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Digital Environment, Disciplinary Climate, and Educational Inequality in Brazilian Schools: A Critical Evidence Synthesis and a Proposed Analytical Framework

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Abstract. The post-pandemic Brazilian school combines two apparently opposite technological problems: the exclusion that amplified learning losses while schools were closed, and the weakly regulated presence of personal devices that has since been associated with distraction and a less favourable disciplinary climate. This paper presents a critical synthesis of the evidence connecting the school digital environment, disciplinary climate, psychosocial safety and socioeconomic inequality in Brazil, drawing on official indicators from the 2018 and 2022 cycles of the Programme for International Student Assessment, on the 2024 National Survey of School Health, and on peer-reviewed studies. The paper does not estimate new psychometric models, and it states that scope explicitly: it is a structured review whose original contribution is an analytical instrument derived from the reviewed evidence. We propose the Digital Environment and Equity Profile, a four-layer framework that separates access, classroom attentional conditions, psychosocial safety and equity outcomes; maps each layer onto variables already available in official Brazilian and international databases; specifies an estimation protocol consistent with plausible values, replication weights and school-level socioeconomic composition; and defines screening rules that translate estimates into prioritisation decisions. We also document a measurement constraint that is frequently overlooked: in the 2022 cycle, the digital-distraction items belong to the same item set used to build the disciplinary climate index, which restricts how the two constructs may enter a single model. The framework is offered as a testable proposal, and its empirical validation is left to future work.

Keywords: School Digital Environment; Disciplinary Climate; Educational Inequality; Large-Scale Assessment; Analytical Framework.

1. Introduction

The closure of schools during the COVID-19 pandemic produced the largest simultaneous interruption of formal instruction on record, and its effects on learning have since been documented across a wide range of countries and assessment instruments (Engzell et al., 2021; Schady et al., 2023). In Brazil, as elsewhere, the emergency shift to remote instruction did not equalise access to knowledge. It reproduced, and in several dimensions widened, socioeconomic gaps that were already present before 2020 (Lichand et al., 2022).

A second problem became visible only after schools reopened. Until the middle of the previous decade, educational technology policy in Brazil was largely organised around provision: devices, connectivity and digital resources were treated as inputs whose expansion would, in itself, raise proficiency (Queiroga et al., 2024). The post-pandemic evidence complicates that assumption. Where personal devices are present but weakly regulated, students report higher levels of classroom distraction, and those reports are associated with lower measured performance (OECD, 2023c). The policy problem therefore shifted from whether students can connect to whether schools can govern attention, instructional time and the pedagogical use of devices that are now ubiquitous.

These two problems are frequently discussed as if they were opposites, and the pairing is sometimes described as a technological paradox. The framing is useful only if it is read institutionally rather than chronologically. During closures, the binding constraint was unequal access to devices, connectivity, quiet study space and adult mediation (Engzell et al., 2021; Lichand et al., 2022; Schady et al., 2023). After reopening, the binding constraint became the institutional capacity to set and enforce rules of use. The relevant question is not whether technology is beneficial or harmful in the abstract, but under which organisational conditions it is incorporated into teaching, supervision and school climate (OECD, 2023c; Xavier, 2024).

A third element must be added, because in the Brazilian case the deterioration of the school environment is not reducible to device use. National health survey data indicate substantial levels of peer victimisation, physical aggression and absence motivated by insecurity, together with indicators of compromised adolescent mental health (Instituto Brasileiro de Geografia e Estatistica [IBGE], 2026). Instruments developed to measure school climate treat safety, belonging and the quality of interpersonal relations as constitutive dimensions of the educational environment rather than as peripheral concerns (Moro et al., 2019). Any account of the post-pandemic school that considers only screens will therefore be incomplete.

The three elements interact, but they are analytically distinct, and treating them as a single undifferentiated problem has a concrete methodological cost. Large-scale assessment data can be used to describe associations between the digital environment, climate and achievement; they cannot, without careful modelling, distinguish what a school adds from what it inherits through the socioeconomic composition of its intake (Alves & Soares, 2007; Duarte, 2023). That distinction requires an explicit treatment of latent proficiency, complex sampling and multilevel structure (Huang, 2024; Karakolidis et al., 2022; Mang et al., 2021).

The remainder of the paper is organised as follows. Section 2 states the scope of the study and the review procedure. Sections 3 and 4 synthesise the evidence on learning loss, cumulative advantage, device-related distraction and school safety in Brazil. Section 5 sets out the methodological requirements for working with the official indicators, including a measurement constraint specific to the 2022 cycle that has received little attention. Section 6 presents the proposed framework, its indicator crosswalk, its estimation protocol and its screening rules. Section 7 discusses sector comparisons, data governance and limitations, and Section 8 concludes.

2. Scope, Contribution and Review Procedure

This section makes explicit what the paper does and does not do. The clarification is deliberate: work of this kind is sometimes presented in terms that suggest primary estimation, and the resulting mismatch between framing and content weakens both the argument and its reception.

2.1. What This Paper Does and Does Not Do

This paper is a structured critical review with a design contribution. It synthesises published evidence and official indicators, and it derives from that synthesis an analytical framework intended for subsequent empirical use. It does not fit item response models, does not re-estimate proficiency scales, and does not report new coefficients from the microdata of the 2018 or 2022 assessment cycles. All quantities reported in Sections 3 and 4 are taken from the cited sources and are attributed to them.

The methodological material in Section 5 is therefore not a report of analyses performed here. It is a specification: it states the requirements that any empirical application of the proposed framework must satisfy, and it identifies the errors that would compromise such an application. Presenting those requirements without executing them is a legitimate contribution only if the distinction is stated plainly, which is the purpose of this subsection.

The original contribution of the paper is the Digital Environment and Equity Profile presented in Section 6: a four-layer analytical framework, an indicator crosswalk over data sources that already exist, an estimation protocol, and a set of screening rules that convert estimates into prioritisation decisions. The framework is a proposal. It has not been validated, and Section 7.3 states what would be required to validate it.

2.2. Review Procedure

The evidence base was assembled in three strands. The first comprises official statistical products: the reports and technical documentation of the 2018 and 2022 assessment cycles (National Center for Education Statistics [NCES], 2021; OECD, 2023a, 2023b, 2023c, 2024) and the 2024 National Survey of School Health (IBGE, 2026). These were used for descriptive indicators and for the definition of derived indices.

The second strand comprises methodological literature on the analysis of large-scale assessment data, selected for its direct treatment of plausible values, replication weights and multilevel structure (Huang, 2024; Karakolidis et al., 2022; Mang et al., 2021). The third comprises substantive studies on Brazilian education addressing learning loss, school effects, socioeconomic composition, school climate and educational data infrastructure (Alves & Soares, 2007; Bozza & Vinha, 2023; Cito & Marôco, 2025; Dias et al., 2023; Duarte, 2023; Franklin et al., 2024; Lichand et al., 2022; Moro et al., 2019; Queiroga et al., 2024; Xavier, 2024).

Inclusion was restricted to peer-reviewed publications, official statistical reports and documented technical materials. Where a quantity is reported, the source and the reference population are stated, because several figures that circulate in the public debate as national statistics are in fact averages across participating countries. Section 4.1 corrects one such attribution.

3. Learning Loss and Cumulative Advantage

Interpreting the current configuration of educational inequality in Brazil requires an account of the magnitude and the distribution of the losses generated during the health crisis. The two are distinct questions, and the second is the more consequential for equity policy.

3.1. Magnitude and Distribution of Learning Loss

Loss during the pandemic was not limited to the suspension of new learning. Comparative evidence indicates active regression, that is, the erosion of previously consolidated knowledge: for every thirty consecutive days of closure, students lost on average the equivalent of thirty-two days of learning (Schady et al., 2023). Brazilian evidence from secondary education is consistent with this pattern and documents substantial losses under remote instruction (Lichand et al., 2022).

At global scale, roughly one billion children were deprived of approximately one and a half years of instruction, and the cognitive deficits observed in early childhood are projected to translate into reductions of up to twenty-five per cent in adult earnings for the affected cohorts, with an aggregate estimated liability in the order of twenty-one trillion United States dollars over their working lives (Schady et al., 2023). These projections rest on assumptions about recovery that are themselves uncertain, and they should be read as orders of magnitude rather than as point predictions.

The distributive dimension is more relevant to the argument developed here. The literature does not describe a uniform interruption but a stratified shock whose intensity depended on household resources, prior achievement, connectivity and the institutional capacity of school systems to maintain contact with students (Engzell et al., 2021; Schady et al., 2023). In Brazil, losses were concentrated among students with weaker conditions for sustained study at home (Lichand et al., 2022). The damage was therefore simultaneously quantitative, in the form of reduced learning time, and distributive, in the form of more unequal learning conditions. Table 1 summarises the principal reported quantities and their sources.

Table 1. Reported Magnitudes of Pandemic Learning Loss and Their Sources

Indicator	Reported magnitude	Reference population and source
Instructional time lost	About 1.5 years for approximately 1 billion children	Global estimate (Schady et al., 2023)
Rate of cognitive attrition	32 days of learning lost per 30 days of closure	Global estimate (Schady et al., 2023)
Projected earnings reduction	Up to 25% for cohorts affected in early childhood	Low- and middle-income countries (Schady et al., 2023)
Aggregate lifetime earnings loss	Order of US$21 trillion	Global estimate (Schady et al., 2023)
Loss under remote instruction	Substantial losses and widening of pre-existing gaps	Brazilian secondary education (Lichand et al., 2022)

3.2. From Cumulative Advantage to Digital Capital

The mechanism underlying this stratification is not new. It corresponds to the pattern of cumulative advantage described by Merton (1968), in which initial differences operate as amplifiers of subsequent opportunity. What the pandemic altered was the medium through which the mechanism operated. Students who already had more books, more adult mediation, more stable routines and better access to devices and connectivity were also better positioned to convert emergency remote schooling into usable learning (Lichand et al., 2022; Schady et al., 2023).

Describing this as digital capital does not introduce a sociology unrelated to prior inequality; it names the technological re-expression of an older mechanism. Students at the unfavourable end of these gradients faced a compound penalty: weaker access during closure and weaker conditions for recovery after reopening. The relevant risk is therefore not a temporary discrepancy in scores but divergence in academic trajectories over a longer cycle (Engzell et al., 2021; Merton, 1968).

4. Device-Related Distraction, Disciplinary Climate and School Safety

Average results for Brazil in the 2022 cycle were statistically stable relative to 2018, at 379 points in mathematics, 410 in reading and 403 in science, at a time when many member countries of the Organisation for Economic Co-operation and

Development recorded declines of approximately fifteen points in mathematics and ten points in reading (OECD, 2023b). Stability at a low baseline, however, is not equivalent to resilience. A system may remain stable because it protected learning, or because the pre-existing bottlenecks were already severe enough to dominate the variation. In the Brazilian case, students remain concentrated in low proficiency bands, and the analytically relevant question concerns the quality of the baseline rather than change over time alone (OECD, 2023b).

4.1. Distraction as a Classroom-Level Externality

In the 2022 cycle, 45% of students in Brazil reported being distracted by their own use of digital devices in most or all mathematics lessons, against an average of 30% across member countries, and 40% reported being distracted by other students using such devices, against an average of 25% (OECD, 2023a). The same source records that 32% of students in Brazil reported not being able to work well in most or all lessons, against 23% on average, and 38% reported that students do not listen to the teacher, against 30% on average.

Two features of these figures deserve emphasis. The first is that distraction caused by peers operates as a classroom-level externality rather than as an individual habit. A student may intend to concentrate and nonetheless bear the cost of an environment saturated by competing stimuli and intermittent interruptions. Across member countries, students reporting frequent distraction scored approximately fifteen points lower in mathematics than students reporting that it never or almost never occurs (OECD, 2023c). Because the cost is collective, it cannot be addressed through recommendations about individual self-control alone; it requires school-level rules, teacher backing and predictable routines governing when and how devices may enter instructional activity (OECD, 2023c; Xavier, 2024).

The second concerns attribution, and here a correction is warranted. The frequently cited figure according to which 45% of adolescents report anxiety when separated from their smartphones is an average across member countries, not a Brazilian statistic (OECD, 2023c). Reporting it as national is a measurement error with rhetorical consequences, and it illustrates a broader problem addressed in Section 5: indicators produced under a complex sampling design are routinely detached from their reference population when they circulate outside their technical documentation.

4.2. Violence, Safety and Adolescent Well-Being

The Brazilian school environment presents difficulties that are not reducible to device use. The 2024 edition of the National Survey of School Health reports that 27.2% of students aged 13 to 17 experienced bullying on two or more occasions in the thirty days preceding the survey, and that 17.0% reported having been physically assaulted by classmates (IBGE, 2026). The same survey records that 12.5% missed school because of insecurity on the route between home and school and 13.7% because they did not feel safe at school itself, alongside substantial proportions reporting persistent sadness and frequent irritability.

These indicators bear directly on educational effectiveness. School climate is not an ornamental variable appended to instruction; safety, belonging, respect and the quality of interactions are constitutive dimensions of the educational environment (Moro et al., 2019). Where fear, humiliation or recurrent victimisation become normalised, attendance, concentration and participation are predictably undermined (Bozza & Vinha, 2023; Dias et al., 2023; IBGE, 2026). The climate agenda is therefore not a soft alternative to academic rigour; in contexts of high insecurity it is a precondition for ordinary pedagogical functioning.

The burden is also unevenly distributed. Schools serving more vulnerable populations tend to face a heavier accumulation of social pressures, which makes institutional protection more rather than less central for them (IBGE, 2026; Xavier, 2024). Table 2 assembles the indicators discussed in this section with their respective sources and reference populations.

Table 2. Digital Distraction, Climate and Safety Indicators for Brazil, with Reference Populations

Indicator	Value reported for Brazil	Comparator and source
Distraction by own devices	45% of students	30% across member countries (OECD, 2023a)
Distraction by peers' devices	40% of students	25% across member countries (OECD, 2023a)
Students cannot work well	32% of students	23% across member countries (OECD, 2023a)
Students do not listen to the teacher	38% of students	30% across member countries (OECD, 2023a)
Bullying, two or more episodes in 30 days	27.2% of students aged 13–17	National survey (IBGE, 2026)
Physical assault by classmates	17.0% of students aged 13–17	National survey (IBGE, 2026)
Absence due to insecurity on the route	12.5% of students	National survey (IBGE, 2026)
Absence due to insecurity at school	13.7% of students	National survey (IBGE, 2026)

5. Methodological Requirements for Working with the Official Indicators

The indicators discussed above are produced under a complex sampling design and a latent measurement model. Any empirical application of the framework proposed in Section 6 must respect four requirements and one measurement constraint. This section states them; it does not apply them, for the reasons given in Section 2.1.

5.1. Latent Proficiency and Plausible Values

Students do not respond to all items in the assessment. Proficiency is not observed; it is generated as a conditional posterior distribution through item response modelling, and it is distributed in the public databases as ten plausible values per student per domain (NCES, 2021; OECD, 2024). Plausible values are not ten competing estimates of a single true score. They are draws from a posterior distribution designed to support inference at the population level.

The technical documentation is explicit that averaging plausible values at the student level before analysis is incorrect (OECD, 2024). The procedure compresses the imputation variance and yields confidence intervals narrower than the data-generating process warrants (Huang, 2024). The correct procedure is to fit the model separately for each plausible value and to combine the results using the rules for multiple imputation, so that the total variance incorporates both the sampling variance and the variance between imputations.

Combination rule. Let θ□(m) denote the estimate obtained from plausible value m and U(m) its sampling variance, for $m = 1, \ldots, M$ with $M = 10$. The point estimate is the mean of the M estimates. The total variance is the mean of the M sampling variances plus $(1 + 1/M)$ times the variance between the M estimates. Omitting the second term is the operational form of the error described above.

5.2. Replication Weights and Design-Based Variance

Because the sample is clustered and stratified rather than simple random, uncertainty cannot be estimated as if every observation carried the same probability structure. Variance estimation uses balanced repeated replication over a set of eighty replicate weights supplied with the database, with Fay's adjustment factor fixed at 0.5 (Mang et al., 2021; OECD, 2024). The adjustment modulates the weights rather than discarding half of the sample in each replicate, which preserves inferential stability for subgroups that would otherwise be absorbed into estimation error.

The practical implication matters for the argument of this paper. Differences that appear decisive under naive standard errors frequently weaken once design-based uncertainty is propagated correctly. For a study concerned with inequality and school effects, the distinction between a robust and a fragile difference often depends on whether the sampling design was treated seriously (Mang et al., 2021).

5.3. Socioeconomic Composition at the School Level

Schools do not receive individual students only; they receive socially patterned peer environments (Alves & Soares, 2007). A school enrolling a concentration of high-status students may appear more effective even when part of the observed advantage derives from the composition of its intake rather than from its internal processes. Separating the two requires entering the index of economic, social and cultural status at the individual level and its school-level aggregate simultaneously (Cito & Marôco, 2025; OECD, 2024).

In the two-level specification below, i indexes students and j indexes schools, and Y is a plausible value for the outcome domain. $ESCS_{ij}$ is the student value of the socioeconomic index and $ESCS_j$ its mean in school j; X_{kij}, for k = 2 to K, are the remaining student-level covariates. $CLIMATE_j$, $SAFETY_j$ and $DIGITAL_j$ are school-level measures drawn from Layers 2 and 3 of the framework; the source of each must be declared, because indicators taken from the national health survey are collected from a different school sample and cannot be joined to the assessment data at the school level.

$$Y_{ij} = \beta_{0j} + \beta_{1j}\,(ESCS_{ij} - ESCS_j) + \Sigma_{k=2}\,\beta_{kj}X_{kij} + r_{ij} \tag{1}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}ESCS_j + \gamma_{02}CLIMATE_j + \gamma_{03}SAFETY_j + \gamma_{04}DIGITAL_j + u_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + u_{1j} \tag{3}$$

$$\beta_{kj} = \gamma_{k0},\ k = 2, \ldots, K \tag{4}$$

Equation (1) is the level-1 model and equations (2) to (4) the level-2 model. The random terms are assumed normally distributed: r_{ij} at level 1, and u_{0j} and u_{1j} at level 2 with an unstructured covariance matrix. Equation (3) treats the socioeconomic gradient as a random coefficient; the fixed-slope form, obtained by setting u_{1j} to zero, is admissible but must be declared, because only the random form allows the gradient itself to vary across schools, which is the quantity of interest for Layer 4. Because the disciplinary climate index and the digital-distraction items overlap (Section 5.4), $CLIMATE_j$ and $DIGITAL_j$ may enter equation (2) together only under the second or the third of the strategies set out there; under the first, $DIGITAL_j$ is omitted and γ_{04} is not estimated.

Group-mean centring at level 1 with the school mean reintroduced at level 2 separates the within-school association from the between-school one: $\gamma 10$ estimates the individual socioeconomic gradient inside schools, while $\gamma 01$ estimates the between-school, or compositional, effect. The contextual effect proper, that is, the increment attributable to the composition of the intake once the individual gradient has been accounted for, is the difference $\gamma 01 - \gamma 10$, and it should be reported as such rather than read directly off $\gamma 01$ (Enders & Tofighi, 2007). Without this separation, effects that belong to the social ecology of enrolment are attributed to leadership, pedagogy or management (Alves & Soares, 2007; Duarte, 2023).

The consequences for accountability are direct. If performance differences are interpreted without attention to composition, systems may reward schools for the social profile of their intake and penalise others for challenges only partly within their control (Duarte, 2023; Queiroga et al., 2024). This is not an argument for fatalism about school agency. It is an argument for distinguishing what schools add, what they inherit through enrolment, and what broader structures reproduce.

5.4. A Measurement Constraint Specific to the 2022 Cycle

One constraint is easily overlooked and has direct modelling consequences. In the 2022 cycle, the index of disciplinary climate in mathematics lessons is constructed from the seven statements of a single question of the student questionnaire, and two of those statements are precisely the digital-distraction items reported in Section 4.1: distraction by the student's own devices and distraction by devices used by other students (OECD, 2023c).

It follows that the disciplinary climate index and the digital-distraction items are not independent measures of separate constructs. They are, respectively, a composite and two of its own constituents. Entering both on the right-hand side of the same model produces a specification in which a predictor is partially regressed on itself, with the familiar consequences: unstable coefficients, inflated standard errors and, more seriously, an interpretation that appears to isolate the effect of distraction net of climate when in fact it partials out part of the distraction measure itself.

Three admissible strategies follow, and the framework in Section 6 requires that one of them be declared in advance. The first is to use the composite index alone and to treat digital distraction as one of its components, forgoing a separate coefficient. The second is to reconstruct a reduced climate index from the five non-digital statements and to enter the digital items separately, accepting that the resulting scale is not the published index and must be documented as a derived measure. The third is to model the seven items jointly in a measurement model with correlated residuals for the digital pair. The choice changes what the coefficients mean, and it should not be made after inspecting the results.

5.5. Large-Scale Assessment Data Are Not Learning Analytics Traces

A taxonomic distinction should also be preserved. Descriptive statistics from system-level assessments are sometimes classified as learning analytics, a field directed at the mining of interaction traces generated in digital learning platforms (Society for Learning Analytics Research [SoLAR], 2025). Large-scale assessment rests on a different evidentiary basis: sampled populations, latent proficiency estimation, contextual questionnaires and complex weighting (Karakolidis et al., 2022; OECD, 2024).

The distinction is not pedantic. Platform traces concern digitally mediated behaviour under continuous logging; assessment indicators concern population parameters estimated with quantified uncertainty. Treating them as members of the same family invites two specific errors: reading periodic descriptive comparisons as though they were process data, and reading assessment indices as though they captured fine-grained learning interactions. The framework proposed below draws on both traditions but keeps their inferential claims separate.

6. The Digital Environment and Equity Profile

This section presents the contribution of the paper. The Digital Environment and Equity Profile is an analytical framework that organises the evidence reviewed above into four layers, maps each layer onto variables that already exist in official databases, specifies an estimation protocol consistent with Section 5, and defines screening rules that translate estimates into prioritisation decisions.

6.1. Design Requirements

Four requirements governed the design. First, no new data collection: the framework must be computable from instruments already administered, because a proposal that presupposes a new national survey is not actionable in the short term. Second, layer separability: access, attentional conditions, psychosocial safety and equity outcomes must remain distinguishable, since collapsing them is precisely the analytical failure identified in Section 1. Third, methodological conformity: the protocol must respect plausible values, replication weights and compositional separation. Fourth, decision relevance: the output must be a prioritisation, not only a description, since the governance problem identified by Queiroga et al. (2024) is the distance between indicators and action.

6.2. The Four Layers

- Layer 1: Access and infrastructure. Conditions of availability, covering household digital resources, school connectivity and the ratio of devices to students. This layer captures the constraint that dominated the closure period and that remains binding in parts of the system.
- Layer 2: Attentional conditions. The regulation of instructional time, covering disciplinary climate, device-related distraction reported by students, and the existence and enforcement of institutional rules on device use. This is the layer in which the post-reopening problem is located.
- Layer 3: Psychosocial safety. Peer victimisation, physical aggression, absence motivated by insecurity, sense of belonging and perceived teacher support. This layer is measured predominantly by the national health survey and by the non-cognitive scales of the assessment questionnaires.
- Layer 4: Equity outcomes. Proficiency distributions together with the socioeconomic gradient, at both the individual and the school-composition levels. This is the layer against which the preceding three are evaluated.

The layers are ordered by their position in the causal narrative reviewed in Sections 3 and 4, but the ordering is not itself a causal claim. It is an organisational device that prevents an indicator from one layer being read as evidence about another.

6.3. Indicator Crosswalk

Table 3 maps each layer onto candidate indicators available in existing sources. The crosswalk is deliberately conservative: it lists constructs and named indices rather than item codes, because item identifiers vary across cycles and must be verified against the codebook of the cycle actually used (OECD, 2024). Where an indicator exists in more than one source, both are listed, since the choice between them determines the population to which the resulting profile refers.

Table 3. Indicator Crosswalk for the Four Layers of the Proposed Framework

Layer	Construct	Candidate indicator	Source
1	Household digital resources	Home possessions and information technology resources	Student questionnaire
1	School connectivity and devices	Internet availability; device-to-student ratio	School questionnaire; national school census
2	Disciplinary climate	Published index of disciplinary climate in mathematics lessons	Student questionnaire
2	Device-related distraction	Distraction by own and by peers' devices	Student questionnaire, same item set as the climate index
2	Rules on device use	School policy on mobile telephone use	School questionnaire; school regulations
3	Peer victimisation	Bullying and physical aggression in the previous 30 days	National survey of school health
3	Absence due to insecurity	Missed school on the route or at school	National survey of school health
3	Belonging and teacher support	Published indices of belonging and of teacher support	Student questionnaire
4	Proficiency	Ten plausible values per domain	Assessment database; national assessment scale scores
4	Individual socioeconomic status	Index of economic, social and cultural status	Student questionnaire; national socioeconomic indicator
4	School socioeconomic composition	School mean of the socioeconomic index	Aggregated by school identifier; national school-level indicator

6.4. Estimation Protocol

Table 4 states the protocol as an ordered sequence. Each step corresponds to a requirement established in Section 5, and the mapping is given in the third column so that departures can be identified and justified rather than made silently.

Table 4. Estimation Protocol for an Empirical Application of the Framework

Step	Operation	Requirement
1	Declare in advance the strategy for the overlap between the climate index and the digital items	Section 5.4
2	Fit the two-level model separately for each of the ten plausible values	Section 5.1
3	Repeat each fit over the eighty replicate weights with Fay adjustment at 0.5	Section 5.2
4	Combine estimates and variances using the multiple-imputation rules	Section 5.1

Step	Operation	Requirement
5	Group-mean centre the socioeconomic index and enter the school mean at level 2	Section 5.3
6	Report missingness by stratum for every contextual covariate	Section 7.2
7	Re-estimate under the alternative overlap strategies as a sensitivity analysis	Section 5.4
8	Report design-based standard errors and effective sample sizes, never nominal ones	Section 5.2

6.5. Screening Rules and Priority Classes

The final component converts estimates into decisions. For each school or administrative unit, the four layers are summarised as positions in the national distribution of the corresponding indicators, and the combination of positions defines a priority class with an associated first action. Table 5 states the rules. The thresholds are expressed as distributional positions rather than as absolute values so that the instrument remains usable across cycles and networks.

Table 5. Screening Rules and Priority Classes of the Proposed Framework

Class	Condition	First recommended action
A	Unfavourable on Layer 1 regardless of the remaining layers	Restore conditions of access before any measure addressing use
B	Adequate on Layer 1, unfavourable on Layer 2, favourable on Layer 3	Institutional rules on device use and protection of instructional time
C	Unfavourable on Layer 3 regardless of Layer 2	Safety and coexistence measures, with climate measures subordinated to them
D	Unfavourable on Layers 2 and 3 simultaneously	Integrated intervention, with sequencing decided locally and documented
E	Adequate on Layers 1 to 3 with an unfavourable Layer 4 gradient	Investigate composition and pedagogical processes before attributing the gap to the school

Class E is the rule that most directly encodes the methodological argument of Section 5.3. A unit whose environmental conditions are adequate but whose socioeconomic gradient remains steep is not, on that evidence alone, an ineffective school; it may be a school whose intake reproduces the gradient. The rule requires the compositional question to be asked before an effectiveness judgement is issued.

6.6. Intended Use and What the Framework Cannot Do

The framework produces a comparative profile and a prioritisation. It does not produce causal estimates, and no step in the protocol licenses a causal reading. It also does not replace the pedagogical judgement of the school; the priority classes indicate where attention should be directed first, not which intervention will work in a particular context.

The framework is likewise not an early warning system in the operational sense, although it is compatible with one. An operational system requires data at a frequency the assessment cycles do not provide; the profile proposed here operates on a triennial cycle for the assessment layers and an intermediate cycle for the health survey layer. Its function is diagnostic and allocative, and its integration with higher-frequency administrative data on attendance is a direction for subsequent work.

7. Discussion

7.1. Sector Comparisons Revisited

The public and private sectors in Brazil are frequently compared, and the comparison illustrates the compositional problem well. In raw differences the private-sector advantage is large, and it appears in the official products of the 2022 cycle (OECD, 2023b, 2023c). That difference cannot be read as a net school effect.

Once the socioeconomic profile of students and schools is controlled, the picture changes but does not become uniform across sources. Using data from the national assessment, Duarte (2023) found a substantial narrowing of the differential and, towards the end of the historical series, adjusted differences that were not statistically significant. In the international assessment, by contrast, the average across member countries after socioeconomic adjustment favours public schools (OECD, 2023c), while for Brazil the adjusted mathematics difference associated with private schooling remains positive; Cito and Marôco (2025) estimate a larger residual advantage still.

The defensible conclusion is not that one source is wrong. The two instruments are not interchangeable measures of the same construct: they differ in scale design, curricular proximity, sampling logic and the cognitive demands they privilege (Duarte, 2023; OECD, 2023b). A system may appear more equivalent under one framework and more stratified under another without either being invalid. Claims about sectoral superiority are therefore highly sensitive to what is measured, how, and with which controls, which is the principal reason the framework in Section 6 requires the data source to be declared as part of the profile rather than treated as interchangeable.

7.2. Governance, Interoperability and Data Quality

Evidence on the leadership of school principals in Brazilian upper secondary education indicates that leadership practices are associated with both academic and relational climate, but that only the academic dimension is consistently associated with academic results at that stage (Franklin et al., 2024). This supports a layered reading rather than a hierarchy of importance: relational security underpins coexistence and protection, while academic climate is the more immediate channel through which leadership translates into measured performance. The framework preserves this by keeping Layers 2 and 3 distinct instead of merging them into a single climate score.

The feasibility of the data infrastructure required is established rather than speculative. Queiroga et al. (2024) integrated microdata from the national assessment with the school census and identified school-related factors associated with performance across the national territory, demonstrating that open educational data in Brazil already support analyses of this kind. What the framework adds is not new infrastructure but a specification of which quantities to compute and how to act on them, together with evaluative attention to equity of the sort proposed by Xavier (2024).

Data quality remains the binding constraint. Assessments frequently exhibit high rates of non-response in the contextual questionnaires completed by principals and students, which forces the exclusion of covariates such as school infrastructure from the models (Cito & Marôco, 2025). The damage is cumulative and asymmetric: if infrastructure, climate or leadership indicators are disproportionately missing in more vulnerable contexts, the resulting models may be technically sophisticated and substantively incomplete at the same time. Step 6 of the protocol makes reporting missingness by stratum mandatory for this reason.

7.3. Limitations

Four limitations should be stated. The first concerns the status of the contribution: the framework has not been applied to microdata, and its layers, crosswalk and screening rules are proposals whose empirical adequacy is untested. Validation would require, at minimum, fitting the specification of Section 5.3 to the 2022 microdata for Brazil under each of the three overlap strategies of Section 5.4, and examining whether the priority classes of Table 5 discriminate between units in a stable and interpretable way.

The second concerns design. The assessment is cross-sectional and age-based rather than grade-based, so the profile describes cohorts rather than trajectories, and no step in the protocol identifies a causal effect. The third concerns measurement: climate, distraction and safety are measured by self-report, which is subject to reference-group effects that complicate comparisons across schools with different normative environments. The fourth concerns coverage: the layers draw on instruments with different periodicities, populations and age ranges, and combining them at the unit level requires assumptions about comparability that should be documented in any application.

A further caution applies to the interpretation of the comparative literature reviewed in Section 7.1. Divergence between instruments is not resolved by preferring the one that yields the expected result, and the framework does not adjudicate between them; it requires the choice to be declared.

8. Conclusion

The Brazilian post-pandemic school presents an intertwined problem that is frequently discussed as three separate ones. Exclusion from digital resources amplified learning losses during school closures, and those losses were distributed according to pre-existing socioeconomic gradients rather than uniformly. After reopening, the weakly regulated presence of personal devices became associated with high reported levels of classroom distraction, at rates well above the average of the participating member countries, and distraction caused by peers operates as a collective cost rather than an individual habit. Alongside this, national health survey data document levels of peer victimisation, physical aggression and absence motivated by insecurity that place psychosocial safety among the preconditions of ordinary pedagogical work rather than among its accessories.

This paper synthesised that evidence and, in response to the limitation that a synthesis alone does not constitute an analytical contribution, derived from it the Digital Environment and Equity Profile: a four-layer framework with an indicator crosswalk over existing official sources, an estimation protocol conforming to the requirements of plausible values, replication weights and compositional separation, and screening rules that convert estimates into prioritisation decisions.

The paper also documented a measurement constraint that conditions any such analysis, namely that in the 2022 cycle the digital-distraction items form part of the item set from which the disciplinary climate index is constructed, so that the two cannot be entered into a single model as independent predictors without an explicit and pre-declared strategy. The framework is a proposal; its validation against microdata, and its integration with higher-frequency administrative data, are the immediate directions for subsequent work.

9. References

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Appendix 1. Operational Instrument of the Proposed Framework

This study did not administer a questionnaire of its own; it draws on instruments already applied by the official statistical producers cited in the references. The research instrument of this paper is therefore the operational specification of the framework presented in Section 6, reproduced here in the form in which it would be applied. Item identifiers are deliberately omitted, as they must be verified against the codebook of the cycle actually used.

A. Unit of analysis and scope. The unit is the school where school identifiers are available, and the administrative network otherwise. The reference population, the assessment cycle and the survey edition must be declared before estimation and reported alongside every profile.

B. Layer construction. For each layer of Table 3, compute the listed indicators with the design weights of the source, express each as a position in the national distribution of units, and record the proportion of units for which the indicator could not be computed.

C. Declaration of the overlap strategy. Before estimation, record which of the three strategies of Section 5.4 will be used for the relationship between the disciplinary climate index and the digital-distraction items, and justify the choice on substantive grounds.

D. Estimation. Execute steps 2 to 5 of Table 4 in the stated order. Report point estimates with design-based standard errors, the between-imputation variance component separately, and the effective sample size for every subgroup reported.

E. Missingness report. For each contextual covariate, report the proportion missing overall and by stratum of the school socioeconomic composition, and state which covariates were excluded from the model as a consequence.

F. Classification. Apply the rules of Table 5. Where a unit satisfies the condition of more than one class, assign the class appearing earlier in the table and record the ambiguity.

G. Sensitivity analysis. Re-estimate under the two overlap strategies not selected in step C, and report whether any unit changes priority class. Instability in classification is itself a finding and must be reported.

H. Reporting. Every profile must state the source, cycle, reference population, overlap strategy, missingness summary and classification stability. Profiles that omit any of these elements should not be used for prioritisation decisions.