

Article

How Rare and How Stable? Resilient and Vulnerable School Profiles in Hungary Before and After the COVID-19 Pandemic

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Abstract

Educational resilience commonly refers to better-than-expected academic outcomes among socioeconomically disadvantaged students or schools. However, little is known about its temporal stability, particularly in highly stratified and selective education systems such as Hungary's, especially following major disruptions like the COVID-19 pandemic. This study investigates the prevalence and stability of resilient and vulnerable elementary school profiles in Hungary using data from the National Assessment of Basic Competencies (NABC). School-level pedagogical value-added (PVA) indicators were estimated separately for mathematics and reading comprehension and aggregated across two three-year periods: the pre-pandemic period (2017–2019) and the post-pandemic recovery period (2023–2025). Schools were categorized into resilient and vulnerable groups based on the intersection of social disadvantage and performance. The profile analyses included 2048 schools; regression models included 192–201 cases depending on data completeness. Results show that resilient schools are rare and only partially stable, with fewer than one-quarter maintaining this status after the pandemic. Logistic regression analyses show that prior resilience, lower levels of disciplinary problems, and maintainer type were associated with a higher likelihood of post-pandemic resilience, while school size, regional location, disadvantage level, and teacher shortages lost explanatory power. Overall, the findings support a dynamic, context-dependent interpretation of school resilience.

Keywords: educational resilience; resilient schools; vulnerable schools; pedagogical value-added; school effectiveness; educational inequality; school climate; COVID-19 pandemic; Hungary



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1. Introduction

Educational inequality remains one of the most persistent challenges facing contemporary education systems. International research has consistently shown that students' socioeconomic background is strongly associated with academic achievement, educational trajectories, and later life chances (Bourdieu & Passeron, 1977; Coleman et al., 1966; OECD, 2018; Reardon, 2011). This relationship is not only a matter of individual family resources but also reflects how education systems structure access to learning opportunities, school quality, and peer environments. In systems characterized by strong social selectivity and segregation, disadvantaged students are more likely to attend schools with less favorable learning conditions, lower average achievement, and weaker compensatory capacity (OECD, 2012, 2016, 2023a, 2023c). The recent PISA 2022 results confirm that socioeconomic status remains a powerful predictor of student performance across OECD countries; in

Hungary, it accounted for 25% of the variation in mathematics performance, compared with the OECD average of 15% (OECD, 2023b).

In this context, the concept of educational resilience has become increasingly important in research on educational effectiveness and equity-oriented education policy. Educational resilience originally referred to disadvantaged students who achieve unexpectedly favorable academic outcomes despite adverse socioeconomic circumstances (OECD, 2011; M. C. Wang et al., 1994). More recent PISA-based research defines academically resilient students as those from disadvantaged backgrounds who perform at levels that enable them to participate successfully in further learning and social life (Agasisti et al., 2018). The concept is therefore closely connected to the broader question of how education systems and schools may mitigate the effects of social disadvantage rather than merely reproduce them.

Educational resilience has traditionally been conceptualized at the student level, referring to socioeconomically disadvantaged students who achieve better-than-expected academic outcomes despite adverse circumstances (Borman & Overman, 2004; OECD, 2011; M. C. Wang et al., 1994). More recent reviews have shown that resilience research has progressively expanded beyond individual students to include schools, teachers, and education systems, although the conceptualization and operationalization of resilience differ across these levels of analysis (Rudd et al., 2021; Borazon & Chuang, 2023). In this broader interpretation, resilient schools are institutions that serve socially disadvantaged student populations while producing comparatively favorable outcomes or higher-than-expected pedagogical value-added (PVA) indicators (Day & Gu, 2014; Lörz et al., 2024).

It is important, however, to distinguish conceptually between student-level and school-level resilience. Student-level resilience refers to individual students' favorable outcomes despite socioeconomic disadvantage, whereas school-level resilience refers to institutional performance profiles among schools serving disadvantaged populations. The latter does not imply that schools possess resilience as a fixed trait or that the same mechanisms operate at the student and institutional levels. Rather, it captures the extent to which schools produce higher-than-expected average outcomes after accounting for student intake and school composition. Accordingly, the present study treats school-level resilience as an analytical classification of institutional performance rather than as direct evidence of specific organizational processes. This interpretation is consistent with process-oriented and ecological approaches to resilience, which emphasize adaptation within changing organizational and social contexts rather than stable attributes (Day & Gu, 2014; Ungar, 2021).

The literature on school effectiveness has long emphasized that schools can make a difference, particularly through instructional quality, leadership, school climate, high expectations, orderly learning environments, and supportive organizational cultures (Creemers & Kyriakides, 2008; Edmonds, 1979; Sammons et al., 1995; Teddlie & Reynolds, 2000). These factors are especially relevant when examining schools serving disadvantaged populations, where institutional practices may either reinforce or partially compensate for unequal social conditions.

At the same time, school resilience should not be interpreted too quickly as a fixed or stable institutional trait. Educational outcomes are shaped by changing cohorts, local demographic processes, teacher turnover, organizational capacity, school climate, policy environments, and broader social disruptions (Creemers & Kyriakides, 2008; Fullan, 2016). As a result, yearly indicators of school effectiveness or pedagogical added value may fluctuate considerably. This is particularly important for resilience classifications because a school identified as resilient in one year may not necessarily exhibit the same profile in another year. A more cautious interpretation is therefore needed: resilience may be better understood as a period-specific institutional performance profile rather than a permanent school characteristic.

This issue became especially salient after the COVID-19 pandemic. PISA 2022 was the first large-scale international assessment to capture student performance, well-being, and equity after the pandemic disruption (OECD, 2023a, 2023c). Across OECD countries, average performance declined sharply in mathematics and reading compared with previous PISA cycles, and the pandemic placed substantial pressure on schools, families, and education systems (OECD, 2023a, 2023c). Empirical studies have documented learning losses associated with school closures, with disadvantaged students and low-SES schools often more strongly affected or less able to mitigate them (Engzell et al., 2021; Maldonado & De Witte, 2022; Vit, 2023). These findings suggest that post-pandemic school performance cannot be interpreted in isolation from disruption, recovery capacity, and pre-existing inequalities.

The Hungarian education system provides a particularly relevant case for examining resilient and vulnerable school profiles. Previous research has shown that family background, school composition, and ethnic segregation are strongly associated with educational outcomes in Hungary (Kertesi & Kézdi, 2011, 2013; Messing, 2017). Recent evidence further highlights the concentration of disadvantaged students in certain schools, the exceptionally high level of socio-economic segregation, and the particular exposure of disadvantaged schools to teacher shortages (European Commission, 2025; OECD, 2023b). Moreover, the institutional capacity of Hungarian education to adapt to future challenges and mitigate inequalities has been called into question in recent policy analyses (Radó, 2021). These characteristics make Hungary a relevant setting for studying whether some disadvantaged schools exhibit more favorable average performance profiles than others, and whether these profiles persist over longer educational periods.

The present study addresses this issue by adopting a multi-year comparative perspective based on the Hungarian National Assessment of Basic Competencies (NABC). Instead of treating school resilience as a stable institutional property, the study focuses on broader average performance profiles across two periods: the pre-pandemic period (2017–2019) and the post-pandemic recovery period (2023–2025). Schools were classified as resilient or vulnerable using three-year average pedagogical added value indicators and the proportion of disadvantaged students. This strategy aims to reduce the influence of short-term yearly fluctuations and to provide a more robust description of institutional performance profiles.

The study has four main objectives. First, it identifies resilient and vulnerable school profiles across the two periods using aggregated pedagogical added-value indicators. Second, it examines transition patterns between pre-pandemic and post-pandemic profiles. Third, it compares resilient and vulnerable schools across selected institutional characteristics, including school size, settlement type, disciplinary climate, and teacher shortage. Fourth, it investigates, using binary logistic regression, whether pre-pandemic school profiles and institutional characteristics predict the likelihood of belonging to the resilient school group in the post-pandemic period. By doing so, the study contributes to the literature on educational inequality, school effectiveness, and institutional resilience by proposing a temporally cautious interpretation of resilient school profiles in a highly stratified education system.

2. Materials and Methods

2.1. Data Source and Analytical Framework

The study is based on data from the NABC, a nationwide standardized assessment system administered annually in Hungary under the provisions of the Hungarian Public Education Act (Act CXC of 2011, Hungarian Parliament, 2011), which mandates regular national assessments of students' competencies and the public reporting of school-level results. The Act also permits the longitudinal linkage of assessment records through

permanent measurement identifiers while ensuring that personal identification data remain inaccessible for research purposes. The datasets used in the present study were fully de-identified and contained no personally identifiable information. All analyses were therefore conducted on anonymized student- and school-level data in compliance with national data-protection regulations.

The assessment evaluates students' competencies primarily in mathematics and reading comprehension and is linked to institutional and background information at both the student and school levels (Oktatási Hivatal, 2012). The analyses focused on school-level PVA indicators and institutional resilience profiles. The analytical unit of the study was the elementary school site.

The study adopted a comparative school-level design examining two broader educational periods: (1) the pre-pandemic period (2017–2019) and (2) the post-pandemic recovery period (2023–2025). The exclusion of the 2020 assessment cycle was necessary because the assessment was not administered due to the COVID-19 pandemic. The year 2021 was also excluded from the final aggregation procedure because it represented a transition period characterized by substantial disruption and atypical educational conditions. The 2022 cycle was not included in the post-pandemic aggregation because it was the first assessment year after the major disruption and still reflected immediate recovery conditions rather than a more consolidated post-pandemic period. The post-pandemic period was therefore defined as 2023–2025 to capture a more stable recovery phase and maintain symmetry with the three-year pre-pandemic aggregation.

The analytical strategy was motivated by two methodological considerations. First, preliminary analyses revealed relatively modest correlations between yearly PVA across assessment cycles, suggesting substantial temporal instability in yearly school-level effectiveness estimates. Second, previous research demonstrated that the COVID-19 pandemic substantially affected learning processes and educational inequalities, particularly among disadvantaged students and schools (Bacher-Hicks et al., 2021; Blaskó et al., 2022; Engzell et al., 2021; Haeck & Lefebvre, 2020; Lannert & Varga, 2022; Maldonado & De Witte, 2022; OECD, 2023a, 2023c). Under such conditions, single-year institutional classifications may reflect temporary cohort effects and disruption-related fluctuations rather than broader institutional tendencies.

Consequently, the study conceptualized school resilience not as a fixed institutional trait but as a broader multi-year institutional performance profile. Given that school value-added estimates may be sensitive to cohort variation, measurement error, and short-term fluctuations, institutional indicators were aggregated across three-year periods to provide more stable estimates of school-level performance (Leckie & Goldstein, 2019; OECD, 2008).

2.2. Data Preparation and Inclusion Criteria

Student-level databases were first merged across years and subsequently aggregated to the school level.

The initial database contained yearly student-level data between 2017 and 2025. The number of schools included in the raw yearly databases ranged from 2561 to 2644, while the number of students ranged from approximately 72,000 to 89,000, depending on the assessment year.

Several validity criteria were applied in order to ensure stable institutional estimates. Following data cleaning and validity filtering procedures, yearly PVA models were estimated on somewhat smaller analytical samples. Schools were retained only if:

- At least five students per school had valid mathematics and reading achievement scores in the given year and valid prior achievement scores measured two years earlier;

- At least 50% of the participating students in each school had valid mathematics and reading achievement scores in the given year and valid prior achievement scores measured two years earlier;
- Valid school-level disadvantage indicators were available.

Schools that did not meet these criteria were excluded from further analysis. As a result, yearly PVA estimation samples ranged between 2450 and 2501 schools.

Schools were retained in the final longitudinal dataset only if valid PVA estimates were available for all years included in the aggregation procedure in both examined periods. The final longitudinal aggregation dataset used for constructing post-pandemic three-year average institutional profiles included 2048 schools. These schools had valid PVA estimates in all three post-pandemic years (2023–2025) and met the longitudinal inclusion criteria for multi-year aggregation procedures.

Data preparation and school-level aggregation procedures were conducted using IBM SPSS Statistics, version 31 (IBM Corp., Armonk, NY, USA).

2.3. Estimation of PVA Indicators

School-level PVA indicators were estimated separately for mathematics and reading comprehension using multilevel random-intercept models. This modeling approach follows the standard value-added modeling framework, in which school effects are estimated while controlling for differences in prior achievement and student composition (Goldstein, 2011; Leckie & Goldstein, 2019; OECD, 2008).

Separate PVA models were estimated annually for both mathematics and reading comprehension. Student achievement was modeled as a function of prior achievement measured two years earlier, gender (boy/girl), special educational needs (SEN; yes/no), behavioral, learning, or adjustment difficulties (BLD; yes/no), individual multiply disadvantaged status (yes/no), and school-level disadvantage composition (%).

At the student level, disadvantage was operationalized using the Hungarian “multiply disadvantaged status” indicator. This administrative category is defined by the Hungarian Child Protection Act (Act XXXI of 1997, Hungarian Parliament, 1997) and captures students exposed to multiple forms of social disadvantage. Students are classified as multiply disadvantaged if at least two major dimensions of disadvantage are simultaneously present, including low parental educational attainment, low parental employment status, and inadequate housing conditions. In addition, children in state care and those receiving aftercare support are automatically classified into this category under Hungarian legislation.

At the school level, compositional disadvantage was measured as the proportion of multiply disadvantaged students enrolled in the school.

The inclusion of both individual-level and school-level disadvantage indicators reflects extensive evidence that school composition influences educational outcomes beyond individual student background characteristics (Sirin, 2005; Van Ewijk & Sleegers, 2010). Previous Hungarian studies have similarly highlighted the substantial role of school composition and segregation in shaping differences in institutional achievement (Kertesi & Kézdi, 2011; Messing, 2017).

Mathematics achievement models were specified as:

$$M_{ij} = \beta_0 + \beta_1 M_{prior_{ij}} + \beta_2 MDS_{ij} + \beta_3 MDS_{prop_j} + \beta_4 Gender_{ij} + \beta_5 SNI_{ij} + \beta_6 BTM_{ij} + u_j + e_{ij}$$

Reading comprehension models were specified analogously:

$$O_{ij} = \beta_0 + \beta_1 O_{prior_{ij}} + \beta_2 MDS_{ij} + \beta_3 MDS_{prop_j} + \beta_4 Gender_{ij} + \beta_5 SNI_{ij} + \beta_6 BTM_{ij} + u_j + e_{ij}$$

where:

- i denotes students;
- j denotes schools;
- M_{ij} and O_{ij} denote current mathematics and reading achievement scores;
- $M_{prior_{ij}}$ and $O_{prior_{ij}}$ denote prior achievement measured two years earlier;
- MDS_{ij} represents individual multiply disadvantaged status;
- MDS_{prop_j} represents school-level disadvantage composition;
- u_j denotes the school-level random intercept;
- e_{ij} represents the individual-level residual component.

School-level PVA indicators were extracted as empirical Bayes predictions (Best Linear Unbiased Predictors; BLUPs) of the school-level random intercepts. Because empirical Bayes predictions shrink school effects toward the overall mean, especially for schools with fewer students, this approach reduces the influence of unstable estimates from very small schools. At the same time, it may make extreme positive or negative PVA values less likely among small schools, which was considered when interpreting school profile classifications. Thus, the estimated PVA values reflected school-level deviations from expected achievement after controlling for students' prior achievement, individual background characteristics, and school composition. Positive PVA values indicated more favorable-than-expected institutional performance, whereas negative values reflected lower-than-expected achievement outcomes.

Subsequently, three-year average school-level PVA indicators were calculated separately for the pre-pandemic (2017–2019) and post-pandemic (2023–2025) periods.

2.4. Construction of Resilient and Vulnerable School Profiles

The operationalization of resilient and vulnerable school profiles was based on the intersection of school-level social disadvantage, PVA in mathematics, and PVA in reading comprehension.

Schools were first classified according to their level of social disadvantage using the institutional proportion of multiply disadvantaged students. Schools in the upper quartile of disadvantage were categorized as disadvantaged. Quartile-based classifications were subsequently created for the aggregated PVA indicators in mathematics and reading comprehension. This strategy follows the broader logic of educational resilience research, in which resilience is defined as the combination of relatively high social disadvantage and relatively high academic performance (Agasisti et al., 2018; Borman & Overman, 2004; OECD, 2011).

Schools were classified as resilient if they belonged to the most disadvantaged quartile and to the highest quartile of PVA in both competence domains. By contrast, schools were classified as vulnerable if they belonged to the most disadvantaged quartile and to the lowest quartile of PVA in both domains. The quartile-based classification was selected to identify schools with clearly distinguishable institutional performance profiles while retaining sufficient numbers of schools for subsequent comparative and regression analyses. This approach is consistent with PISA-based educational resilience research, which commonly uses relative distributional cut-offs to identify students who succeed academically despite adverse circumstances (Agasisti et al., 2018; OECD, 2011). At the same time, previous research has shown that academic resilience classifications may be sensitive to the choice of thresholds and operational definitions (Ye et al., 2021), which further supports the use of supplementary sensitivity analyses. Quartiles also provide a transparent and easily interpretable operationalization for distinguishing relatively high- and low-performing groups within the disadvantaged school population.

This dual-domain classification strategy was applied to reduce the likelihood of single-domain classification artifacts and to ensure that resilient schools demonstrated consistently favorable institutional performance profiles across both major competence areas. The classification procedure was implemented separately for the pre-pandemic and post-pandemic periods. The resulting distributions indicated relatively small but analytically meaningful groups of resilient and vulnerable schools. In the pre-pandemic period, 78 schools were classified as resilient and 115 as vulnerable. In the post-pandemic period, 79 schools were in the resilient category and 122 in the vulnerable category.

In addition to period-specific classifications, transition categories were created to examine changes in institutional profiles between the two periods. Schools were categorized by their combinations of pre- and post-pandemic status (e.g., resilient-to-resilient, vulnerable-to-vulnerable, resilient-to-vulnerable, and other transition patterns).

To assess the robustness of the quartile-based classification, supplementary sensitivity analyses were conducted using alternative classification thresholds. In addition to the main 25% cut-off, stricter 20% and more inclusive 33% cut-offs were applied to the disadvantage and PVA distributions. These analyses examined whether the main conclusions regarding the rarity and temporal stability of resilient and vulnerable school profiles depended on the specific classification threshold.

2.5. School Background Variables

Several school background variables were derived from the post-pandemic period (2023–2025). These indicators were selected to capture differences in student composition, organizational capacity, school climate, institutional selectivity, and structural characteristics of schools.

For continuous variables, annual school-level values were first extracted for 2023, 2024, and 2025. Schools had to be present in all three years of the post-pandemic period, but the aggregated value of a given continuous indicator was calculated from all available non-missing yearly observations. Thus, if a school had valid information for a given indicator in only one or two of the three years, the three-year period value was still calculated from the available data. For categorical variables, the most recent available non-missing value within the 2023–2025 period was retained.

The student composition index captured the socioeconomic composition of the school and was derived from the school-site questionnaire administered to school principals. The index incorporated information on the proportion of students living in above-average or very poor material circumstances, receiving regular child protection support, being classified as disadvantaged or at risk, receiving free or subsidized meals or textbooks, receiving social support, having unemployed parents, and having tertiary-educated parents. Following the methodology of the Hungarian NABC, the component variables were standardized and combined into a composite index (Oktatási Hivatal, 2012). Indicators reflecting favorable socioeconomic conditions were included in the index with positive signs, whereas indicators reflecting disadvantage were included with negative signs. For ease of interpretation in the regression analyses, the resulting index was multiplied by -1 , so that higher values indicated a more disadvantaged student composition. The resulting standardized measure may therefore assume both negative and positive values.

Teacher shortage was operationalized as a count index indicating the number of professional areas in which the school reported staffing shortages in the given school year. The index covered nine areas: primary teachers, foreign-language teachers, mathematics teachers, science teachers, information technology teachers, humanities teachers, arts, music, physical education or other skill-development teachers, special education teachers,

and other teachers. The indicator ranged from 0 to 9, with higher values indicating shortages across more teaching areas.

School disciplinary climate was measured using an eight-item index derived from principal questionnaire responses. The index captured how often different forms of student behavior caused problems at the school site, including regular absenteeism, classroom disruption, vandalism, physical aggression among students, verbal aggression or shouting, aggressive behavior toward school staff, and theft. The index also included a general item indicating the extent to which students were perceived as undisciplined. The index was computed as the mean of eight items measured on seven-point scales, resulting in values ranging from 1 to 7, with higher values indicating more frequent or more severe disciplinary problems.

Selection was operationalized as a binary indicator reflecting whether the school reported selecting applicants during general education admission. The variable was coded as 1 if the school reported selecting students on any basis and 0 otherwise.

School size was measured using the total number of students enrolled at the school site. Because the distribution of enrolment was positively skewed, the variable was entered into subsequent analyses in logarithmic form.

The level of urbanization was operationalized as a binary indicator distinguishing schools located in major urban centers (county seats or Budapest) from schools located in villages or other towns. The variable therefore served as a proxy for the level of urbanization of the school's local environment.

Regional location was represented by a binary indicator that distinguished schools located in less-developed and more-developed regions of Hungary. Less-developed regions included Northern Hungary, Northern Great Plain, Southern Transdanubia, and Southern Great Plain. This classification reflects broader territorial inequalities within the Hungarian education system, as all four regions were among the 20 least-developed NUTS-2 regions in the European Union in 2024 based on GDP per inhabitant in purchasing power standards (PPS), expressed as a percentage of the EU27 average (Eurostat, 2026). Thus, the term "less-developed regions" refers primarily to regional economic development measured at the NUTS-2 level, although such regional differences may also be associated with broader territorial inequalities, including rural settlement structure and access to services.

The maintainer type distinguished schools by their governance structure. The variable was coded as 1 for state-maintained schools and 0 for schools operated by non-state maintainers, including church and private providers.

2.6. Statistical Analyses

The empirical analyses were conducted in four main stages. First, descriptive analyses examined the distribution of resilient and vulnerable school profiles across the two examined periods. Second, transition analyses were conducted to identify changes in membership of institutional profiles between the pre-pandemic and post-pandemic periods. Third, resilient and vulnerable schools were compared across selected institutional characteristics. Fourth, binary logistic regression models were estimated to examine whether previous resilience status and selected institutional characteristics were associated with the likelihood of belonging to the resilient school group in the post-pandemic period.

The dependent variable in the logistic regression analyses was post-pandemic institutional status, coded as 1 for schools classified as resilient and 0 for schools classified as vulnerable. Consequently, the regression dataset included only schools classified as either resilient or vulnerable during the 2023–2025 period. The models, therefore, distinguish between two extreme institutional performance profiles rather than modeling variation across the full population of Hungarian elementary schools. Accordingly, the regression

results should be interpreted as factors associated with belonging to the resilient rather than the vulnerable group within this restricted analytical sample.

The main longitudinal predictor was pre-pandemic resilience status, indicating whether a school was already in the resilient category during the 2017–2019 period. The institutional background variables described in Section 2.5 were subsequently included as explanatory variables.

A sequence of nested binary logistic regression models was estimated. Predictors were entered sequentially in conceptually defined blocks to evaluate their incremental contribution to model performance. The first model included only the student composition index. The second model included only pre-pandemic resilience status. The third model combined student composition and previous resilience status. Subsequent models introduced organizational and contextual characteristics, including teacher shortage, discipline problems, selection practices, school size, urban location, regional location, and maintainer type. A final parsimonious model was then estimated using the subset of predictors that provided the most interpretable and statistically robust specification. The final parsimonious model was selected based on explanatory performance, theoretical interpretability, model stability, and the principle of parsimony rather than on automated variable-selection procedures.

Missing data were handled using model-specific listwise deletion. As a result, sample sizes varied slightly across models because observations with missing values on model-specific predictors were excluded from the corresponding model. The differences were small, with model-specific sample sizes ranging from 192 to 201 schools, and did not materially affect the composition of the analytical sample.

Model fit and predictive performance were evaluated using the Akaike Information Criterion (AIC), McFadden pseudo- R^2 , Nagelkerke pseudo- R^2 , and the area under the receiver operating characteristic curve (AUC). Because the models were not always estimated on identical observations, AIC values were used only as descriptive indicators of model fit and were not interpreted as formal evidence of model superiority across specifications with different sample sizes. To further assess the robustness of the final parsimonious logistic regression model, internal validation was performed using bootstrap resampling (1000 replications). Model discrimination was evaluated using the apparent and optimism-corrected AUC, while calibration was assessed using the Brier score and a bootstrap bias-corrected calibration curve.

Multicollinearity was assessed using variance inflation factors (VIFs). Potentially influential observations were identified using Cook's distance. Because several cut-off values have been proposed in the literature and no single universally accepted threshold exists, observations with Cook's distance exceeding the commonly used $4/n$ rule of thumb were flagged for diagnostic inspection to evaluate their influence on model estimates. These diagnostic procedures were used to evaluate model stability and the potential influence of extreme institutional cases.

Given the relatively small number of schools classified as resilient or vulnerable, the logistic regression results were interpreted cautiously. The full model was used primarily for exploratory purposes, while the final parsimonious model was preferred to reduce the risk of overfitting and improve interpretability. In the final parsimonious model, 79 schools were classified as resilient, and four predictors were retained, corresponding to approximately 19.8 events per variable. This provided a more stable basis for interpretation than the full exploratory model.

All statistical analyses and graphical visualizations were performed using R, version 4.6.0 (R Core Team, 2026).

3. Results

3.1. Distribution of PVA Indicators and School Profiles

The final longitudinal dataset included 2048 school sites with valid PVA estimates for both the pre-pandemic (2017–2019) and post-pandemic (2023–2025) periods. Descriptive statistics for the aggregated PVA indicators and the distribution of school profiles are presented in Table 1.

Table 1. Descriptive statistics of aggregated pedagogical value-added (PVA) indicators and school profile classifications.

Variable	Pre-Pandemic (2017–2019)	Post-Pandemic (2023–2025)
Aggregated mathematics PVA		
Mean	1.99	1.94
Median	4.02	5.58
Minimum	−160.55	−186.99
Maximum	160.86	170.17
Aggregated reading PVA		
Mean	0.79	1.39
Median	1.30	2.96
Minimum	−126.83	−156.74
Maximum	107.73	147.03
School profile classification, <i>n</i> (%)		
Resilient	78 (3.8)	79 (3.9)
Vulnerable	115 (5.6)	122 (6.0)
Other disadvantaged	319 (15.6)	311 (15.2)
Not disadvantaged	1536 (75.0)	1536 (75.0)
Total schools	2048	2048

Across both periods, three-year average PVA values were close to zero, reflecting the centering properties of the multilevel value-added models. Nevertheless, substantial between-school variation was observed. Aggregated mathematics PVA ranged from −160.55 to 160.86 in the pre-pandemic period and from −186.99 to 170.17 in the post-pandemic period. Similar dispersion was observed for reading PVA. These findings indicate marked heterogeneity in schools' estimated educational contribution after accounting for prior achievement, gender, special educational needs, behavioral or learning difficulties, individual disadvantage status, and school-level disadvantage composition.

The distribution of school profiles was largely similar across periods. Resilient schools accounted for 3.8% of schools in the pre-pandemic period and 3.9% in the post-pandemic period, while the proportion of vulnerable schools increased slightly from 5.6% to 6.0% (Table 1).

Correlations among annual PVA estimates were generally low to moderate (Appendix A Table A1), with most coefficients remaining below 0.30. The strongest associations were observed between consecutive post-pandemic years, suggesting that school-level PVA estimates contain substantial year-to-year variability. This pattern supports the use of aggregated three-year PVA indicators in subsequent analyses.

3.2. Comparison of Schools with and Without Valid PVA Estimates

To assess potential selection effects associated with the availability of PVA estimates, schools with valid PVA indicators were compared with schools for which PVA estimates could not be calculated due to incomplete assessment records.

A comparison of schools with and without valid PVA estimates is presented in Appendix A Table A2. Several statistically significant differences were observed between the two groups. Schools with valid PVA estimates achieved higher mathematics and reading achievement scores, enrolled fewer multiply disadvantaged students, and exhibited lower levels of overall disadvantage. In addition, they were substantially larger and more likely to be state-maintained institutions than schools without valid PVA estimates. By contrast, differences in teacher shortages, school selectivity, urban location, and regional development were small and statistically non-significant. Overall, schools with valid PVA estimates tended to be larger, higher-performing, and socioeconomically more advantaged than schools without valid PVA estimates.

3.3. Transitions Between Pre-Pandemic and Post-Pandemic School Profiles

Most schools classified as not disadvantaged during the pre-pandemic period remained in the same category during the post-pandemic period (94.9%). By contrast, schools in the other disadvantaged category displayed substantially greater mobility, with only 53.9% remaining in the same category across the two periods.

Among the 78 schools classified as resilient during the pre-pandemic period, 18 (23.1%) remained resilient in the post-pandemic period. Thirty-eight schools moved to the other disadvantaged category, 13 became non-disadvantaged, and 9 shifted to the vulnerable category.

Among the 115 schools classified as vulnerable before the pandemic, 41 (35.7%) remained vulnerable, while 12 became resilient, 46 moved to the other disadvantaged category, and 16 became non-disadvantaged.

Overall, the results indicate considerable movement between school categories across the two periods, with relatively few schools maintaining resilient or vulnerable status over time.

Transitions between school categories across the two periods are presented in Table 2.

Table 2. Transition matrix of school categories between the pre-pandemic (2017–2019) and post-pandemic (2023–2025) periods.

Pre-Pandemic Category	Post-Pandemic Category				Total
	Not Disadvantaged	Other Disadvantaged	Resilient	Vulnerable	
Not disadvantaged	1457 (94.9%)	55 (3.6%)	9 (0.6%)	15 (1.0%)	1536
Other disadvantaged	50 (15.7%)	172 (53.9%)	40 (12.5%)	57 (17.9%)	319
Resilient	13 (16.7%)	38 (48.7%)	18 (23.1%)	9 (11.5%)	78
Vulnerable	16 (13.9%)	46 (40.0%)	12 (10.4%)	41 (35.7%)	115
Total	1536	311	79	122	2048

Note. Percentages are row percentages and indicate the proportion of schools within each pre-pandemic category that transitioned to a given post-pandemic category.

Supplementary sensitivity analyses using alternative classification thresholds (20%, 25%, and 33%) yielded highly similar substantive conclusions. Although the number of resilient and vulnerable schools and the estimated stability rates varied moderately across thresholds, resilient school profiles remained relatively rare and only partially stable over time under all specifications. Across the alternative thresholds, the proportion

of resilient schools ranged from 2.4% to 6.2%, while the proportion of pre-pandemic resilient schools that remained resilient after the pandemic ranged from 17.9% to 26.1% (Appendix A Table A3). These findings indicate that the main conclusion regarding the rarity and limited temporal stability of resilient school profiles did not depend on the specific quartile-based cut-off.

3.4. Descriptive Comparison of Resilient and Vulnerable Schools

The logistic regression analyses focused on schools classified as either resilient ($n = 79$) or vulnerable ($n = 122$) during the post-pandemic period. Descriptive comparisons between the two groups, along with statistical significance tests and effect-size estimates for all comparisons, are presented in Table 3. In addition to mean achievement scores, Table 3 reports all variables subsequently included in the regression analyses.

Table 3. Descriptive comparison of resilient and vulnerable schools across variables included in the regression analyses.

Variable	Vulnerable Schools ($n = 122$)	Resilient Schools ($n = 79$)	p	Effect Size
Mean mathematics achievement score	1375	1535	<0.001	$d = 2.00$
Mean reading achievement score	1310	1459	<0.001	$d = 2.13$
Proportion of multiply disadvantaged students (%)	26.3	35.4	0.008	$d = 0.42$
Student composition disadvantage index	8.46	6.89	0.057	$d = 0.28$
Pre-pandemic resilient status (%)	7.4	22.8	0.004	$V = 0.21$
Teacher shortage index (0–9)	3.16	2.96	0.451	$d = 0.11$
Disciplinary problems index (1–7)	3.27	2.80	<0.001	$d = 0.54$
Selective admission practices (%)	19.7	16.7	0.728	$V = 0.02$
Average school size (students)	183	180	0.815	$d = 0.03$
Schools located in major urban centers (county seats or Budapest) (%)	9.0	1.3	0.050	$V = 0.14$
Schools in more developed regions (%)	10.7	12.7	0.835	$V = 0.01$
State-maintained schools (%)	92.6	78.5	0.007	$V = 0.19$

Note. Continuous variables were compared using Welch's t -tests, and categorical variables were compared using chi-square tests. Cohen's d is reported for continuous variables and Cramer's V for categorical variables.

Resilient schools achieved substantially higher mathematics and reading achievement scores than vulnerable schools. Although resilient schools enrolled a higher proportion of multiply disadvantaged students, they exhibited a lower student composition disadvantage index than vulnerable schools, suggesting that the two indicators capture partially overlapping but not identical dimensions of disadvantage. The multiply disadvantaged indicator is a legally defined, individual-level administrative category based on a limited set of severe-disadvantage criteria. By contrast, the student composition index is a broader school-level composite measure derived from principals' reports and includes multiple indicators of material conditions, social support, parental employment, and parental education. Thus, resilient schools may serve a higher proportion of students officially classified as multiply disadvantaged while still having a somewhat less unfavorable overall school composition profile.

Beyond differences in achievement and student composition, resilient schools were substantially more likely to have been classified as such before the pandemic and to have reported fewer disciplinary problems. Furthermore, resilient schools were less frequently located in county seats or Budapest and were less likely to be state-maintained institutions

than vulnerable schools. By contrast, teacher shortages, school selectivity, average school size, and regional location showed only minor differences between the two groups.

3.5. Predictors of Post-Pandemic Resilience

Binary logistic regression models were estimated to identify factors associated with belonging to the post-pandemic resilient rather than the vulnerable school group within the restricted sample of schools classified into these two extreme profiles. The dependent variable distinguished resilient schools (coded 1) from vulnerable schools (coded 0). Results are presented in Table 4, while complete model outputs are reported in Appendix A Table A4.

Table 4. Logistic regression models predicting post-pandemic resilient school status.

Predictor	M1	M2	M3	M4A	M4B	M5A	M5B
Student composition disadvantage index	0.95 ^	–	0.94 *	0.99	0.99	0.98	–
Pre-pandemic resilient status	–	3.70 **	4.25 **	3.88 **	3.91 **	4.08 **	3.48 **
Teacher shortage index	–	–	–	1.03	–	1.07	–
Disciplinary problems index	–	–	–	0.52 **	0.52 **	0.55 *	0.56 **
Selective admission practices	–	–	–	0.84	–	0.87	–
Log school size	–	–	–	–	–	0.98	–
Schools located in major urban centers (county seats or Budapest)	–	–	–	–	–	0.11 ^	0.13 ^
Schools in more developed regions	–	–	–	–	–	1.52	–
State-maintained schools	–	–	–	–	–	0.27 **	0.28 **
N	196	201	196	192	192	192	197
AIC	262.90	263.81	254.37	244.30	240.60	240.22	239.60
Nagelkerke R ²	0.026	0.063	0.095	0.158	0.156	0.231	0.210
AUC	0.580	0.577	0.634	0.706	0.704	0.742	0.740
Influential cases	3	9	11	6	9	7	11

Note. The dependent variable distinguished post-pandemic resilient schools (1) from post-pandemic vulnerable schools (0). Values are odds ratios (ORs). AIC = Akaike Information Criterion; AUC = area under the receiver operating characteristic curve. ^ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Model 1 included only the student composition disadvantage index. The coefficient was negative and approached statistical significance ($OR = 0.95$, $p = 0.056$). Model 2 examined pre-pandemic resilience status and indicated that schools previously classified as resilient were significantly more likely to belong to the resilient category in the post-pandemic period ($OR = 3.70$, $p = 0.003$). When both predictors were entered simultaneously (Model 3), pre-pandemic resilience ($OR = 4.25$, $p = 0.002$) and the disadvantage index remained significant ($OR = 0.94$, $p = 0.035$).

The introduction of organizational variables (Model 4A) indicated that disciplinary climate was the only organizational predictor significantly associated with resilience. Higher levels of disciplinary problems were consistently associated with a lower likelihood of belonging to the resilient rather than the vulnerable group within the analyzed sample ($OR = 0.52$, $p = 0.004$), whereas teacher shortages and school selectivity were not statistically significant predictors. Pre-pandemic resilience status remained significant. After removing the non-significant organizational variables in Model 4B, the negative association between disciplinary problems and resilience remained virtually unchanged ($OR = 0.52$, $p = 0.004$), indicating the robustness of this relationship.

The full model (Model 5A) additionally incorporated school size, urban location, regional location, and maintainer type. Pre-pandemic resilience status ($OR = 4.08$, $p = 0.004$) and disciplinary problems ($OR = 0.55$, $p = 0.011$) remained significant predictors. Maintainer type also became a significant predictor ($OR = 0.27$, $p = 0.010$), indicating that state-maintained

schools were significantly less likely to belong to the resilient group than non-state schools. Schools located in major urban centers (county seats or Budapest) showed a marginally significant negative association with resilience ($p = 0.064$). School size, regional location, teacher shortages, school selectivity, and the disadvantage index were not significant predictors.

The final parsimonious model (Model 5B) retained four predictors. Schools classified as resilient before the pandemic were approximately 3.5 times more likely to belong to the resilient group in the post-pandemic period ($OR = 3.48, p = 0.006$). Higher levels of disciplinary problems remained negatively associated with belonging to the resilient rather than the vulnerable group ($OR = 0.56, p = 0.004$), while state-maintained schools continued to show significantly lower odds of resilience than non-state schools ($OR = 0.28, p = 0.010$). Schools located in major urban centers remained marginally less likely to be classified as resilient ($p = 0.070$).

Model fit generally improved across the model sequence. Nagelkerke's pseudo- R^2 increased from 0.026 in Model 1 to 0.231 in the full specification (Model 5A), while the area under the receiver operating characteristic curve (AUC) increased from 0.580 to 0.742. Because the analytical sample differed slightly across models owing to complete-case estimation, AIC values should be interpreted descriptively rather than as strictly comparable evidence of model superiority. The reduced Model 5B achieved nearly identical predictive performance (Nagelkerke $R^2 = 0.210$; $AUC = 0.740$), indicating that a smaller set of predictors captured most of the explanatory power of the full model. Variance inflation factors remained below 1.5 in all models, suggesting no evidence of problematic multicollinearity.

Diagnostic analyses identified a limited number of observations with elevated Cook's distance across models (3–11 cases). Sensitivity checks excluding these observations showed that the direction of most main effects remained consistent, but some odds-ratio estimates, particularly for sparse categorical predictors, varied substantially in magnitude. Therefore, the regression results were interpreted cautiously, and the final parsimonious model was used primarily for substantive interpretation.

The final parsimonious model (Model 5B) achieved an AUC of 0.740, indicating moderate discriminatory capacity. The model distinguished resilient from vulnerable schools better than chance, but it is not suitable for high-stakes classification or prediction of individual schools. At the same time, the pseudo- R^2 values indicate that a substantial share of variation in post-pandemic resilience remained unexplained. These findings suggest that additional unmeasured factors, such as leadership practices, teacher collaboration, instructional quality, and school improvement strategies, may also contribute to post-pandemic resilience.

Model Validation

Bootstrap internal validation of the final parsimonious logistic regression model (Model 5B) further supported the robustness of the reported findings. The apparent AUC of 0.740 decreased only slightly to an optimism-corrected value of 0.728, indicating limited optimism in discrimination. The Brier score was 0.202. The bootstrap bias-corrected calibration curve indicated reasonable agreement between predicted and observed probabilities across the central range of predicted risks (Appendix A Figure A1), with a mean absolute calibration error of 0.048 and a 0.9 quantile of absolute error of 0.098.

4. Discussion

The present study examined resilient and vulnerable school profiles in Hungary using three-year average PVA indicators before and after the COVID-19 pandemic. The findings provide a nuanced perspective on school resilience in a highly selective education system and highlight the importance of distinguishing between the existence of resilient

schools and the sustainability of resilience over time. Four main findings emerge from the analyses. First, resilient and vulnerable school profiles represented only a small proportion of Hungarian schools. Second, resilient status proved considerably less stable than expected. Third, school climate-related factors, particularly disciplinary problems, emerged as the most consistent factor distinguishing resilient from vulnerable schools within the post-pandemic analytical sample. Fourth, several structural variables frequently emphasized in educational policy debates, including school-level disadvantage composition, teacher shortage, school size, and regional development, were no longer independently associated with resilient profile membership after adjustment for the other variables included in the regression models.

The first important finding is that resilient schools constituted only a small minority of Hungarian elementary schools in both examined periods. Although resilient schools were identifiable both before and after the pandemic, they represented less than 4% of all schools. This pattern is consistent with international research showing that schools capable of achieving unexpectedly positive outcomes under adverse social conditions exist, but are relatively uncommon (Agasisti et al., 2018; OECD, 2011). Recent evidence from Germany similarly found that resilient schools can be identified even among highly disadvantaged institutions, yet they represent only a limited segment of the educational system (Lörz et al., 2024). These findings support the view that resilience is an exceptional but observable institutional phenomenon rather than a widespread characteristic of disadvantaged schools.

Perhaps the most important contribution of the present study concerns the temporal stability of resilience. Although the overall proportion of resilient schools remained relatively stable between the two periods, only a minority of pre-pandemic resilient schools maintained their status after the pandemic. In contrast, vulnerable schools showed somewhat greater continuity. This finding suggests that resilience should not be interpreted as a fixed institutional characteristic. Instead, it appears to represent a dynamic, context-dependent institutional performance profile rather than a stable institutional characteristic. At the same time, transitions between pre- and post-pandemic profile classifications should not automatically be interpreted as evidence of genuine organizational change. Some profile transitions may also result from measurement error, cohort differences, regression to the mean, or movement around the selected classification thresholds. Consequently, the observed temporal instability should be interpreted as reflecting both possible substantive changes and the inherent uncertainty associated with profile classification.

This interpretation is consistent with contemporary resilience theory. Day and Gu (2014) argue that resilience in educational settings should be understood as an ongoing process of adaptation rather than a stable attribute. Similarly, Ungar (2021) conceptualizes resilience as a multisystemic phenomenon emerging from interactions among individuals, organizations, and broader social environments. Applying this perspective to schools implies that resilience is produced through continuous adaptation to changing contextual demands rather than by possessing a fixed set of characteristics. Silva and Silva (2022) reach a similar conclusion in their ecological interpretation of resilient schools, emphasizing that resilience is deeply embedded in local, organizational, and systemic contexts. The Hungarian results strongly support this perspective, as they demonstrate that resilience is only partly maintained even across relatively short time periods.

The limited stability of resilience also aligns with recent developments in school effectiveness and school improvement research. According to the dynamic approach developed by Kyriakides and colleagues, educational effectiveness should not be understood as a static outcome but as the result of continuous improvement processes operating at multiple levels of the education system (Creemers & Kyriakides, 2008; Kyriakides et al., 2024). Their recent longitudinal evidence demonstrates that the duration and sustainability of school

improvement efforts are critical determinants of student achievement gains. From this perspective, the finding that many previously resilient schools did not remain resilient is not necessarily evidence of failure. Rather, it highlights the difficulty of sustaining effective organizational processes amid changing conditions, particularly during and after an unprecedented disruption such as the COVID-19 pandemic.

A second major finding concerns the role of previous resilience status. Schools classified as resilient before the pandemic were substantially more likely to remain resilient afterward. This suggests that although resilience is not fully stable, the persistence of resilient status in a subset of schools is consistent with the possible presence of organizational capacities that may contribute to maintaining higher-than-expected school performance over time. However, these capacities were not measured directly in the present study and should therefore be examined explicitly in future research. Previous research has repeatedly emphasized the importance of organizational learning, professional collaboration, teacher leadership, leadership capacity, and collective efficacy in sustaining school improvement (Bryk et al., 2010; Hargreaves & Fullan, 2012; Leithwood et al., 2020; Muijs & Harris, 2006). Such organizational resources may provide one plausible explanation for why some schools are better able to respond to external challenges and recover from disruptions, but this interpretation remains theoretical because these processes were not directly observed in the present data. However, the relatively low proportion of schools maintaining resilient status also indicates that such capacities alone are insufficient to guarantee long-term resilience.

The strongest and most consistent predictor of resilience in the present study was disciplinary climate, operationalized as the frequency and severity of disciplinary problems. Within the analyzed sample of post-pandemic resilient and vulnerable schools, schools reporting more severe disciplinary problems were significantly less likely to belong to the resilient rather than the vulnerable group. Conversely, lower levels of disciplinary problems are consistent with a more orderly and supportive learning environment. This finding is highly consistent with several decades of school effectiveness research. Classic studies identified orderly and supportive learning environments as one of the defining characteristics of effective schools (Edmonds, 1979; Sammons et al., 1995), while more recent work has highlighted the central role of school climate in promoting academic achievement, engagement, and well-being (Thapa et al., 2013; M.-T. Wang & Degol, 2016). OECD analyses similarly show that positive disciplinary climate is associated with better student outcomes across diverse educational contexts (OECD, 2019).

The importance of disciplinary climate is particularly relevant in disadvantaged settings. Schools serving socially disadvantaged populations often face more complex behavioral, social, and instructional challenges. In such contexts, a supportive and orderly learning environment may serve as a protective organizational resource, enabling effective teaching and learning despite adverse circumstances. The present findings therefore suggest that resilience is not simply a function of who attends a school, but also of how the school organizes everyday educational processes.

The Hungarian results are also consistent with previous national research. Earlier studies identified several organizational characteristics—including school climate, disciplinary climate, pedagogical culture, organizational functioning, and internal coherence—as key factors distinguishing resilient and vulnerable schools (Széll, 2018). In the present study, however, only disciplinary climate was measured directly. The convergence of findings across different datasets, methodologies, and time periods strengthens confidence in the conclusion that organizational processes play a crucial role in shaping school resilience within the Hungarian educational context.

Another important finding is that the association between the student composition disadvantage index and resilience became non-significant after organizational variables

were introduced into the models. This result should not be interpreted as evidence that social disadvantage is unimportant. Equally, the loss of statistical significance after the inclusion of additional variables does not, by itself, demonstrate that organizational factors mediate or explain the association between disadvantage and resilience.

This finding contributes to ongoing debates regarding educational inequality and school effectiveness. Theories of social reproduction emphasize the powerful influence of family background and social structure on educational outcomes (Bourdieu & Passeron, 1977). Hungarian studies similarly document the strong relationship between socioeconomic disadvantage, school segregation, and educational achievement (Kertesi & Kézdi, 2011, 2013; Messing, 2017). The present results do not challenge these broader patterns. Instead, they suggest that within structurally constrained environments, measured differences in school disciplinary climate are associated with resilient profile membership. Future research should examine whether other institutional characteristics, such as leadership practices, teacher collaboration, instructional quality, and school improvement strategies, also contribute to resilient school profiles. In this regard, the findings align with the broader school effectiveness tradition, which argues that schools can make a meaningful difference even under challenging circumstances (Creemers & Kyriakides, 2008).

The findings of Lörz et al. (2024) provide further support for this interpretation. Their study demonstrated that differences between resilient and non-resilient schools cannot be fully explained by student composition alone and that organizational characteristics play a critical role in understanding resilience. The similarities between their findings and the present results suggest that this pattern may not be unique to Hungary but may represent a more general feature of resilient schools across educational systems.

The significant association between maintainer type and resilience also deserves careful consideration. Compared with state-maintained institutions, non-state schools were significantly more likely to belong to the resilient rather than the vulnerable group. This result should be interpreted cautiously, as the study was not designed to identify causal effects of governance arrangements. It should therefore not be interpreted as evidence that non-state governance produces better outcomes. The non-state category includes heterogeneous institutions that may differ in autonomy, resources, admissions practices, parental involvement, and organizational culture. In the Hungarian context, the post-2010 expansion of church-run schooling has been linked to new patterns of school choice, social selection, and the restructuring of segregated educational provision, suggesting that maintainer type may partly capture broader institutional and compositional differences rather than governance effects alone (Kertesi & Kézdi, 2013; Neumann, 2025). The models controlled for the student composition index and reported selective admission practices, but these variables cannot fully capture all forms of social selection, parental choice, or informal differences in school intake. Therefore, the maintainer-type effect should be interpreted as an association that may partly reflect unobserved compositional and organizational differences. At the same time, the finding points to the need for further research on how governance arrangements, school composition, institutional flexibility, and organizational culture are jointly related to resilience in centralized educational systems. Radó (2021) argues that organizational adaptability may become increasingly important in educational environments characterized by rapid social and policy changes. Future research should therefore explore the specific mechanisms through which these factors may shape resilient and vulnerable school profiles.

Several structural variables frequently highlighted in educational policy discussions did not remain significant in the final models. Teacher shortage, school size, selective admission practices, and regional development showed limited explanatory power once organizational factors were considered. The non-significant effect of teacher shortage

should not be interpreted as evidence that staffing conditions are unimportant. Rather, within the present post-pandemic resilient–vulnerable comparison, disciplinary climate and previous resilience status captured more of the explainable variation than teacher shortage. Staffing conditions may still shape resilience indirectly or under different model specifications. Future research should also examine whether staffing shortages influence resilience indirectly through school climate or interact with disciplinary problems, but the relatively small regression sample in the present study limited the reliable estimation of such interaction effects. Hanushek and Woessmann (2011) argue that educational outcomes depend less on the quantity of resources than on how effectively those resources are used. This interpretation is consistent with educational effectiveness research, which emphasizes that structural and system-level conditions influence student outcomes largely through school organization, classroom processes, and instructional quality (Creemers & Kyriakides, 2008; Mejía-Rodríguez & Kyriakides, 2022).

The post-pandemic context provides additional significance to these findings. International research has documented substantial learning losses and growing inequalities following COVID-19-related disruptions (Engzell et al., 2021; Maldonado & De Witte, 2022; OECD, 2023a, 2023c). Although the present study did not directly estimate pandemic learning losses, it offers insight into how resilient and vulnerable school profiles evolved across this period. The results suggest that resilience was neither completely stable nor entirely disrupted. Instead, post-pandemic resilience may reflect the combined influence of prior institutional performance, school climate, and possible organizational capacities that help schools maintain supportive learning environments during periods of uncertainty. Because these organizational mechanisms were not directly measured, this interpretation should be treated as a theoretically informed explanation rather than a causal finding.

Several limitations should be acknowledged. First, the analyses relied on administrative and assessment data and therefore could not directly examine leadership practices, teacher collaboration, instructional quality, parental engagement, or school improvement strategies. Second, although using three-year-average PVA indicators reduced annual fluctuations, value-added estimates remain sensitive to measurement error and cohort variation. A further limitation concerns selection into the final PVA sample. Schools with valid PVA estimates were larger, higher-performing, and socioeconomically more advantaged than schools without valid PVA estimates. This suggests that the most disadvantaged and smallest schools may be underrepresented in the profile analyses. Consequently, the reported proportions of resilient and vulnerable schools should not be interpreted as population estimates for all Hungarian elementary schools. The selection process may have led to a conservative picture of vulnerability and may have excluded some schools facing the most severe structural constraints. Third, the logistic regression analyses compared only schools classified as resilient or vulnerable in the post-pandemic period. Therefore, the results identify factors distinguishing these two extreme profiles and should not be directly generalized to all Hungarian elementary schools or to schools with intermediate disadvantage–performance profiles. In addition, the models were estimated on a relatively small subset of schools, which may limit the stability of partial odds-ratio estimates, particularly in the full model with several predictors. Finally, the observational design does not allow causal interpretations.

5. Conclusions

This study contributes to the literature in several ways. First, it applies a multi-year value-added approach to identify resilient and vulnerable schools in a highly stratified and selective educational system. Second, it demonstrates that resilience is relatively rare and only partially stable over time. Third, it highlights the central role of school disciplinary

climate while showing that structural disadvantage alone does not fully explain differences among disadvantaged schools. Most importantly, the findings support a dynamic interpretation of school resilience as a period-specific and context-dependent institutional performance profile rather than as direct evidence of an underlying organizational process or a fixed institutional characteristic.

Overall, the results suggest that disadvantaged schools are not inevitably vulnerable, but neither is resilience easily sustained. The maintenance of resilient school profiles appears to be associated with prior institutional performance and school disciplinary climate. Other organizational characteristics not measured in this study should be examined directly in future research. While social disadvantage remains an important constraint, the findings suggest that differences in school disciplinary climate may help explain why some disadvantaged schools are more likely than others to exhibit resilient institutional performance profiles.

From a policy perspective, efforts to reduce educational inequalities should focus not only on compensating for socioeconomic disadvantage but also on better understanding and supporting the organizational conditions associated with effective schooling in disadvantaged contexts. However, the findings of the present study should not be interpreted as causal evidence about which specific interventions would directly produce resilient school profiles. Supporting a positive school climate, reducing disciplinary problems, and fostering sustainable school improvement processes may therefore represent promising areas for further policy attention and empirical investigation.

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Institutional Review Board Statement: Ethical review and approval were waived for this study because it relied exclusively on anonymized secondary data from the Hungarian National Assessment of Basic Competencies (NABC). The datasets used for analysis contained no personally identifiable information and were made available for research purposes in a fully de-identified form, in accordance with the Hungarian Public Education Act (Act CXC of 2011) and applicable national data protection regulations. No direct contact with participants occurred, and no intervention involving human subjects was conducted.

Data Availability Statement: The data used in this study were obtained from the Hungarian Educational Authority under an institutional data-sharing agreement and are not publicly available. Access to the data is subject to the approval procedures and regulations of the Hungarian Educational Authority. Researchers seeking access to the data should contact the Authority directly. The analytical code used for data preparation and model estimation is available from the author upon reasonable request.

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Abbreviations

The following abbreviations are used in this manuscript:

NABC	National Assessment of Basic Competencies
PVA	Pedagogical value-added

Appendix A

Table A1. Correlations among annual pedagogical value-added (PVA) estimates (2017–2025).

Year	2017	2018	2019	2021	2023	2024	2025
Mathematics PVA							
2017	1.000						
2018	0.189	1.000					
2019	0.007	0.241	1.000				
2021	0.148	0.145	0.017	1.000			
2023	0.084	0.122	0.140	0.083	1.000		
2024	0.061	0.102	0.133	0.092	0.303	1.000	
2025	0.082	0.083	0.094	0.120	0.104	0.269	1.000
Reading PVA							
2017	1.000						
2018	0.199	1.000					
2019	0.042	0.201	1.000				
2021	0.158	0.146	0.109	1.000			
2023	0.041	0.087	0.126	0.079	1.000		
2024	0.041	0.081	0.073	0.072	0.257	1.000	
2025	0.030	0.100	0.077	0.106	0.096	0.224	1.000

Note. Pearson correlation coefficients among annual school-level PVA estimates based on multilevel random-intercept models. Correlations were generally low to moderate across years in both competence domains, with the strongest associations observed between adjacent post-pandemic years (2023–2024 and 2024–2025). These findings support the use of three-year aggregated PVA indicators to reduce measurement error and year-specific fluctuations in school classifications.

Table A2. Characteristics of schools with and without valid PVA estimates.

Variable	No Valid PVA Estimates (<i>n</i> = 644)	Valid PVA Estimates (<i>n</i> = 2048)	<i>p</i>	Effect Size
Mean mathematics achievement score	1489	1540	<0.001	<i>d</i> = 0.50
Mean reading achievement score	1423	1466	<0.001	<i>d</i> = 0.44
Proportion of multiply disadvantaged students (%)	11.8	8.1	<0.001	<i>d</i> = 0.22
Student composition disadvantage index	2.17	0.68	<0.001	<i>d</i> = 0.26
Teacher shortage index (0–9)	2.43	2.44	0.875	<i>d</i> = 0.01
Disciplinary problems index (1–7)	2.58	2.45	0.011	<i>d</i> = 0.17
Selective admission practices (%)	40.9	40.6	0.903	<i>V</i> = 0.00
Average school size (students)	154	270	<0.001	<i>d</i> = 0.75
Schools located in major urban centers (county seats or Budapest) (%)	28.1	25.0	0.128	<i>V</i> = 0.03
Schools in more developed regions (%)	43.2	45.9	0.234	<i>V</i> = 0.02
State-maintained schools (%)	59.2	81.9	<0.001	<i>V</i> = 0.23

Note. Continuous variables were compared using Welch’s *t*-tests, and categorical variables were compared using chi-square tests. Cohen’s *d* is reported for continuous variables and Cramer’s *V* for categorical variables.

Table A3. Sensitivity analysis of resilient and vulnerable school classifications using alternative thresholds.

Threshold	Resilient Pre, <i>n</i> (%)	Resilient Post, <i>n</i> (%)	Stable Resilient, <i>n</i> (% of Pre-Pandemic Resilient)	Vulnerable Pre, <i>n</i> (%)	Vulnerable Post, <i>n</i> (%)	Stable Vulnerable, <i>n</i> (% of Pre-Pandemic Vulnerable)
20%	56 (2.7%)	50 (2.4%)	10 (17.9%)	68 (3.3%)	73 (3.6%)	17 (25.0%)
25%	78 (3.8%)	79 (3.9%)	18 (23.1%)	115 (5.6%)	122 (6.0%)	41 (35.7%)
33%	115 (5.6%)	126 (6.2%)	30 (26.1%)	200 (9.8%)	203 (9.9%)	71 (35.5%)

Note. The 25% threshold corresponds to the main quartile-based classification used in the primary analyses. Stable resilient and stable vulnerable categories indicate the number and percentage of pre-pandemic resilient or vulnerable schools that retained the same status in the post-pandemic period.

Table A4. Full logistic regression results predicting post-pandemic resilient school status.

Model	Predictor	B	SE	OR [95% CI]	p
M1	Intercept	−0.042	0.250	0.96 [0.59, 1.56]	0.866
M1	Student composition disadvantage index	−0.051	0.027	0.95 [0.90, 1.00]	0.056
M2	Intercept	−0.617	0.159	0.54 [0.40, 0.74]	<0.001
M2	Pre-pandemic resilient status	1.310	0.438	3.70 [1.57, 8.74]	0.003
M3	Intercept	−0.178	0.257	0.84 [0.51, 1.38]	0.488
M3	Student composition disadvantage index	−0.059	0.028	0.94 [0.89, 1.00]	0.035
M3	Pre-pandemic resilient status	1.447	0.465	4.25 [1.71, 10.58]	0.002
M4A	Intercept	1.361	0.632	3.90 [1.13, 13.46]	0.031
M4A	Student composition disadvantage index	−0.011	0.033	0.99 [0.93, 1.06]	0.730
M4A	Pre-pandemic resilient status	1.356	0.472	3.88 [1.54, 9.78]	0.004
M4A	Teacher shortage index	0.031	0.088	1.03 [0.87, 1.23]	0.726
M4A	Disciplinary problems index	−0.657	0.227	0.52 [0.33, 0.81]	0.004
M4A	Selective admission practices	−0.169	0.419	0.84 [0.37, 1.92]	0.686
M4B	Intercept	1.369	0.613	3.93 [1.18, 13.06]	0.025
M4B	Student composition disadvantage index	−0.008	0.032	0.99 [0.93, 1.06]	0.800
M4B	Pre-pandemic resilient status	1.363	0.472	3.91 [1.55, 9.85]	0.004
M4B	Disciplinary problems index	−0.647	0.223	0.52 [0.34, 0.81]	0.004
M5A	Intercept	2.372	1.984	10.72 [0.22, 523.41]	0.232
M5A	Student composition disadvantage index	−0.019	0.036	0.98 [0.91, 1.05]	0.599
M5A	Pre-pandemic resilient status	1.407	0.488	4.08 [1.57, 10.63]	0.004
M5A	Teacher shortage index	0.064	0.092	1.07 [0.89, 1.28]	0.484
M5A	Disciplinary problems index	−0.591	0.231	0.55 [0.35, 0.87]	0.011
M5A	Selective admission practices	−0.137	0.467	0.87 [0.35, 2.18]	0.769
M5A	Log school size	−0.019	0.361	0.98 [0.48, 1.99]	0.958
M5A	Schools located in major urban centers (county seats or Budapest)	−2.188	1.180	0.11 [0.01, 1.13]	0.064
M5A	Schools in more developed regions	0.418	0.554	1.52 [0.51, 4.50]	0.450
M5A	State-maintained schools	−1.302	0.504	0.27 [0.10, 0.73]	0.010
M5B	Intercept	2.276	0.739	9.74 [2.29, 41.45]	0.002
M5B	Pre-pandemic resilient status	1.248	0.458	3.48 [1.42, 8.55]	0.006
M5B	Disciplinary problems index	−0.577	0.199	0.56 [0.38, 0.83]	0.004
M5B	Schools located in major urban centers (county seats or Budapest)	−2.004	1.108	0.13 [0.02, 1.18]	0.070
M5B	State-maintained schools	−1.264	0.489	0.28 [0.11, 0.74]	0.010

Note. The dependent variable distinguished post-pandemic resilient schools (1) from post-pandemic vulnerable schools (0). B = unstandardized logistic regression coefficient; SE = standard error; OR = odds ratio; CI = confidence interval; p = probability value.

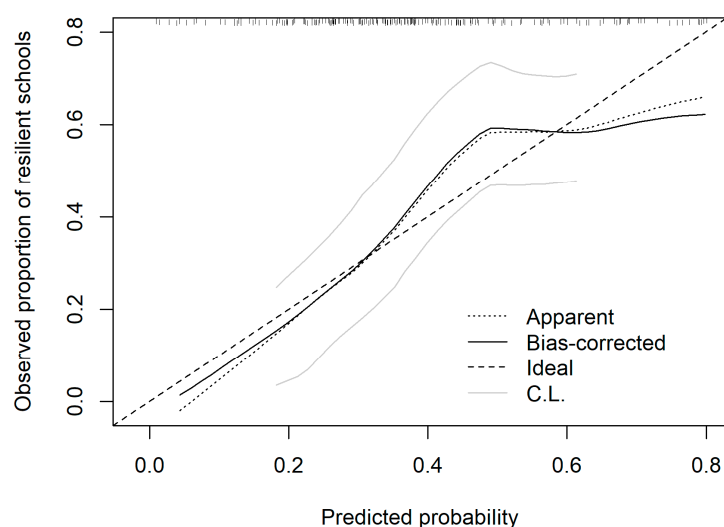


Figure A1. Bootstrap bias-corrected calibration curve for the final parsimonious logistic regression model. Note. Internal validation was performed using 1000 bootstrap resamples. The dashed diagonal

line represents perfect calibration, whereas the calibration curve shows the agreement between predicted and observed probabilities after optimism correction. Rug marks on the x-axis indicate the distribution of predicted probabilities.

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