 2021	Administrative data	Cross-country	Cross-country	2012	No information available	Unspecified
7	INVALSI- Istituto nazionale per la valutazione del sistema educativo di istruzione e di formazione	13 studies: INVALSI, 2013; Borgonovi & Ferrara, 2023; Istituto Regionale Programmazione Economica della Toscana, 2021; Triventi et al., 2021; Barbetta et al., 2023; Barone, 2017; Bianconcini, 2023; Borgonovi & Ferrara, 2022; Branchetti et al., 2015; Contini et al., 2017; Contini et al., 2023; Contini & Salza, 2024; Passaretta & Skopek, 2018	Competency-based assessment & surveys	Italy	National	2012-2022	N=15.132 up to 1.5 million	Students from 3rd to 13th grade
8	PRIMA - Cohortonderzoek Primair Onderwijs	1 study: Gijsberts & van der Ploeg, 2016	Competency-based assessments in language and mathematics	Netherlands	National	1988-2005	N=60.000	Students in primary schools

³⁶ The Eurydice Network consists of national units located in European countries and is coordinated by the European Education and Culture Executive Agency (EACEA) providing descriptions of national education systems, comparative studies devoted to specific topics, indicators and statistics.

9.2 Appendix B: Quantitative methods identified through the in-depth analysis

Methods	Short description	Analysed studies referred to the method
1 ANOVA – Analysis of Variance	Analysis of variance (ANOVA) is a collection of statistical models and their associated estimation procedures (such as the "variation" among and between groups) used to analyse the differences among means. ANOVA is based on the law of total variance, where the observed variance in a particular variable is partitioned into components attributable to different sources of variation.	6 studies: Widlund et al., 2021; Trebits et al., 2022; Papadopoulou, 2016; Dimosthenous, 2018; Fischer et al., 2009; Warwas et al., 2009
2 BOD - Blinder Oaxaca Decomposition	Blinder-Oaxaca decomposition is a method used in labour economics to analyse differences in outcomes, such as wages, between groups. It decomposes these differences into portions attributable to various factors, such as education or experience, and portions due to unexplained factors, often interpreted as discrimination.	2 studies: Hippe et al., 2018; Oppedisano & Turati, 2015
3 CA - Cluster Analysis	Cluster Analysis is a statistical method used to group similar objects into clusters based on their characteristics. It aims to maximise the similarity within each cluster while minimising the similarity between different clusters. This technique is widely used in various fields, including market research, biology, and machine learning.	4 studies: OECD, 2003; García Gracia & Sanchez Gelabert, 2020; Ichou, 2013; Robert-Bobée, 2013
4 CFA - Confirmatory Factor Analysis	Confirmatory Factor Analysis (CFA) is a statistical technique used to verify the factor structure of a set of observed variables. It tests the hypothesis that relationships between observed variables and their underlying latent constructs exist, confirming the theory-driven model. CFA is commonly applied in social sciences to validate measurement model	8 studies: Widlund et al., 2021; Lemos et al., 2020; Hietajärvi et al., 2020; Rautanen et al., 2022; Salmela-Aro, 2015; Widlund et al., 2023; Dimosthenous, 2018; De Faria et al., 2023
5 CI - Concentration Index	The concentration index measures the inequality of a variable, often used in economics and health studies. It quantifies how a variable, like income or health outcomes, is distributed across a population, highlighting disparities. A value of zero indicates perfect equality, while higher values signify greater inequality.	1 study: Felouzis, 2003
6 CLPM - Cross-lagged Panel Model	A Cross-lagged Panel Model (CLPM) is a statistical technique used in longitudinal research to analyse the relationships between variables over time. It examines how one variable at an earlier time point predicts another variable at a later time point while controlling for the stability of both variables.	1 study: Motti-Stefanidi et al., 2015

7	CN - Change Neighbour	Change Neighbour is a concept or tool used in computational algorithms, particularly optimisation problems. It involves modifying a current solution by altering one or more elements to explore the solution space. This approach helps find optimal or near-optimal solutions by iteratively adjusting the neighbouring configurations.	1 study: Nett et al., 2022
8	CT - Contingency Tables	A contingency table is a type of data matrix that displays the frequency distribution of variables. It has used in statistics to show the relationship between two or more categorical variables, enabling the analysis of patterns and interactions within the data. Each cell in the table represents a count or frequency.	16 studies: Broccolichi & Sinthon, 2011; Stéfanou, 2017; Ben Ali & Vourc'h, 2015; Farges & Monso, 2024; Duru-Bellat & Mingat, 1997; Felouzis, 2003; Caille, 2004a; Caille, 2004b; Cosnefroy & Rocher, 2004; Caille, 2001; Cretin, 2012; Caille & Rosenwald, 2006; Robert-Bobée, 2013; Brinbaum & Kieffer, 2010; Davailon & Nauze-Fichet, 2004; Caille, 2014
9	DEA - Conditional Data Envelopment Analysis	Data Envelopment Analysis (DEA) is a performance measurement technique used to evaluate the efficiency of decision-making units (DMUs) like public sector organisations. It utilises linear programming to compare multiple inputs and outputs, identifying the most efficient units and benchmarking others against these best practices. Conditional Data Envelopment Analysis (Conditional DEA) is an extension of traditional DEA, incorporating environmental variables into the efficiency analysis. It adjusts performance assessments by considering external factors, allowing for a more accurate evaluation of decision-making units' (DMUs) efficiency under varying conditions, thus enhancing the robustness of benchmarking results.	1 study: Lagravinese et al., 2020
10	DID - Difference in Differences	Difference in Differences (DiD) is a statistical technique used in econometrics and social sciences to estimate causal relationships. It compares the changes in outcomes over time between a group that is exposed to treatment and a group that is not, helping to control for confounding variables and unobserved factors.	7 studies: European Commission, 2022c; Arenas & Gortazar, 2024; Lavrijsen & Nicaise, 2015; Triventi et al., 2021; INVALSI, 2013; Contini, 2023; Strello, 2021
11	DS - Descriptive Statistics	Descriptive statistics summarise and organise data to provide a clear overview. They include measures like mean, median, mode, and standard deviation, as well as visual tools like charts and graphs. These techniques help identify patterns, trends, and distributions, making data easier to understand and interpret.	3 studies: IRPET, 2021; Lehmann et al., 2004; Barone et al., 2017

12	EAG - Estimating Achievement Gaps	Estimating achievement gaps involves analysing differences in academic performance between groups of students, typically defined by race, ethnicity, gender, or socioeconomic status. This process helps identify educational disparities, providing insights for targeted interventions to promote equity and improve educational outcomes for all students.	2 studies: Sandsør et al., 2023; Bianconcini, 2023
13	EFA - Exploratory Factor Analysis	Exploratory Factor Analysis (EFA) is a statistical method used to identify underlying relationships between measured variables. It aims to uncover latent constructs by grouping variables that are highly correlated. EFA is commonly used in psychology, social sciences, and market research to simplify complex data sets and enhance theoretical understanding.	1 study: Dimosthenous, 2018
14	EX - Exact Matching	Exact matching refers to the precise identification or retrieval of content that exactly matches a specified query or pattern without considering variations or synonyms. It ensures accuracy in information retrieval by strictly adhering to the specified criteria without flexibility.	3 studies: Ichou, 2013; Ichou, 2015; Contini & Salza, 2024
15	FIML - Full-Information Maximum Likelihood	Full-Information Maximum Likelihood (FIML) is a statistical method for estimating parameters in models where data may be missing or incomplete. Unlike other methods, FIML utilises all available information in the dataset to maximise the likelihood function, providing more accurate parameter estimates.	4 studies: Hübner et al., 2019; Lazarides & Rubach, 2017; Hietajärvi et al., 2020; Salmela-Aro et al., 2021
16	GCM - Growth Curve Modelling	Growth Curve Modelling is a statistical technique used to analyse longitudinal data by modelling changes in variables over time. It helps identify patterns, trends, and individual differences in growth trajectories, making it valuable in fields like psychology, biology, and economics for studying development and change processes.	6 studies: Baumert et al., 2012; Verhaeghe et al., 2018; Virtanen et al., 2021; Berendes et al., 2018; Rodrigues, 2023; Santos, 2023
17	GLM - Generalised Linear Models	Generalised linear models (GLMs) are a flexible statistical framework for modelling relationships between variables. They extend traditional linear regression to handle non-normal distributions and nonlinear relationships through link functions, making them suitable for various data types, including binary, count, and continuous outcomes.	2 studies: Guimard et al., 2007; Marchesi et al., 2004
18	GMM - Growth Mixture Modelling	Growth Mixture Modelling (GMM) is a statistical technique used to identify latent subgroups within a population that exhibit distinct developmental trajectories over time. It helps to uncover heterogeneous growth patterns by modelling individual variation in growth parameters, providing insights into complex longitudinal data structures.	1 study: Widlund et al., 2021

19	IPA - Interpretative Phenomenological Analysis	Interpretative Phenomenological Analysis (IPA) is a qualitative research approach focusing on exploring how individuals make sense of their personal and social world through their unique experiences. It emphasises understanding subjective perceptions and interpretations, aiming to uncover deep meanings and the complexity of lived experiences.	1 study: Derrington, 2007
20	IRT - Item Response Theory (IRT) Model	Item Response Theory (IRT) is a statistical framework used to analyse the relationship between individuals' performance on test items and their latent traits. It models how the probability of a correct response depends on both the item's characteristics and the individual's ability, offering insights into item difficulty and discrimination.	2 studies: Hübner et al., 2019; Triventi et al., 2021
21	IV - Instrumental Variables	Instrumental variables are used in statistics to address endogeneity issues by finding variables that correlate with the explanatory variable but not the error term. They help estimate causal relationships in situations where direct observation is challenging due to unobserved factors influencing both the explanatory and dependent variables.	6 studies: Farges & Monso, 2024; Davezies, 2005; Grenet, 2010; Barbetta et al., 2023; Passaretta & Skopek, 2018; Passaretta et al., 2022
22	IV-BPR - Instrumental Variables in The Form of a Bivariate Probit Regression	Instrumental variables in the form of a bivariate probit regression are used to address endogeneity in econometric models. By simultaneously modelling two correlated binary outcomes, it allows for the identification of causal effects in situations where direct observation of the treatment effect is biased.	1 study: Fougère et al., 2017
23	K+R - Kenward and Roger Adjustment	The Kenward and Roger adjustment is a method used in statistical analysis to refine the degrees of freedom estimation in linear mixed models. It addresses potential biases in the model's standard error calculations, which is particularly useful when dealing with small sample sizes or unequal variances among groups.	1 study: Rosário et al., 2017
24	KHB - Krylov-Householder-Block Decomposition Technique	The KHB decomposition technique, also known as Krylov-Householder-Block decomposition, is a numerical method used in linear algebra to efficiently decompose large matrices into structured forms. It combines Krylov subspace methods with Householder reflections and block matrix operations, offering a powerful tool for solving complex matrix equations and optimizing computational efficiency.	1 study: Passaretta & Gil-Hernández, 2023
25	LCLM - Latent Cross-Lagged Model	A Latent Cross-Lagged Model (LCLM) is a statistical method used in longitudinal studies to explore reciprocal relationships between variables over time. It assesses how one variable influences another across different	2 studies: Grazia, 2022; Hietajärvi et al., 2020

		time points while accounting for latent (unobserved) constructs underlying the observed measures.	
26	LCSM - Latent Change Score Models	Latent change score models are statistical tools used to analyse variable changes over time. They estimate latent variables representing initial status and change rates, offering insights into developmental trajectories without direct measurement of change scores. These models are valuable in longitudinal studies for understanding growth or decline across multiple time points.	1 study: Eriksen et al., 2023
27	LGM - Latent Growth Models	Latent growth models are statistical techniques used to analyse change over time in variables that are not directly observed (latent variables). They estimate initial levels and rates of change, offering insights into developmental trajectories and factors influencing them.	2 studies: Lemos et al., 2020; Paetsch et al., 2016
28	LiRA - Linear Regression Analysis	Linear regression analysis is a statistical technique used to examine the relationships between multiple independent variables and a single dependent variable. It extends simple regression by accommodating several predictors simultaneously, allowing researchers to assess how different factors collectively influence an outcome of interest.	42 studies: Arenas & Gortazar, 2024; Borgonovi & Ferrara, 2023; Contini & Cugnata, 2020; Daniele, 2021; Demir & Leyendecker, 2018; DeWitt et al., 2014; Hakkarainen et al., 2015; Herrera-Sosa et al., 2018; Hippe et al., 2018; Holtmann & Solga, 2023; Mikus et al., 2021; OECD, 2003; Schubert & Becker, 2010; Virtanen et al., 2021; Papadopoulou, 2016; Asquini & Sabella, 2018; IRPET, 2021; Albrecht et al., 2018; Mercader et al., 2017; Cayouette-Remblière & Moulin, 2019; Ichou, 2013; Stéfanou, 2017; Grelet, 2005; Ben Ali & Vourc'h, 2015; Davezies, 2005; Fougère et al., 2017; Duru-Bellat & Mingat, 1997; Felouzis, 2003; Caille, 2004a; Caille, 2001; Cebolla Boado, 2008; Brinbaum & Kieffer, 2010; Caille, 2004b; Burger, 2019; Borgonovi & Ferrara, 2022; Contini et al., 2017; Di Tommaso, 2024; Pensiero et al., 2019; Skopek & Passaretta, 2021; Passaretta & Gil-Hernández, 2023; Passaretta & Skopek, 2018; Passaretta et al., 2022

29	LMS - Latent Moderated Structural (LMS) Modelling	Latent Moderated Structural (LMS) modelling is a statistical technique used to analyse complex relationships among latent variables in research. It integrates structural equation modelling with moderation analysis, allowing researchers to explore how the effects of one variable on another vary depending on the levels of a third variable.	1 study: 1 study: Hietajärvi et al., 2020
30	LoRA - Logistic Regression	Logistic regression analysis is a statistical model used for binary classification tasks. It predicts the probability of an event's occurrence by fitting data into a logistic curve. Unlike linear regression, it is suited for categorical outcomes, providing insights into relationships between predictors and the likelihood of specific outcomes.	25 studies: Guetto & Vergolini, 2017; Kindt et al., 2023; Mikus et al., 2021; OECD, 2003; Paget et al., 2018; Salza, 2022; Wohlkinger & Ditton, 2023; Argentin et al., 2017; IRPET, 2021; Albrecht et al., 2018; Ditton, 2013; Nagy et al., 2017; Pfof et al., 2018; Merino et al., 2020; Tavan, 2004; Guimard et al., 2007; Fougère et al., 2017; Felouzis, 2003; Cretin, 2012; Caille & Rosenwald, 2006; Brinbaum & Kieffer, 2010; Caille, 2014; Ichou & Vallet, 2012; Caille, 2004a; Barone et al., 2017
31	LPM - Linear Probability Model	The Linear Probability Model (LPM) is a basic regression model used in statistics and economics to estimate the probability of an event occurring based on linear relationships between predictor variables and the probability outcome. It assumes constant effects of predictors on the probability and is simple to interpret but may violate the probability constraints.	3 studies: Gil-Hernández, 2021; Holtmann & Solga, 2023; Davailon & Nauze-Fichet, 2004
32	MA - Mediation Analysis	Mediation analysis explores how one variable influences another by examining the intermediate variables that carry the effect. It helps to understand the underlying mechanisms and pathways of relationships between variables in statistical models.	2 studies: Mikus et al., 2021; Kähler et al., 2023
33	MCA - Multiple Correspondence Analysis	Multiple Correspondence Analysis (MCA) is a statistical technique used to analyse the relationships between categorical variables. It extends the principles of Correspondence Analysis to more than two variables, visualising patterns and associations in high-dimensional categorical data through graphical representations.	2 studies: Ichou, 2013; Grelet, 2005
34	MGCFA - Multiple Group Confirmatory Factor Analysis	Multiple Group Confirmatory Factor Analysis (MGCFA) is a statistical technique used to compare the measurement properties of a latent variable model across different groups. It assesses whether the relationships between observed variables and latent constructs are equivalent across	2 studies: Salmela-Aro, 2015; Widlund et al., 2023

		multiple groups, helping to determine if the model holds true across diverse populations or conditions.	
35	MMRM - Mixed Model for Repeated Measures	A Mixed Model for Repeated Measures is a statistical approach used to analyse data where multiple measurements are taken from the same subjects over time. It accounts for both within-subject correlation and between-subject variability, offering robust insights into how variables change over repeated observations.	1 study: Rosário et al., 2017
36	MSM - Marginal Structural Modelling	Marginal structural modelling (MSM) is a statistical method used to analyse longitudinal data while accounting for time-varying confounding variables. It allows researchers to estimate causal effects in the presence of complex relationships and time-dependent exposures, making it valuable in epidemiology and social sciences.	1 study: Dockx et al., 2020
37	Multi - Multilevel Modelling/Hierarchical Models	Multilevel modelling, also known as hierarchical modelling, is a statistical technique used to analyse data with a nested or hierarchical structure. It allows for examining relationships at different levels of aggregation, such as individuals within groups, while accounting for dependencies and variations across these levels.	31 studies: European Commission & PPMI, 2022; Ferraro & Pöder, 2018; Belfi et al., 2016; Caro & Lehmann, 2009; DeVries et al., 2020; DeWitt et al., 2014; Gijssberts & van der Ploeg, 2016; Haugan et al., 2019; Herrmann et al., 2022; Hettinger et al., 2023; Motti-Stefanidi et al., 2015; Ribeiro et al., 2023; Sammons, 1995; Straková et al., 2016; Trebits et al., 2022; Verhaeghe et al., 2018; Papadopoulou, 2016; Dimosthenous, 2018; Berendes et al., 2018; Bonefeld, 2017; Fischer & Rustemeyer, 2007; Kähler et al., 2023; Nett et al., 2022; Nachbauer, 2023; Roos & Schöler, 2009; Stanat et al., 2010; Klieme, 2006; Burger, 2019; Moreira & Lee, 2020; Helbling et al., 2019; Bianconcini, 2023
38	OMS - Optimal Matching Of Sequences	Optimal matching of sequences refers to a method in computational biology and bioinformatics used to align pairs of sequences by maximizing similarity and minimizing gaps. It aims to find the best alignment that reflects evolutionary relationships or functional similarities between biological sequences like DNA, RNA, or proteins.	1 study: Cayouette-Remblière & de Saint Pol, 2013

39	PA - Path Analysis	Path analysis is a statistical method used to explore relationships among variables in a complex model. It assesses direct and indirect effects to understand how different factors influence an outcome, providing insights into causal pathways within a dataset.	4 studies: Sprong & Skopek, 2023; Straková et al., 2016; Ditton, 2013; Nachbauer, 2023
40	PCA - Principal Component Analysis	Principal Component Analysis (PCA) is a statistical technique used for dimensionality reduction in data analysis. It identifies patterns in data by transforming variables into a set of linearly uncorrelated components, allowing complex datasets to be simplified while preserving important information.	3 studies: Salza, 2022; Merino et al., 2020; García Gracia & Sanchez Gelabert, 2020
41	PSM - Propensity Score Matching	Propensity score matching is a statistical technique used to reduce bias in observational studies by matching individuals with similar propensity scores, which estimate the probability of receiving a treatment based on observed covariates. This method aims to simulate a randomised controlled trial by creating comparable groups, thereby improving the validity of causal inference.	6 studies: European Commission, 2022c; Belfi et al., 2016; INVALSI, 2013; Pfost et al., 2010; Farges & Monso, 2024; Contini & Salza, 2024
42	QCA - Qualitative Content Analysis	Qualitative Content Analysis is a method used to systematically analyse qualitative data, such as text, images, or audio. It focuses on identifying patterns, themes, and meanings within the data, often through coding and categorisation techniques. This approach aims to uncover deeper insights and understanding from complex qualitative information.	1 study: Niittylahti et al, 2023
43	QR - Quantile Regression	Quantile Regression is a statistical technique used to model the relationship between variables when traditional methods like ordinary least squares regression are inadequate. It estimates different quantiles of the dependent variable's distribution, offering insights into how predictors affect different parts of the distribution beyond just the mean.	2 studies: Costanzo & Desimoni, 2017; Contini, 2017
44	QSM - Quasi-Simplex Modelling	Quasi-Simplex modelling is a statistical approach used in psychological research to analyse data from Likert-type scales. It combines elements of factor analysis and item response theory, aiming to uncover underlying dimensions and the structure of measurement instruments with robustness against non-normal distributions.	1 study: Baumert et al., 2012
45	RA (CA) - Reliability Analysis (Cronbach Alpha)	Reliability Analysis, specifically Cronbach's Alpha, assesses the internal consistency of a scale or questionnaire by measuring how closely related a set of items is as a group. It quantifies the extent to which items in a test consistently measure the same construct, indicating the instrument's reliability.	1 study: Dimosthenous, 2018

46	RI-CLPM - Random Intercept Cross-Lagged Panel Model	The Random Intercept Cross-Lagged Panel Model (RI-CLPM) is a statistical technique used in longitudinal data analysis to explore reciprocal relationships between variables over time. It assesses how variables influence each other across multiple time points while accounting for individual differences with random intercepts.	2 studies: Salmela-Aro, 2015; Widlund et al., 2023
47	RIRT - Rasch-Item Response Theory	Rasch-Item Response Theory (IRT) is a statistical framework used to analyse responses to test items, aiming to measure latent traits like abilities or attitudes. It models the probability of a correct response based on item difficulty and person ability, providing insights into item quality and test fairness.	1 study: Dimosthenous, 2018
48	SBM - Slack Based Measure (SBM) Model	The Slack Based Measure (SBM) model is a performance evaluation framework that assesses the efficiency of decision-making units (DMUs) by considering both input reduction and output increase from slack variables. It aims to enhance productivity and optimise resource allocation in organisations.	1 study: Lagravinese et al., 2020
49	SCC - Spearman's Rank Correlation Coefficient	Spearman's rank correlation coefficient is a statistical measure used to assess the strength and direction of association between two ranked variables. It evaluates how well the relationship between variables can be described using a monotonic function, regardless of the specific values of the variables themselves.	2 studies: Ditton & Krüsken, 2009; Guimard et al., 2007
50	SD - Shapley Decomposition	Shapley decomposition is a method derived from cooperative game theory, used to attribute the total value of a system to individual contributors fairly. It calculates each player's marginal contribution by considering all possible coalitions, ensuring a fair distribution based on each player's impact on the overall outcome.	1 study: Holtmann & Solga, 2023
51	SEM - Structural Equation Modelling	Structural Equation Modelling (SEM) is a statistical technique used for testing and estimating causal relationships using a combination of statistical data and qualitative causal assumptions. It encompasses multiple regression, factor, and path analyses, enabling researchers to analyse complex relationships among observed and latent variables simultaneously.	18 studies: Blondal & Adalbjarnardottir, 2014; Ditton, 2019; Lazarides & Rubach, 2017; Poorthuis et al., 2015; Rautanen et al., 2022; Sprong & Skopek, 2023; Van de Gaer et al., 2009; Duzy, 2013; Fischer et al., 2009; Gehrler & Nusser, 2020; Nachbauer, 2023; De Faria et al., 2023; Rodrigues, 2023; Santos, 2023; Branchetti et al., 2015; Ribeiro, 2023; Passaretta & Skopek, 2018

52	SLD - Synthetic Longitudinal Data	Synthetic longitudinal data are artificially generated datasets that mimic real-world longitudinal data. These datasets track the same subjects over time, capturing changes and trends. Used primarily for research and analysis, they preserve privacy while enabling studies on temporal patterns and relationships without using sensitive, real-world data.	1 study: Schubert & Becker, 2010
53	SS - Standardised Scores	Standardised scores, also known as z-scores, measure how far a data point is from the mean in units of standard deviations. They allow comparison between different datasets by standardising values, enabling an assessment of where a particular score lies within its distribution. This is essential in statistics for normalisation and comparison.	2 studies: Fougère et al., 2017; Olczyk et al., 2021
54	WCLC – ROS - Within-Class Latent Change and Rank-Order Stability	Within-class latent change refers to variations in behaviour or traits within a specific group over time. Rank-order stability denotes the consistency of individuals' relative positions within a group on a particular trait across time. Both concepts are crucial for understanding development and individual differences in psychological research.	1 study: Salmela-Aro et al., 2021

9.3 Appendix C: Mapping of analysed studies to the variables of educational inequalities

Clusters	Sub-clusters	Variables	Analysed studies referred to the variable
Student (C1)	Student characteristics (C1.1)	Gender	53 studies: Barone et al., 2017; Berendes et al., 2018; Borgonovi & Ferrara, 2023; Brinbaum & Kieffer, 2009b; Caille, 2004a; Caille, 2014; Cayouette-Remblière & Moulin, 2019; Cebolla Boado, 2008; Contini et al., 2017, 2023; Costanzo & Desimoni, 2017; Cretin, 2012; Davaillon & Nauze-Fichet, 2004; Demir & Leyendecker, 2018; Di Tommaso et al., 2024; Dockx et al., 2020; Duru-Bellat & Mingat, 1997; Engels et al., 2017; European Commission, 2022c; European Commission/EACEA/Eurydice, 2010; Fischer et al., 2009; Fischer & Rustemeyer, 2007; Pensiero et al., 2019; UNESCO, 2006; Guetto & Vergolini, 2017b; Helbling et al., 2019; Hettinger et al., 2023; Hübner et al., 2019; Ichou, 2015; Klieme, 2006; Lazarides & Rubach, 2017; Lehmann et al., 2004; Merino et al., 2020; Nagy et al., 2017; Bianconcini et al., 2023; OECD, 2003, 2013b; Rautanen et al., 2022; Roos & Schöler, 2009; Sammons, 1995; Stéfanou, 2017; Van de Gaer et al., 2009; Verhaeghe et al., 2018; Virtanen et al., 2021; Volante et al., 2022; Widlund et al., 2023; Wohlking & Ditton, 2023; Demosthenous, 2019; Papadopoulou, 2016; García Gracia & Sanchez Gelabert, 2020; Esteves Rodrigues, 2023; Sousa Monteiro Santos, 2023
		Age	16 studies: Barone et al., 2017; Caille, 2004a; Caille, 2014; Caille & Rosenwald, 2006; Dockx et al., 2020; Duru-Bellat & Mingat, 1997; Grenet, 2010; Guetto & Vergolini, 2017a; Lehmann et al., 2004; Sammons, 1995; Schubert & Becker, 2010; Stéfanou, 2017; UNESCO, 2006; Verhaeghe et al., 2018; Widlund et al., 2023; Demosthenous, 2019
		Language spoken at home	15 studies: Arenas & Gortazar, 2024; DeVries et al., 2020; Dockx et al., 2020; Duzy, 2013; European Commission, 2022c; European Commission & PPMI, 2022; Felouzis, 2003; Helbling et al., 2019; Herrera-Sosa et al., 2018; Ichou, 2013; Klieme, 2006b; Paetsch et al., 2016; Roos & Schöler, 2009; Verhaeghe et al., 2018; Papadopoulou, 2016
		Migrant background	42 studies: Arenas & Gortazar, 2024; Barone et al., 2017; Berendes et al., 2018; Bianconcini et al., 2023; Bonefeld et al., 2017; Brinbaum & Kieffer, 2009b, p. 20; Caille, 2001, 2014; Cayouette-Remblière & Moulin, 2019; Cebolla Boado, 2008; Contini et al., 2023; Contini & Salza, 2024; Costanzo & Desimoni, 2017; Davaillon & Nauze-Fichet, 2004; Di Tommaso et al., 2024; Duru-Bellat & Mingat, 1997; European Commission, 2022c; European Commission & PPMI, 2022; European Commission/EACEA/Eurydice, 2023; Fougère, Kieffer, et al., 2017; García Gracia & Sanchez Gelabert, 2020; Herrera-Sosa et al., 2018b; Herrmann et al., 2022; Hippe et al., 2018; Hübner et al., 2019; Ichou, 2013; Kähler et al., 2023; Klieme, 2006; Lehmann et al., 2004; Merino et al., 2020; Motti-Stefanidi et al., 2015; Nagy et al., 2017; OECD, 2003; Olczyk et al., 2021; Pensiero et al., 2019; Salza, 2022; Sprong & Skopek, 2023; Termes, 2022; UNESCO, 2006; Verhaeghe et al., 2018; Volante et al., 2022; Wohlking & Ditton, 2023; Passaretta & Skopek, 2018

		Ethnic minority	10 studies: Derrington, 2007; European Commission 2022c; European Commission & PPMI 2022; European Commission/EACEA/Eurydice, 2023; Fougère, Kiefer, et al., 2017; Gijssberts & van der Ploeg, 2016; Olczyk et al., 2021; Sammons, 1995; UNESCO, 2006; Papadopoulou, 2016
		Cognitive ability	2 studies: Gil-Hernández, 2021; Hübner et al., 2019
		Learning disabilities	10 studies: Asquini & Sabella, 2018; Di Tommaso et al., 2024; European Commission/EACEA/Eurydice, 2023; Herrmann et al., 2022; Mercader et al., 2017; OECD, 2003; Paget et al., 2018; Ribeiro et al., 2023; Termes, 2022; UNESCO, 2006
		Mental health	4 studies: Dockx et al., 2020; Niittylahti et al., 2023; OECD, 2003; Paget et al., 2018
	Learning achievement & performance (C1.2)	Academic achievement	39 studies: Arenas & Gortazar, 2024; Baumert et al., 2012; Ben Ali & Vourc'h, 2015b; Brinbaum & Kieffer, 2009b; Caille, 2004a; Caille, 2014; Caille & Rosenwald, 2006; Cebolla Boado, 2008; Davailon & Nauze-Fichet, 2004; Ditton, 2013; Dockx et al., 2020; European Commission, 2022c; European Commission & PPMI, 2022; Grelet, 2005; Guimard et al., 2007; Hakkarainen et al., 2015; Haugan et al., 2019; Hübner et al., 2019; Lemos et al., 2020; Monso et al., 2019; Motti-Stefanidi et al., 2015; OECD, 2015, 2023; Olczyk et al., 2021; Paetsch et al., 2016; Poorthuis et al., 2015; Robert-Bobée, 2013; Sandsør et al., 2023; Stéfanou, 2017; Straková et al., 2016; Strello et al., 2021; Triventi et al., 2021; Virtanen et al., 2021; Widlund et al., 2021; Wohlkinge & Ditton, 2023; Hietajärvi et al., 2020; Passaretta et al., 2022; Skopek & Passaretta, 2021; Passaretta & Skopek, 2018
		Math skills	15 studies: Ben Ali & Vourc'h, 2015b; Brinbaum & Kieffer, 2009b; Caille & Rosenwald, 2006; Cebolla Boado, 2008; Hakkarainen et al., 2015; Holtmann & Solga, 2023; Hübner et al., 2019; OECD, 2013b, 2023; Robert-Bobée, 2013; Straková et al., 2016; Strello et al., 2021; Verhaeghe et al., 2018; Widlund et al., 2023; Wohlkinge & Ditton, 2023
		Reading skills	10 studies: Brinbaum & Kieffer, 2009b; Hakkarainen et al., 2015; Paetsch et al., 2016; Pfost et al., 2010; Robert-Bobée, 2013; Sammons, 1995; Strello et al., 2021; Van de Gaer et al., 2009; Verhaeghe et al., 2018; Wohlkinge & Ditton, 2023
		Science skills	3 studies: Ditton et al., 2019; Hippe et al., 2018; Strello et al., 2021
		Grade repetition	12 studies: Brinbaum & Kieffer, 2009b; Caille, 2004, 2014; Contini & Salza, 2024; Cosnefroy & Rocher, 2004; European Commission, 2022c; Herrera-Sosa et al., 2018b; Hübner et al., 2019; OECD, 2013b; Salza, 2022; Sousa Monteiro Santos, 2023; Termes, 2022
		Burnout	3 studies: Salmela-Aro, 2015b; Salmela-Aro et al., 2021a; Widlund et al., 2023
	School engagement (C1.3)	Student engagement	11 studies: Esteves Rodrigues, 2023; European Commission, 2022c; Moreira & Lee, 2020; Niittylahti et al., 2023; OECD, 2013b; Rautanen et al., 2022; Salmela-Aro, 2015b; Sousa Monteiro Santos, 2023; Virtanen et al., 2021; Widlund et al., 2021, 2023
		Emotional engagement	1 study: Poorthuis et al., 2015

		Behavioural engagement	2 studies: Engels et al., 2017; Virtanen et al., 2021
		Cognitive engagement	1 study: Moreira & Lee, 2020
		Peer relationships	10 studies: Davezies, 2005; Demir & Leyendecker, 2018; Ditton & Krüsken, 2009; Engels et al., 2017; Eriksen et al., 2023; European Commission & PPMI, 2022; Moreira & Lee, 2020; Niittylahti et al., 2023; Virtanen et al., 2021; Demosthenous, 2019
		Social skills	4 studies: Eriksen et al., 2023, 2023; Ribeiro et al., 2023; Salmela-Aro et al., 2021a
		Well-being	7 studies: Arenas & Gortazar, 2024; De Faria et al., 2023; European Commission, 2022c; European Commission/EACEA/Eurydice, 2023; Niittylahti et al., 2023; Salmela-Aro, 2015b; Salmela-Aro et al., 2021b; Widlund et al., 2021
		Participation in school activities	6 studies: OECD, 2003, 2013b; Rosário et al., 2017; Salmela-Aro, 2015; Virtanen et al., 2021; Papadopoulou, 2016
		Sense of belonging	6 studies: Burger, 2019; European Commission, 2022c; European Commission & PPMI, 2022; European Commission/EACEA/Eurydice, 2023; Haugan et al., 2019; OECD, 2003
		Bullying	4 studies: Derrington, 2007; European Commission, 2022c; European Commission & PPMI, 2022; European Commission/EACEA/Eurydice, 2023
		Student-teacher relationships	4 studies: OECD, 2003; Paget et al., 2018; Ribeiro et al., 2023; Demosthenous, 2019
		Digital learning engagement	1 study: Hietajärvi et al., 2020
	Self-image (C1.4)	Self-efficacy	2 studies: Niittylahti et al., 2023; Ribeiro et al., 2023
		Perceived competence	2 studies: Ditton et al., 2019; Lazarides & Rubach, 2017
		Intrinsic motivation	6 studies: Ditton et al., 2019; European Commission, 2022c; Lazarides & Rubach, 2017; OECD, 2013b; Ribeiro et al., 2023; Virtanen et al., 2021
		Individual aspirations	4 studies: DeWitt et al., 2014; Hippe et al., 2018; Kindt et al., 2023; Widlund et al., 2021
Family (C2)	Economic, social & cultural status (C2.1)	Socioeconomic status (ESCS)	57 studies: Arenas & Gortazar, 2024; Argentin et al., 2017; Ben Ali & Vourc'h, 2015b; Berendes et al., 2018; Bianconcini et al., 2023; Borgonovi & Ferrara, 2023; Burger, 2019; Caro & Lehmann, 2009; Cayouette-Remblière & de Saint Pol, 2013; Cayouette-Remblière & Moulin, 2019; Contini & Cugnata, 2020; Costanzo & Desimoni, 2017; Cretin, 2012; Daniele, 2021; DeVries et al., 2020; Ditton & Krüsken, 2009; Dockx et al., 2020; Engels et al., 2017; European Commission & PPMI, 2022; European Commission, 2022b; 2023c; European Commission/EACEA/Eurydice, 2023; European

			Commission/EACEA/Eurydice, 2010; Farges & Monso, 2024; Fischer et al., 2009; Fougère, Kiefer, et al., 2017; Gil-Hernández, 2021; Guetto & Vergolini, 2017b; Guimard et al., 2007; Helbling et al., 2019; Hippe et al., 2018; Hübner et al., 2019; Ichou, 2015; Ichou & Vallet, 2012; IRPET, 2021; Kähler et al., 2023; Lagravinese et al., 2020; Marchesi et al., 2004; Nachbauer, 2023; Nagy et al., 2017; OECD, 2003, 2013b; Olczyk et al., 2021; Oppedisano & Turati, 2015; Paget et al., 2018; Sammons, 1995; Schubert & Becker, 2010; Sprong & Skopek, 2023; Stéfanou, 2017; Tavan, 2004; Volante et al., 2022; Wohlking & Ditton, 2023; Passaretta et al., 2022; Skopek & Passaretta, 2021; Passaretta & Skopek, 2018; Passaretta & Gil-Hernández, 2023; Ribeiro, 2023
		Parental educational attainment (ESCS)	44 studies: Argentin et al., 2017; Brinbaum & Kieffer, 2009; Broccolichi & Sinthon, 2011; Caille, 2004a; Caille, 2001, 2014; Caille & Rosenwald, 2006; Cayouette-Remblière & de Saint Pol, 2013; Cebolla Boado, 2008; Contini et al., 2023; Contini & Salza, 2024; Davaillon & Nauze-Fichet, 2004; Demir & Leyendecker, 2018; Di Tommaso et al., 2024; Ditton & Krüsken, 2009; Dockx et al., 2020; Engels et al., 2017; Esteves Rodrigues, 2023; European Commission, 2022c; Ferraro & Pöder, 2018; García Gracia & Sanchez Gelabert, 2020; Guetto & Vergolini, 2017; Herrmann et al., 2022; Ichou, 2013, 2015; Marchesi et al., 2004; Merino et al., 2020; Mikus et al., 2021; Olczyk et al., 2021; Pensiero et al., 2019; Robert-Bobée, 2013; Salza, 2022; Sandsør et al., 2023; Schubert & Becker, 2010; Straková et al., 2016; Strello et al., 2021; Tavan, 2004; Trebits et al., 2022; Verhaeghe et al., 2018; Volante et al., 2022; Wohlking & Ditton, 2023; Demosthenous, 2019; Papadopoulou, 2016; Passaretta et al., 2022
		Parental occupation (ESCS)	22 studies: Argentin et al., 2017; Brinbaum & Kieffer, 2009b; Caille, 2001, 2004a; 2014; Caille & Rosenwald, 2006; Davaillon & Nauze-Fichet, 2004; Ditton, 2013b; European Commission, 2022c; Fougère, Monso, et al., 2017; Ichou, 2013, 2015; Ichou & Vallet, 2012; IRPET, 2021; Kroezen & Alieva, 2022; Marchesi et al., 2004; OECD, 2013b; Olczyk et al., 2021; Robert-Bobée, 2013; Sandsør et al., 2023; Verhaeghe et al., 2018; Demosthenous, 2019; Papadopoulou, 2016
		Cultural background (ESCS)	18 studies: Argentin et al., 2017; Ben Ali & Vourc'h, 2015b; Bianconcini et al., 2023; Broccolichi & Sinthon, 2011; Costanzo & Desimoni, 2017; Cretin, 2012; Daniele, 2021; Ditton et al., 2019; European Commission, 2023b; European Commission & PPMI, 2022; Hippe et al., 2018; Klieme, 2006a; Lagravinese et al., 2020; Marchesi et al., 2004; OECD, 2015; Schubert & Becker, 2010; Stéfanou, 2017; Wohlking & Ditton, 2023
		Household income (ESCS)	4 studies: Ditton & Krüsken, 2009; Olczyk et al., 2021; Sandsør et al., 2023; Verhaeghe et al., 2018
		Wealth/ Household possessions (ESCS)	3 studies: Olczyk et al., 2021; Schubert & Becker, 2010; UNESCO, 2006
		Books available at home (ESCS)	7 studies: Argentin et al., 2017; Hübner et al., 2019; Marchesi et al., 2004; Volante et al., 2022; Papadopoulou, 2016 (Argentin et al., 2017; Strello et al., 2021

	Family structure & functioning (C2.2)	PC at home (ESCS)	2 studies: Marchesi et al., 2004; Papadopoulou, 2016
		Family structure	9 studies: Cretin, 2012; European Commission/EACEA/Eurydice, 2023; Hübner et al., 2019; Ichou, 2013, 2015; OECD, 2003; Olczyk et al., 2021; Stéfanou, 2017; UNESCO, 2006
		Family difficulties	1 study: Robert-Bobée, 2013
		Parental support (to student)	12 studies: Blondal & Adalbjarnardottir, 2014; Caille, 2004; Cretin, 2012; European Commission, 2022c; Haugan et al., 2019; Herrera-Sosa, Katia et al., 2018b; Paget et al., 2018; Stéfanou, 2017; Tavan, 2004; Virtanen et al., 2021; Wohlking & Ditton, 2023; Demosthenous, 2019
		Parental aspirations	4 studies: Derrington, 2007; Ditton et al., 2019; Grelet, 2005; OECD, 2013b
		School-family relationship	1 study: Ditton et al., 2019
		Out-of-school-time lessons	1 study: Hippe et al., 2018
Teacher (C3)	Teachers' characteristics & practices (C3.2)	Teacher support (to student)	12 studies: Argentin et al., 2017; Demir & Leyendecker, 2018; European Commission, 2022c; European Commission & PPMI, 2022; European Commission/EACEA/Eurydice, 2023; Guimard et al., 2007; Haugan et al., 2019; Hettinger et al., 2023; Lazarides & Rubach, 2017; Moreira & Lee, 2020; Virtanen et al., 2021; Wohlking & Ditton, 2023
		Teaching methods	8 studies: DeVries et al., 2020; Gehrler & Nusser, 2020; Hietajärvi et al., 2020; Hippe et al., 2018; Lazarides & Rubach, 2017; Niittylahti et al., 2023; OECD, 2013b; Demosthenous, 2019
		Teacher work experience	1 study: Davezies, 2005
		Teacher interest	1 study: European Commission, 2022c
		Teacher education and training on early leaving	1 study: European Commission/EACEA/Eurydice, 2023
School & education system (C4)	School characteristics (C4.1)	Geographical area	13 studies: Ballas et al., 2010; Cayouette-Remblière & Moulin, 2019; Contini et al., 2023; Costanzo & Desimoni, 2017; Ditton & Krüsken, 2009; European Commission, 2022c; Ferraro & Pöder, 2018; Fougère, Monso, et al., 2017; Grelet, 2005; Guetto & Vergolini, 2017b; Pensiero et al., 2019; UNESCO, 2006; Volante et al., 2022
		School type	17 studies: Arenas & Gortazar, 2024; Caille, 2001; Cayouette-Remblière & Moulin, 2019; Davezies, 2005; Helbling et al., 2019; Herrmann et al., 2022; Hippe et al., 2018; Holtmann & Solga, 2023; Nagy et al., 2017; Olczyk et al., 2021; Oppedisano & Turati, 2015; Pfost et al., 2018; Schubert & Becker, 2010; Termes, 2022; Triventi et al., 2021; Virtanen et al., 2021; Papadopoulou, 2016
		School size	2 studies: Belfi et al., 2016; DeVries et al., 2020

		Class size	1 study: Di Tommaso et al., 2024
		Socioeconomic school composition	11 studies: Belfi et al., 2016; DeVries et al., 2020; Duru-Bellat & Mingat, 1997; European Commission, 2022c; Helbling et al., 2019; Kähler et al., 2023; Monso et al., 2019; Nagy et al., 2017; OECD, 2003; Verhaeghe et al., 2018; Volante et al., 2022
		School ethnic composition	2 studies: Belfi et al., 2016; Verhaeghe et al., 2018
		School climate/culture	8 studies: European Commission, 2022c; European Commission & PPMI, 2022; European Commission/EACEA/Eurydice, 2023; Grazia, 2022; OECD, 2003; Ribeiro et al., 2023; Salza, 2022; Schubert & Becker, 2010
	School- and/or system-level policies (C4.2)	Top-level policies/measures	1 study: European Commission/EACEA/Eurydice, 2023
		Public expenditure on education	4 studies: European Commission, 2022c; OECD, 2023a; Olczyk et al., 2021; Oppedisano & Turati, 2015
		Exposure to preschool education	2 studies: Herrera-Sosa et al., 2018b; Olczyk et al., 2021
		Tracking	16 studies: Barone et al., 2017; Caille, 2001; Contini et al., 2023; Contini & Cugnata, 2020; Contini & Salza, 2024; European Commission, 2022cc; Hippe et al., 2018; Lavrijsen & Nicaise, 2015; Paget et al., 2018; Pensiero et al., 2019; Pfof et al., 2018; Stéfanou, 2017; Straková et al., 2016; Strello et al., 2021; Triventi et al., 2021; Volante et al., 2022
		School resources	2 studies: Barbetta et al., 2023; Trebits et al., 2022
		School autonomy	2 studies: Arenas & Gortazar, 2024; European Commission, 2022c
		School-based management	1 study: Herrera-Sosa et al., 2018a
		School-level policies	4 studies: European Commission, 2022c; Ferraro & Pöder, 2018; Herrera-Sosa et al., 2018a; Oppedisano & Turati, 2015
		School expectations	2 studies: Derrington, 2007; OECD, 2003
		Multigrade classes	1 study: Barbetta et al., 2023
		Teaching time	4 studies: Di Tommaso et al., 2024; European Commission & PPMI, 2022; Hippe et al., 2018; Pfof et al., 2010
		Advanced course	1 study: Warwas et al., 2009

	Other variables (C4.3)	Impact of COVID-19 pandemic education	7 studies: Arenas & Gortazar, 2024; Borgonovi & Ferrara, 2022, 2023; Contini et al., 2023; De Faria et al., 2023; European Commission, 2022c; Salmela-Aro et al., 2021
		Poverty rate	3 studies: Daniele, 2021; European Commission, 2022c; OECD, 2003