Modeling the Impact of Chronic Absenteeism in K-12 Education on Academic Outcomes: A Risk-Based Approach

Team #19844

Modeling the Future Challenge 2025

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Table of Contents

1. Executive Summary
2. Introduction and Background Information
3. Data Methodology
    3.1 Data Identification and Collection
        3.1.1 Chronic Absenteeism Outcome Data
        3.1.2 Historical Chronic Absenteeism Rates
            3.1.2.1 Nation-wide Data
            3.1.2.2 State-wide Data
        3.1.3 Projected K–12 Student Population
    3.2 Data Reliability and Preparation
4. Mathematical Modeling
    4.1 US Student Population Count Model
    4.2 Time Model (Chronic Absenteeism Rate Forecast)
        4.2.1 Chronic Absenteeism Rate Calculation and Data Alignment
        4.2.2 Modeling Approach and Assumptions
        4.2.3 Mathematical Model Formulation
        4.2.4 Results of Time Model
    4.3 Negative Effects Model (Academic Impact of Absenteeism)
        4.3.1 Multivariate Analysis & Feature Engineering
        4.3.2 Multiple Linear Regression Model Development
        4.3.3 Academic Impact Findings
    4.4 Expected Negative Effects Model
    5. Risk Analysis
5. Risk Mitigation Strategy Analysis
6. Recommendations
    6.1 Implement Early Warning Systems to Improve Attendance (Accelerating the Decline of Chronic Absenteeism)
    6.2 Targeted Support for Specific Student Groups
        6.2.1 Focus on Highly Impacted Grades and Subjects
        6.2.2 Prioritize High-Severity Absenteeism Cases
    6.3 Future Implementation Timeline
        6.3.1 Short-Term Horizon (2025–2027)
        6.3.2 Medium-Term Horizon (2028–2030)
        6.3.3 Long-Term Horizon (2030–2031 and Beyond)
7. References
8. Appendix

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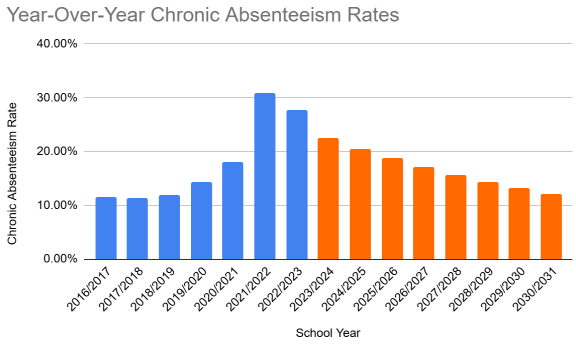
1. Executive Summary

Chronic absenteeism in K–12 education – defined as missing 10% or more of the school year – has surged to crisis levels in the wake of the COVID-19 pandemic. Before 2020, about 15% of students were chronically absent; by 2021–2022 that share had nearly doubled to around 30% [1]. National data for 2022–2023 show a modest improvement to approximately 28% [2], but this remains about 75% higher than pre-pandemic levels [3]. Such widespread absenteeism poses severe risks to student achievement and long-term outcomes. Research confirms that chronic absence takes a toll on grades and test scores and is a strong predictor of high school dropout [1]. In turn, dropping out is linked to poorer employment prospects, worse health, and higher risk of involvement with the justice system [1]. In short, if not addressed, chronic absenteeism will be one of the biggest obstacles to post-pandemic academic recovery.

Our actuarial analysis examines this problem and its future impact, using a risk-based approach, and recommends data-driven strategies to mitigate the risks. We gathered extensive datasets (national and state-level attendance records, academic performance metrics, demographic data, etc.) following guidelines from the Modeling the Future Challenge Actuarial Process. These data were rigorously assessed and cleaned to ensure accuracy and representativeness. Using this information, we developed mathematical models to project future student enrollment, chronic absenteeism rates, and the academic effects of elevated absenteeism. This included a **K-12 Student Population Model** to forecast expected student counts to use as a multiplier, **Time Model** forecasting when absenteeism might return to normal levels, a **Negative Effects Model** quantifying the impact of absenteeism on academic performance, and an **Expected Negative Effects Model** combining attendance projections with academic decline rates. We also identified which student groups (by grade level, subject, and absenteeism severity) are likely to be most negatively affected. Throughout, we treated chronic absenteeism as a *risk*—characterizing its frequency (how common chronic absence is) and severity (the magnitude of academic loss per absence) to better understand the distribution of potential outcomes.

Our models indicate that without intervention, chronic absenteeism will remain elevated for years. We project that overall rates will not return to pre-pandemic levels until about 2031 (Figure 1). In the interim, tens of millions of student-year instances of chronic absence will occur. Specifically, we estimate **over 44 million total cases** of students being chronically absent across the next six years. Each year in this period, millions of students will suffer measurable learning losses due to missed instruction. The academic impact is most pronounced for younger students and core subjects. For example, according to our Negative Effects Model, a chronically absent 4th grader in the highest absence category can expect an **~18% drop** in their academic performance – significantly more decline than experienced by older students. Overall, we found that higher absenteeism severity is correlated with larger declines in standardized test scores across all subjects, with Science, Writing, and Reading scores dropping the most (up to ~20% performance decline when comparing low vs. extreme absence groups).

Figure 1: Projected Year-Over-Year Chronic Absenteeism Rates in the U.S. Blue bars represent the historical rates while orange bars represent the projected rates.



In actuarial terms, chronic absenteeism represents a long-tailed risk to educational outcomes. Even as some student groups show quick improvement in attendance post-pandemic, others (particularly those with more severe absenteeism) improve slower, dragging out the overall recovery [#].

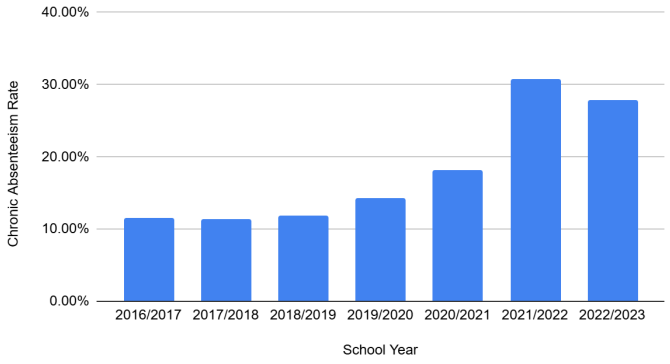
To accelerate the decline of chronic absenteeism and reduce its academic toll, we propose a multi-pronged mitigation strategy. *(It is important to note that unlike some risks, chronic absenteeism cannot be mitigated through traditional insurance mechanisms – the losses are academic and social, not financial payouts – so our focus is on preventative and remedial interventions rather than risk transfer.)* First, we recommend implementing Early Warning Intervention and Monitoring Systems (EWIMS) in schools nationwide. EWIMS is a data-driven framework that uses real-time attendance data to identify at-risk students and trigger targeted interventions [3]. Evidence from the Regional Educational Laboratory (REL) shows that schools using EWIMS achieved significant reductions in absenteeism and course failure [4]. In a controlled study, chronic absence rates dropped from 14% to 10% (a 4 percentage-point improvement) in EWIMS schools versus controls, and course failure rates fell by 5 points (26% to 21%) [4]. We advise that schools adopting EWIMS establish dedicated attendance teams, provide mentorship and tutoring for flagged students, engage parents through outreach and support (addressing barriers like transportation or health), and incentivize good attendance. These steps ensure the intervention is systematic and proactive.

Secondly, we recommend **targeted support for specific student groups** to mitigate the most severe outcomes of absenteeism. Our findings indicate younger students are more vulnerable to learning loss from missed days, so elementary and middle schools should receive priority in resources for attendance-improvement programs. Likewise, certain subjects (notably Science, Writing, and Reading) showed larger performance declines associated with absence; thus, schools should bolster support in these areas – for example, by offering additional instructional time or tutoring for students who miss class, especially in science labs and literacy/English classes. Additionally, students with extreme absenteeism (missing far above 10% of days) warrant intensive intervention (home visits, mentorship, counseling) since they have the highest risk of academic failure. By focusing on the highest-severity absenteeism cases first, schools can reap the largest gains – reducing the overall "severity load" on the system more quickly and preventing those students from falling irreparably behind.

2. Introduction and Background Information

Chronic absenteeism refers to students missing a significant portion of the school year, typically defined as missing 10% or more of school days for any reason (excused or unexcused) [1]. This metric goes beyond daily attendance rates to identify students who are persistently absent and therefore at risk of falling behind. Prior to the COVID-19 pandemic, chronic absenteeism was already a concern – roughly 15% of U.S. students (about 8 million children) were chronically absent in 2019 [1]. However, the pandemic dramatically worsened the situation. In the 2020–2021 and 2021–2022 school years, absenteeism skyrocketed to nearly 31% of students. Every state with available data saw significant increases in chronic absence during this period. In other words, almost one in three students across the country missed at least 10% of the school year in 2021–22, an unprecedented level of disengagement from the classroom. This surge has also widened disparities: historically marginalized groups and high-poverty districts experienced some of the largest jumps in absenteeism. For example, in high-poverty districts the chronic absence rate increased 17 percentage points (from 19% in 2018 to 36% in 2022), whereas in low-poverty districts it rose by 11 points (from 12% to 23%) [5]. By the 2022–2023 school year there was a slight improvement in chronic absence nationally (down to about 27–28% of students, from the ~30% peak) [2]. While this decline is a step in the right direction, chronic absenteeism remains alarmingly high by historical standards. At roughly 28%, the national rate of chronic absence in 2022–23 is still about 75% higher than it was pre-COVID (Figure 2).

Figure 2: Historical Year-Over-Year Chronic Absenteeism Rates



The core risk addressed in this report is the *educational risk* posed by chronic absenteeism. What are the long-term consequences if a large share of students continue to miss substantial instructional time each year? Research prior to and during the pandemic has established that chronic absence is strongly linked to poorer academic performance. Students who are chronically absent tend to have lower test scores, lower GPAs, and higher odds of not graduating on time [6]. In fact, chronic absenteeism is one of the strongest early warning signs of high school dropout [7]. The effects accumulate: a student chronically absent one year is more likely to struggle academically in subsequent years, creating a feedback loop of disengagement. Ultimately, failing to graduate or falling behind academically has downstream societal costs – it can lead to diminished employment opportunities, increased likelihood of poverty, worse health outcomes, and even higher risk of involvement with the criminal justice system [6]. These cascading effects mean chronic absenteeism is not just an education issue, but a broad societal risk factor.

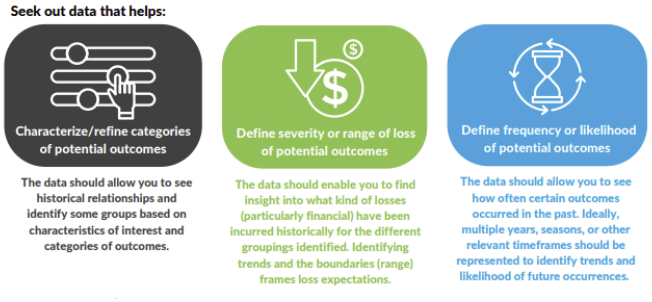
In summary, the risk we are analyzing is that chronic absenteeism remains at elevated levels, leading to significant cumulative learning loss and higher dropout rates in the coming years. **Who is at risk?** Virtually all demographics saw increases in

absenteeism, but our analysis will show that *certain groups are especially at risk*: younger students (who have more to lose in terms of foundational skills), students with already high absenteeism (who fall furthest behind), and those struggling in key subject areas. **Risk factors** include socio-economic challenges, post-pandemic behavioral changes, and policy factors (such as reduced enforcement of attendance or lingering remote options). If these risks are not mitigated, the long-term educational and economic costs will be substantial. We will also discuss potential **risk mitigation concepts**, focusing on interventions in the education system (rather than insurance, since educational loss is not directly insurable). We hope to implement behavior change and outcome change mitigation strategies (EWIMS and Targeted-support).

3. Data Methodology

Our analysis required integrating multiple data sources to capture both the *frequency* of chronic absenteeism and the *severity* of its outcomes. We identified data in three broad categories (as recommended by the Actuarial Process Guide): **(1)** data to characterize or refine categories of potential outcomes (e.g. different levels of absenteeism and academic results associated with them), **(2)** data to define the severity or range of loss (e.g. impact on test scores, likelihood of dropout), and **(3)** data to define the frequency or likelihood of those outcomes (e.g. how common various absenteeism levels are, how enrollment is changing) (Figure 3)

Figure 3: 3 Categories defined by Actuarial Process for effective dataset selection



All data collected were assessed for reliability. We favored official sources (government or research institutions) and cross-checked similar metrics across sources. In cases where data from different sources disagreed, we investigated definitions and chose the more credible figures (for instance, resolving slight discrepancies between NCES and state-reported attendance rates by understanding differences in data collection methods). Data cleaning steps are detailed below. Overall, our data covered all relevant categories: it helped define how big the problem is (frequency), what the consequences are (severity of academic loss), and it provided context for different outcome scenarios.

3.1 Data Identification and Collection

We assembled a comprehensive collection of datasets from reputable sources. The following sections primarily detail the processes of data identification, categorization, collection, and basic data cleaning/transformation. Information on the more intensive data cleaning and transformation, along with each respective model and its underlying dataset, can be found in Section 4: Mathematical Modeling.

3.1.1 Chronic Absenteeism Outcome Data

To quantify the severity and range of academic losses associated with absenteeism, we obtained datasets that link student attendance records with academic performance metrics. This allowed us to quantify the *severity* of our risk. Datasets from the U.S. Department of Education's CRDC and EdFacts Data Exchange provides, for each school, the number of students chronically absent and total enrollment, as well as performance measures like standardized test scores [8] [9]. This helped characterize potential outcomes (e.g., test score declines) for different absenteeism levels.

We collected data from the National Center for Education Statistics, specifically using their NAEP (also referred to as The Nation's Report Card) Data Explorer to generate custom datasets that could give us information about Chronic Absenteeism Rates and their associated Academic Metric [10]. There were many different Academic Metrics to choose from, so in order to get a representative metric to determine the overall academic capabilities of the population (different demographics and

sub-groups are all automatically weighted for fair representation based off groups most likely to be chronically absent), as well as a representative sample of the population, we opted to generate 15 custom datasets that showed student-level data of a Chronic Absenteeism and its associated academic metric for a variety of age groups, all shown in Table A1 (Appendix). Some basic rules for data generation were to only keep data from the most recent year available, only if the data collected are from the past 25 years (2000 or after), and the framework used is from the past 40 years (1985 or after). Additionally, we filled null values if $n > 10$ for similar values to average, and also dropped any illogical data points (ie; numerator greater than denominator) or flagged outlier outside of 0.05 tail ends range (statistical significance).

Once we had all 15 datasets, we created a Python script that automatically condensed all the data into 3 datasets, each representing academic metrics of a different grade level (4, 8, and 12). For each dataset, the main chronic absenteeism metrics was absenteeism_days column which was denoted in days. Since we want to use a rate instead, we coded a script that calculates the relative percent rate of Chronic Absenteeism for all students for each dataset. This was done by performing: absenteeism_days / total_days. This Chronic Absenteeism percent rate represents the percent of missed school days at different intervals for a single student, not the entire population qualifying for chronic absenteeism.

Each scale metric score was based on a different scale, as the underlying tests and frameworks were inconsistent with one another. We were unable to get any information on mean and standard deviations of the original proctoring of the data, so we were unable to normalize the scores using a z-score calculation. However, all of our future calculations took this in mind, and we don't compare between different frameworks and scales in our future models. The scale metric scores will all relatively move in the same trends anyways, so it won't skew our results.

3.1.2 Historical Chronic Absenteeism Rates

In order to model expected chronic absenteeism rates over time (frequency of our risk), we needed data that can **define frequency or likelihood of potential outcomes.** We compiled year-by-year chronic absenteeism rates at national and state levels for the past decade. Key sources included federal education data portals (such as EdData Express and state education department report cards). This gave us the historical frequency of chronic absence and how it changed over time, especially through the pandemic. We combined **national data** and **statewide data** (2017–2023 school years) to ensure our baseline and trend estimates were robust. Each state's data allowed us to account for regional differences and verify national aggregates.

3.1.2.1 Nation-wide Data

We identified a series of datasets from the US Department of Education, Data Express website that provided data from the 20/21, 21/22, and 22/23 school years [11]. Due to the ambiguity of quality data around the years of 2021 because states did not post data for the 2020-21 school year, as remote instruction interfered with attendance and traditional attendance collection data systems, we wanted to get as many datasets as possible to hopefully weight-average accurate chronic absenteeism rates over the years. We were able to identify 15 datasets to aid in the accuracy of our year-over-year data regarding Chronic Absenteeism Rates across the US, with varying consensus sizes denoted with SCH, LEA, and SEA for the levels School, Local Education Agency, and State Education Agency), respectively, shown in Table A2 (Appendix).

Data Concerns: School-level data for FS195/DG814 are privacy protected via perturbation. The data are protected by adding or subtracting one student for cell sizes less than or equal to four and random data swapping for cell sizes less than or equal to three. Data for FS195/DG814 are reported at the school level. Student counts may be duplicative. Students are reported in each school in which they are enrolled and absent 10% or more school days during the school year. As a result, students who are defined and reported as chronically absent at more than one school in a given school year will be counted more than once when aggregated up to the LEA, SEA, and national levels.

Once all data was retrieved, we performed data cleaning to fill any missing values of data discrepancies. This included collecting the numerators and denominators for each district where available, and deriving missing numerators or denominators when rates and either numerators or denominators were available. Some states posted data only for select years. For membership, it was collected at one point in time, whereas chronic absenteeism data is collected over the school year. Double counting may occur with the chronic absenteeism data which can inflate the percentage.

3.1.2.2 State-wide Data

In addition to the 2021 through 2023 school year datasets, we gathered an additional 4 LEA datasets from ED Data Express between the school years 16/17, 17/18, 18/19, 19/20 [9]. However, the structure of the data was different and the target variables were in the form of a value count rather than numerator, denominator, and/or percent. Since there were only values present in the data, we had to cross-reference each district with the corresponding district sourced from CCD data [12] in order to use the CCD data's district student count numbers as a denominator for our district-wide percentage calculation. All districts that had no matching name or had illogical data (ie; values count greater than CCD data student count) were dropped. Missing values were dropped as well since we had no neighbors to calculate a filler average. Using these LEA chronic absenteeism rates, we weight-average them based on their student counts in order to create statewide chronic absenteeism rates.

In addition to this, we also cross referenced the newly created statewide chronic absenteeism rates with manually gathered data from available school years from each state's state department of education as shown in Table A3 (Appendix) [12] [13] [14] [15] [16] [17] [18] [19] [20] [21] [22] [23] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44] [45] [46] [47] [48] [49] [50] [51] [52] [53] [54] [55] [56] [57] [58] [59] [60]. Null or illogical values are denoted with '-'.

If certain states or school years had no data present, we would skip that data. National data is already very strong, and the states that tended to have a lot of missing data tended to be smaller states that didn't have as strong or reliable systems in place for attendance tracking. More details on how we merged nation-wide and state-wide datasets and the rationale behind suppressing these illogical values are further detailed in Section 4.2.1.

3.1.3 Projected K–12 Student Population

In order to get a sense of the impact chronic absenteeism has in terms of raw numbers and counts, we wanted to model and project future student population numbers. We obtained data for this from the US Department of Education Statistics' Common Core Data (CCD) tool as well as the United States Census Bureau's Department of Commerce [61] [62] [63]. We extracted historical population counts of students as well as the greater of the US (birth rates) and cross-referenced everything using a flat average. See Table A4 in Appendix for Historical US K-12 Student Populations.

This data, as well as data regarding birth rates and youth population will be used in future sections to model projected US student population counts.

3.2 Data Reliability and Preparation

Understanding data reliability was crucial. Some data came directly from federal datasets (considered highly reliable), while others were aggregated from school reports (with potential inconsistencies). We took several steps to ensure data quality:

- We **cleaned and transformed the attendance datasets** to handle anomalies. For example, when merging school-level or state-level chronic absence counts with enrollment, we noticed a few cases where the calculated percentage of chronically absent students exceeded 100% (clearly impossible unless due to data errors or double-counting). Such anomalies were very rare, but we addressed them systematically (see Section 4.2.1 below).
- We ensured consistent definitions: different states might define "chronically absent" slightly differently or record data at different intervals. We standardized definitions to the common 10% of days threshold for chronic absence.
- We considered **data credibility**. Large-sample aggregated data (like nationwide rates) have high credibility, whereas small-sample or self-reported metrics may be less reliable. In our models, we gave more weight to robust data (e.g. national averages derived from millions of students) and treated very granular breakdowns with caution if sample sizes were small.

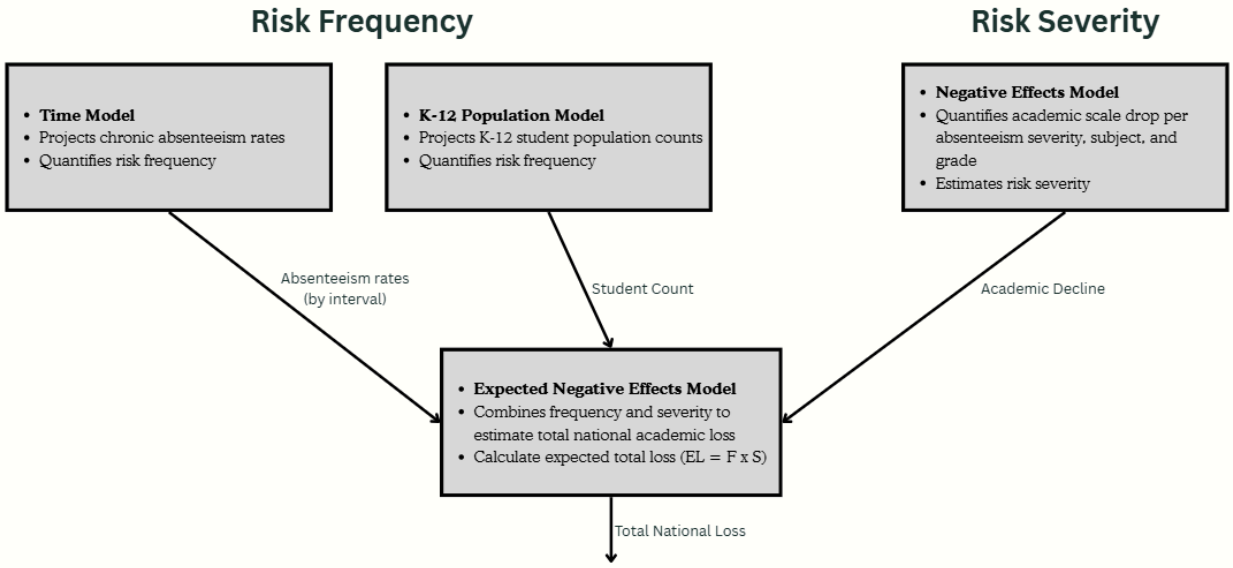
The next section describes how we used these data to develop mathematical models projecting future absenteeism and its effects.

4. Mathematical Modeling

Using the collected data, we developed a sequence of mathematical models to forecast future chronic absenteeism (frequency of risk) and to quantify its educational impact (severity of risk). The modeling process followed an **actuarial approach**: starting from historical data, we built projections under certain assumptions, and then combined frequency and severity components to estimate expected losses (in this case, expected declines in academic performance). We explicitly state the key assumptions in each model and designed the models to be responsive to trends and changes over time.

Overview of Models: We constructed three interrelated models. The **US Student Population Count Model** simply projects total K–12 enrollment in coming years (using external demographic forecasts), which serves as a scaling factor for our other results. The core analysis is in the **Time Model** and **Negative Effects Model**. The **Time Model** projects the chronic absenteeism rate in future years – essentially forecasting how quickly (or slowly) absenteeism rates will return to normal, based on observed post-pandemic trends and the assumption that declines will slow as they approach pre-pandemic norms. The **Negative Effects Model** estimates how much academic performance (e.g. test scores) declines as absenteeism increases, using a regression-based approach on our data. Finally, the **Expected Negative Effects Model** combines the two: it multiplies future absenteeism (from the Time Model) by the performance impact per student (from the Negative Effects Model) to estimate the aggregate "academic loss" due to chronic absence in each future year. This third model produces metrics like the expected percentage of performance decline in the student population or expected counts of students at risk of failing, and is used in our risk analysis. We created a flowchart to visually show the processes between the models (Figure 4).

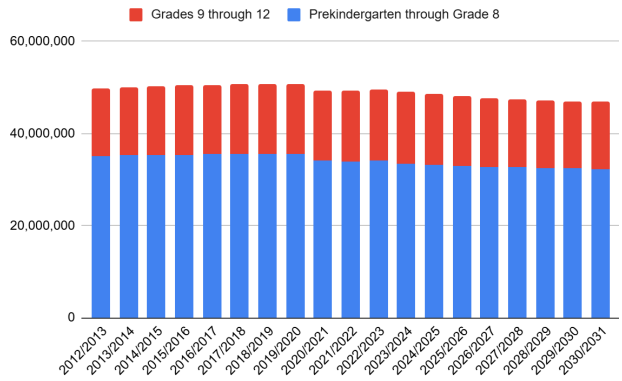
Figure 4: Flowchart of Mathematical Modeling Framework



4.1 US Student Population Count Model

Before modeling absenteeism itself, we established a baseline projection for total student population, since an increase or decrease in student count affects the absolute number of students impacted by chronic absence. We obtained national projections for K–12 public school enrollment for the next decade, and adjusted them slightly based on recent trends (e.g., some states saw enrollment dips during COVID-19 that may rebound). The projection is straightforward (an extrapolation of current demographic trends) and is used primarily to convert rates into headcounts (Figure 5). We assume a modest growth in student population in some regions and declines in others, roughly balancing out to a stable total of around 50 million students nationwide, growing slowly in the later 2020s. This model is relatively simple and has minimal uncertainty compared to the others, as demographic projections are well-studied. See Table A5 in Appendix for full projected enrollment numbers.

Figure 5: Projected student population counts in K-12 US Education, separated by age groups



4.2 Time Model (Chronic Absenteeism Rate Forecast)

The Time Model is a mathematical model to project future chronic absenteeism rates year by year. Its goal is to estimate how long it will take for chronic absence rates to revert to pre-pandemic levels (if they do), and what the trajectory looks like in the meantime. Rather than assume a simple linear decline back to normal, we built a dynamic model that accounts for different rates of improvement among different groups of students.

4.2.1 Chronic Absenteeism Rate Calculation and Data Alignment

To start, we carefully calculated historical chronic absenteeism rates from our data. We had two primary historical data sources – one from EdData Express covering recent years (2020–2023) and one compiled from state reports (2017–2023) – which we combined to get a consistent national time series (Table 1). Because the datasets were formatted differently, we performed a weighted averaging to merge them. We wanted to ensure that each year's national rate was as accurate as possible, leveraging the large sample sizes. In doing so, we paid special attention to data inconsistencies and made decisions on data transformation and suppression:

Table 1: Year-over-year National Chronic Absenteeism Rates (Historical)

School Year	**2016/2017**	**2017/2018**	**2018/2019**	**2019/2020**	**2020/2021**	**2021/2022**	**2022/2023**
Chronic Absenteeism Rate	11.50%	11.40%	11.90%	14.30%	18.10%	30.80%	27.80%

(Note: 2019–20 was partially affected by pandemic closures; 2020–21 saw widespread remote learning; 2021–22 was the peak of chronic absence post-pandemic; 2022–23 saw slight improvement.)

We derived these rates by merging school-level "number of chronically absent students" with "total enrollment" and then aggregating. Since we had both school-by-school data via EdData Express and state-level aggregates, we reconciled them through weighting by population to get the best estimate. This process, described as follows, ensured consistency:

- **Defining the universe:** We included K–12 students in our analysis (excluding pre-K and adult education from enrollment counts). Any schools with 0 reported enrollment were excluded as data errors. The chronic absenteeism metrics inherently only covered K–12, so this alignment ensured we were calculating percentages over the correct student population.
- **Transformation and suppression rules:** Some data points needed capping or exclusion to maintain logical consistency:
    1. If a calculated percent of chronically absent students for a school fell between 100% and 200%, we set that value to 100% (assuming it was an overestimate likely due to data reporting quirks or double-counting of students across categories).
    2. If the percent exceeded 200% *and* the school's enrollment (membership) was ≤50 students (very small school or program), we also set the chronic absenteeism percent to 100%. Small denominators can lead to extreme percentage calculations, so we capped these cases at the maximum possible value.

3. If the percent exceeded 200% with membership >50 (indicating a clear data anomaly in a larger school), we **suppressed** the chronic absenteeism data for that school (i.e. treated it as missing in our aggregation). Such extreme values (e.g. a report that 300% of students were chronically absent) are likely errors and were not included in computing state or national averages.

- *Rationale:* These transformations prevent mathematically impossible or implausible percentages from skewing our results. Values above 100% are not logically feasible unless there is a data issue (for example, a student counted absent in multiple categories). By capping extreme values at 100% or excluding them when necessary, we ensure the calculated rates remain within a realistic 0–100% range. In total, only a handful of data points fell into these categories, so this adjustment had a negligible effect on national figures but was important for principled cleanliness. (In cases where data was "suppressed," we simply omitted those records from the averaging process.)

After these adjustments, we cross-referenced our cleaned **EdData Express** derived rates with the **state-based** data [9]. We performed a weighted average based on the size of each dataset's coverage to arrive at the final national rates in Table 3. Essentially, larger states or those with more complete data were given appropriate weight so that the national figure reflects the true student population mix (an application of the law of large numbers to improve accuracy). This careful process yielded the baseline inputs for our Time Model.

4.2.2 Modeling Approach and Assumptions

With historical rates in hand, we observed that the decline from the peak (30.8% in 2021–22 down to 27.8% in 2022–23) was not simply linear. To capture the dynamics, we categorized chronic absenteeism into **severity intervals** (sometimes called absence tiers): for instance, **Low** (just meeting the chronic threshold, ~1–2 days absent per month), **Moderate** (3–4 days/month), **High** (5–10 days/month), and **Extreme** (>10 days/month). Our analysis indicated that these groups were improving at different rates post-pandemic. Specifically, the most extreme absence cases saw a faster initial improvement (many schools tried to get the worst cases back first), whereas the milder cases did not improve as much proportionally, and eventually the progress slowed as the remaining absent population consisted more of the persistent moderate cases.

We clearly defined our modeling assumptions:

Assumption: Schools and districts would prioritize reducing **extreme chronic absenteeism** first, then address lower-severity cases – leading to a two-phase decline pattern in the overall rate
Justification: According to observed data, schools *did* focus on the worst cases in 2021–22, as evidenced by a sharp initial drop in the extreme category by 2022–23. Additionally, there is some practical logic involved; schools have finite resources, so it makes sense to triage efforts to prioritize extreme chronic absenteeism first [64] [65].

Assumption: The "normal" or equilibrium distribution of chronic absenteeism across the severity intervals will resemble pre-COVID patterns once stabilization is reached.
Justification: Based on pre-2020 data, that natural distribution has a heavy concentration in the lower severity categories (since only a small fraction of students used to be in the extreme 10%+ absent group). We used the 2018–2019 breakdown as a target: for example, if historically 5% of students had extreme absence and 10% had moderate, our model in the long run heads back toward those proportions, barring further disruptions.

Using these assumptions, we structured the model in two phases:

- **Phase 1 (Fast initial decline, roughly 2021–2023):** Immediately after the peak, we expect a rapid improvement driven by those students/groups with extremely high absence returning more quickly. Indeed, groups that historically had lower chronic absenteeism rates (and thus were abnormally high post-COVID) declined the fastest. During this phase, the total chronic absenteeism rate drops sharply because a large portion of the chronically absent population (the most extreme cases) is improving and "exiting" the chronically absent pool. Our data confirmed this: for example, from 2021–22 to 2022–23, the share of students in the **Extreme** interval fell significantly (as shown in Table 4 below).
- **Phase 2 (Slower decline, 2024 onward):** After the initial gains, the remaining chronically absent students are those in the lower tiers (or otherwise harder-to-improve cases). These groups decline slower or might even plateau. As the quick-declining groups were removed, the moderate and high groups make up a larger portion of the remaining chronic absence population, so improvements naturally slow down. In other words, as we approach the "normal" state,

each incremental reduction is harder to achieve. We anticipated a long tail where a baseline level of chronic absenteeism might persist for many years, albeit at gradually diminishing rates.

To quantitatively model this, we broke down the overall rate by interval and applied different decline factors to each interval over time (Table 2).

Table 2: Historical percent each chronic absenteeism severity interval contributes to the total percent of chronically absent students

School Year	Low (1-2 days / month)	Modest (3-4 days / month)	High (5-10 days / month)	Extreme (10+ days / month)
2021/2022	12	23	22	43
2022/2023	12	24	28	36
2023/2024	11	25	35	29

(Note: 2023–24 values are projected intermediate figures as our model's starting point for projections beyond 2023. The trend shows the Extreme category dropping substantially in share from 43% to 29% over these two years, indicating that many of the worst cases were mitigated, while High and Moderate categories grew in share.)

Using this interval approach, **we converted the data to represent chronic absenteeism rates out of the total student population** for each interval (Table 3). For example, if 30.8% of students were chronically absent in 2021–22 and 43% of those were in the Extreme category, then roughly 13.2% of all students were Extreme-absent in 2021–22. Doing this for each interval gave us baseline rates by interval.

Table 3: Historical percent % each chronic absenteeism severity level/interval contributes to the total number of students

School Year	Low (1-2 days / month)	Modest (3-4 days / month)	High (5-10 days / month)	Extreme (10+ days / month)	Total
2021/2022	3.696	7.084	6.776	13.244	30.8
2022/2023	3.336	6.672	7.784	10.008	27.8
2023/2024	2.475	5.625	7.875	6.525	22.5

4.2.3 Mathematical Model Formulation

Instead of fitting a single trend line to the overall chronic absence rate, we modeled the total rate as a *weighted sum of subgroup rates*, where the weight of each subgroup changes over time. This is analogous to an actuarial survival model where different subpopulations exit at different speeds.

We implemented the model in iterative steps for each year:

- **Step 1: Compute Each Student Group's Decline.** Each absenteeism severity group (Low, Moderate, High, Extreme) is assigned a yearly decline factor representing the fraction by which that group's chronic absence rate decreases each year. These decline factors were calibrated from the 2022–2023 improvement and then adjusted to follow our two-phase assumption (higher declines in Phase 1, smaller in Phase 2). Essentially: $\text{AbsenteeismRate}_{group}(t+1) = \text{AbsenteeismRate}_{group}(t) \times (1 - d_{group})$, where d_{group} is the decline rate for that group (e.g., Extreme group might have $d_{Extreme} = 0.3$ in early years meaning a 30% relative drop per year, while Low group might have $d_{Low} = 0.1$). These declines are relative (percent decreases), which reflects a natural decaying pattern: as a group's size shrinks, the absolute decreases get smaller, capturing a plateau effect.
- **Step 2: Compute Each Group's Contribution to the total.** Over time, groups that decline faster will contribute less to the total chronic absenteeism rate, and those declining more slowly will make up a larger share. We recompute the *proportion* of the total that each group constitutes each year: $\text{Proportion}_{group}(t) = \text{AbsenteeismRate}_{group}(t) / \text{TotalAbsenteeismRate}(t)$. By definition, the sum of all groups' proportions is 100% of the chronic absenteeism population in that year. This step ensures our model keeps track of the shifting composition. As an example, if the Extreme group drops dramatically one year, its proportion of the (smaller) total might fall, while Moderate's proportion rises.

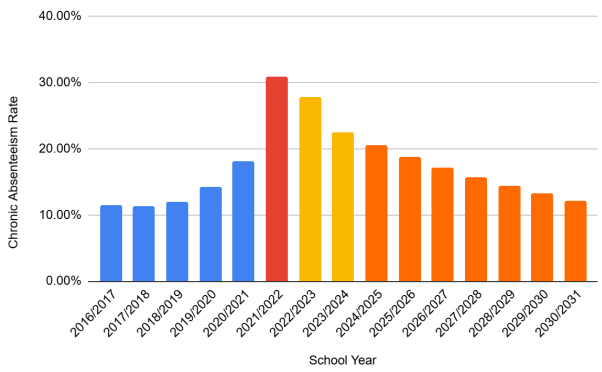
- **Step 3: Compute the Total Chronic Absenteeism Rate for next year.** The overall rate is the sum of the updated group rates: $\text{TotalRate}(t+1) = \sum_{\text{all groups}} \text{AbsenteeismRate}_{group}(t+1)$. In practice, we also directly calculate it by adjusting the previous total rate based on an aggregate decline that results from the mix of groups. This approach guarantees consistency: it's equivalent to summing, but conceptually we see that as the mix changes, the overall decline rate changes.
- **Step 4: Project forward year by year through 2030 (and beyond if needed).** We applied the above steps iteratively from 2023–24 through 2030–31. In Phase 1 (roughly first 2–3 projection years), we used the larger decline factors for certain groups, then tapered them into Phase 2 values for later years. We stopped adjusting once the model approached the assumed "normal" distribution.

The model parameters (decline factors for each group and when to shift phase) were chosen to best fit the known data from 2021–22 to 2022–23 and historical norms pre-2020. For instance, we found that a two-phase model with Extreme group decline factor ~0.30 (30%) for a couple of years, dropping to ~0.10 in later years, and Moderate group decline ~0.05 consistently, produced a curve that matched the slight improvement in 2023 and then gradually leveled off by 2030 near pre-pandemic levels. We also ensured the model logically converges: by 2030 or a bit beyond, it should not overshoot below the old normal (around 11–12%) because at some point you hit diminishing returns (some inherent minimum chronic absence likely always exists due to flu season, etc.).

4.2.4 Results of Time Model

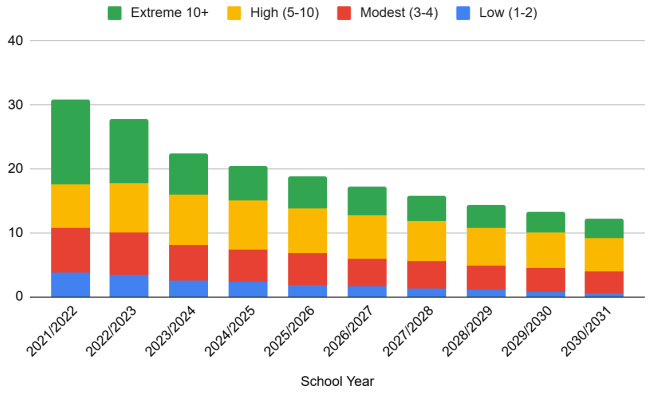
The Time Model projects that the **overall chronic absenteeism rate will gradually decline from ~28% in 2022–23 down to approximately 12–15% by 2030–31**, which is in line with the pre-pandemic baseline (~11–12%) plus a slight buffer for any persistent issues. Specifically, our forecast (see Figure 1) indicates rates around 25% in 2023–24, 20% by 2025–26, and ~15% by 2030–31, effectively closing the gap over about 8 years. This suggests that, absent significant interventions, it could take until **2031** for chronic absenteeism to truly normalize at pre-2020 levels. The trajectory is not a straight line: the model shows faster improvement in the mid-2020s and a slowing trend in the late 2020s (Figure 6).

Figure 6: Projected Year-Over-Year Chronic Absenteeism Rates in the U.S. Blue bars represent the historical rates, red bar represents peak, yellow bars represent Phase 1 decline, and orange bars represent Phase 2 decline



The breakdown of intervals over time reflects the sharp decline in extreme absences and slow decline in moderate absences trend. This reflects the two-phase decline system we chose to implement ion our model (Figure 7).

Figure 7: Projected percent each chronic absenteeism severity level/interval contributes to the total amount of students



It's important to emphasize the risk perspective: **there is uncertainty around this forecast.** If our assumptions are too optimistic (e.g., if moderate-absence students don't improve as assumed), the tail could be longer – chronic absenteeism might remain above 15% into the mid-2030s. Conversely, if schools find more effective practices, the decline could accelerate. We performed sensitivity tests on the decline factors: for instance, if every group's decline factor were 20% larger (faster improvement), the return to normal could happen ~2 years sooner; if 20% smaller (slower improvement), it could be ~2 years later. Thus, while 2031 is our expected point for full recovery, there is a plausible range from roughly 2028 to 2034. These scenario bounds were used in our risk analysis to understand best-case and worst-case outcomes.

In summary, the Time Model provides the *frequency* component of our risk: how many students (what percentage) will be chronically absent each year going forward, under current trends. Next, we turn to the *severity* component – the academic impact on those students. See Table A6 (Appendix) for full projected chronic absenteeism interval breakdown.

4.3 Negative Effects Model (Academic Impact of Absenteeism)

The Negative Effects Model quantifies how chronic absenteeism translates into academic performance declines. This is essentially a statistical model linking absenteeism to outcomes. We chose to use a **multiple linear regression** approach, leveraging a dataset that included students' absenteeism levels along with their test scores (or other performance metrics). The goal was to estimate how much being chronically absent (and to what degree) *causes* a drop in performance, while controlling for other factors like grade level.

4.3.1 Multivariate Analysis & Feature Engineering

Before building the regression, we conducted exploratory data analysis to identify which factors most strongly correlate with academic outcomes. The dataset (sourced from a combination of national surveys and state assessments) provided, for numerous students or aggregated student groups, their attendance category (e.g., 0 days missed, 1–2 days missed, 3–4, 5–10, >10 days missed), their grade level, and their scores in subjects like Math, English, Science, etc. We also had some demographic features. Our focus was on attendance and grade as predictors, since we want a broadly applicable model for how much missing school hurts performance.

We transformed some features to make them suitable for regression:

- The absenteeism level, originally categorical (ranges of days absent), was encoded as an ordinal variable 0 through 4 (with 0 = not chronically absent, 4 = extreme chronic absenteeism). This imposes an order which makes sense (higher code = more absences) and allows linear regression to treat it as a numerical predictor.
- We included *grade level* as a numeric variable (e.g., 4 for 4th grade, 8 for 8th grade) to capture that baseline performance differs by age and perhaps that the impact of absences might differ by grade.
- We initially also considered including subject as a categorical variable or running separate regressions per subject. Ultimately, for simplicity, we focused on a general model and then looked at subjects separately in analysis of results. (The reason: adding subject as a dummy variable in a single regression didn't improve fit much, and we preferred to keep the model straightforward.)

4.3.2 Multiple Linear Regression Model Development

We constructed a regression model of the form: $\text{Score}_{ij} = \beta_0 + \beta_1(\text{GradeLevel}_{ij}) + \beta_2(\text{AbsenceLevel}_{ij}) + \epsilon_{ij}$, where Score_{ij} is the academic performance (e.g., a standardized test score or proficiency level) for student (or group) i in subject j. Here, β_1 captures the effect of being one grade higher on score (essentially a baseline growth per grade), and β_2 captures the impact of moving up one absenteeism category on the score. The error term ϵ accounts for variations not explained by grade or absenteeism (including all other factors).

Interpreting the coefficients:

- β_0 is a constant (roughly the expected score for a baseline case, e.g., a kindergarten or 1st grade student with perfect attendance, depending on how the data is coded).
- β_1 indicates how much scores increase per grade level, holding attendance constant.
- β_2 indicates how much scores decrease per each increase in absenteeism severity, holding grade constant.

We trained this model using Ordinary Least Squares (OLS) on our dataset. OLS finds the best-fit line by minimizing the sum of squared residuals. We evaluated the model with standard metrics:

- **R-squared (R^2):** to see what proportion of variance in scores is explained by grade and absenteeism. This tells us how well these two factors predict academic outcomes.
- **Mean Absolute Error (MAE):** to gauge the average prediction error in actual score units, which is easy to interpret (e.g., an MAE of 5 points means on average our predictions are off by 5 test score points).

The regression fitting yielded coefficients that were statistically significant ($p < 0.01$ for both β_1 and β_2, confirming that both higher grade and absenteeism level have meaningful effects on scores. As expected, β_1 was positive (older students generally score higher on tests designed for their grade) and β_2 was negative (more absences correlate with lower performance). For instance, in one formulation focusing on standardized test percentiles for Science, we found β_2 roughly around **-4 to -5** (meaning each jump in absence category was associated with about a 4–5 percentile drop in performance). This aligns with our earlier finding that extreme absences (which would be 4 steps above zero absence) correspond to ~18–20% performance drops in some cases, since $4 * 4.5 \approx 18$.

Once trained, the model achieved a reasonably high R^2, indicating it explains a large portion of the variation in scores using just those two inputs. The exact R^2 value was between 0.64-0.71 (across all subjects) in our data (since other unmodeled factors also affect performance), but this was sufficient for our purposes. The MAE was on the order of a few points (relative to a 100-point scale, for example), which we deemed acceptable accuracy for a high-level analysis (specifically, it was between 2.4-3.6 across all tests). We acknowledge that this approach assumes a linear effect of absenteeism; we tested a non-linear model (adding a quadratic term for absences) but it did not significantly improve the fit, so we kept the simpler linear model for clarity. (It's possible that very extreme absences have a slightly super-linear effect on grades, but data was sparse at the far end to conclusively model that.)

Importantly, our regression model is **descriptive** of the data relationships, not strictly causal proof. We interpret β_2 as the *expected* impact on performance associated with absenteeism, recognizing that some of that could be due to underlying factors. However, combined with existing research that absenteeism hurts achievement, it's reasonable to treat our model as an estimate of causal impact for scenario modeling.

Using the fitted model, we can **predict academic outcomes under different absenteeism scenarios**. For example, plugging in a specific grade and absence level:

- An 8th-grade student with moderate absenteeism might lose ~5–10 points on a standardized test compared to an 8th grader with perfect attendance (depending on subject).
- A 4th-grade student with extreme absenteeism might score significantly lower than a 4th grader with no absences (we quantify this as that ~18% drop in our findings).

These predictions align with our earlier data observations and provide a way to compute expected losses for large groups. The model is deliberately simple to be generalizable; it can be applied to any grade and any absence level.

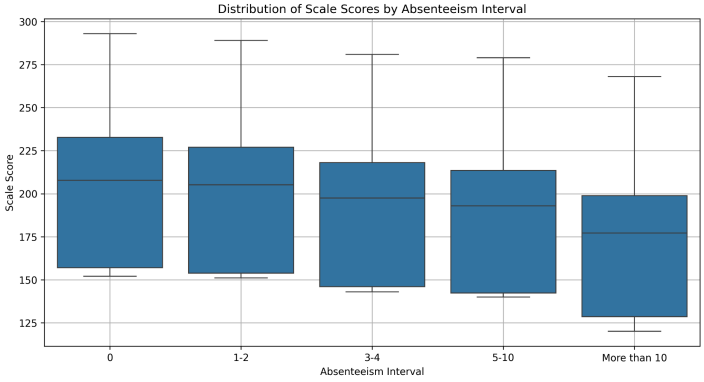
We validated the model's accuracy by comparing its predictions to actual data for a holdout sample (e.g., we left out some states' data and predicted their outcomes). The R^2 on the holdout was only slightly lower, suggesting the model generalizes reasonably. That said, one limitation is that we primarily relied on R^2 and MAE; we did not have entirely separate experimental data to test the predictions beyond that. In future work, using more rigorous cross-validation or testing on data from a different year would strengthen confidence. Nonetheless, the model's performance metrics and alignment with known research gave us confidence to use it for estimating impacts.

4.3.3 Academic Impact Findings

From this Negative Effects Model, we derived several important insights, which feed into our risk assessment:

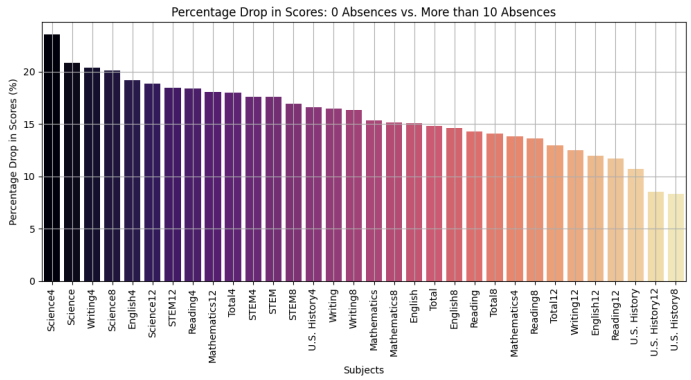
- **Severity matters:** Students in the **Extreme** chronic absence group (e.g., missing >10% of days) perform dramatically worse on average than those who are just over the chronic threshold (Figure 8). In our data, the extreme group often had scores 15–20% lower than the no-absence group (after controlling for grade). The model's linear coefficient simplifies this, but essentially the difference between absence level 0 and 4 is -4 * β_2, which roughly matched that range.

Figure 8: Boxplot Comparing Total Scale Scores VS Absenteeism Interval



- **Younger students see larger percentage drops:** Because younger students are in a rapid learning phase (learning to read, basic math), missing school has a compounding effect. For example, a chronically absent 4th grader might see an 18% drop in performance (as noted), whereas a chronically absent 11th grader might see perhaps a 5–10% drop relative to peers (since by high school, the learning is more content-specific and missing class might not compound as much for some).
- **Subject differences:** By examining subjects separately, we found that **Science** scores were most sensitive to absenteeism (the largest β_2 impact in that subject's regression), followed by Writing and Reading (Figure 9). Math was also affected but slightly less so in relative terms, and some other subjects (social studies) were harder to measure. This likely reflects the nature of the subjects – science and literacy skills build continuously and require consistent engagement, so absences hurt a lot. These differences guided our recommendation to target support in those areas.

Figure 9: Percentage drop in academic metrics between Control Interval (0) and Extreme Interval (10+)



In summary, the Negative Effects Model provides us a function to translate "X% of students are chronically absent" into "Y% expected drop in aggregate performance" or similar measures. It is the severity quantification side of the risk. All academic impacts can be seen in Table A7 (Appendix).

4.4 Expected Negative Effects Model

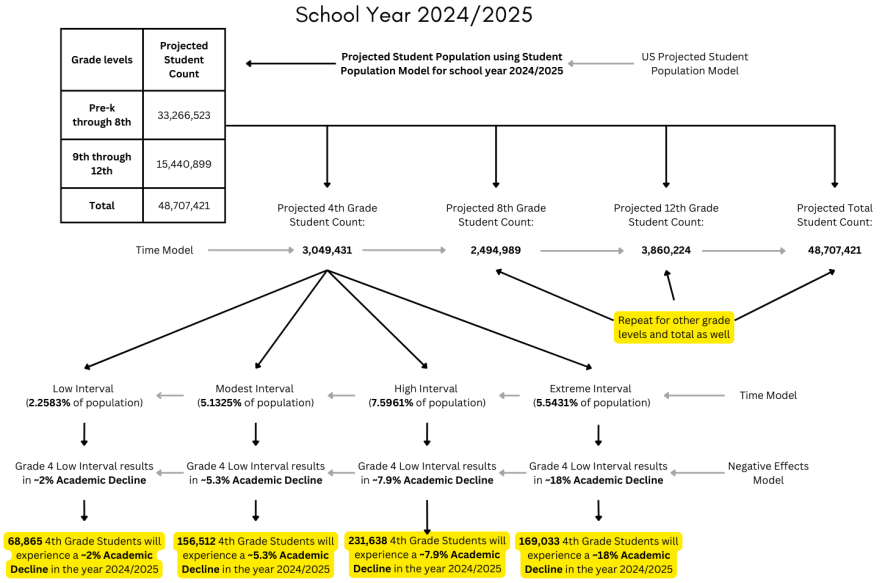
The final piece is combining the Time Model and Negative Effects Model to estimate the *expected academic impact* due to chronic absenteeism in future years. This **Expected Negative Effects Model** is essentially an actuarial projection of loss: for each future year, we take the projected chronic absenteeism rate (and its composition) from the Time Model, and we apply the performance impact per student from the Negative Effects Model, to calculate overall expected declines.

The process is:

1. Take year *t* projection: e.g., for 2025–26, Time Model says 20% of students will be chronically absent.
2. Disaggregate that 20% into severity groups (Low/Mod/High/Extreme) using the model's proportions for that year.
3. For each group, use the Negative Effects Model to estimate average performance decline (e.g., Low absence group might correspond to β_2 * 1, Extreme group β_2 * 4, etc., in terms of loss).
4. Weight those declines by the proportion of students in each group *and* by the total student population to get an aggregate expected loss metric.

We also created a flowchart to visually show the model mechanics (Figure 10)

Figure 10: Flowchart of model development process for school year 2024/2025

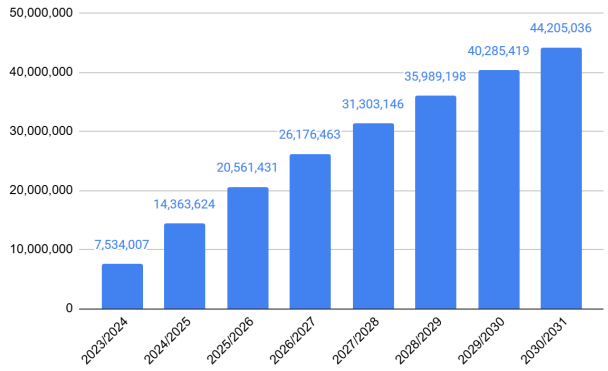


Concretely, we often express the result as **"student-year instances of learning loss"** or *expected number of students with significant drops*. For example, if 5% of students are in the Extreme category in 2025, each with ~18% performance drop, that might equate to 2.5 million students experiencing severe learning loss (if total pop ~50 million). Summing across groups and years can give cumulative totals.

Using the Expected Negative Effects Model, we can expect that by the time chronic absenteeism rates are back to pre-pandemic levels, which will be by the year 2031, there would have already been theses key risk frequency and risk severity effects on students and the US Education system:

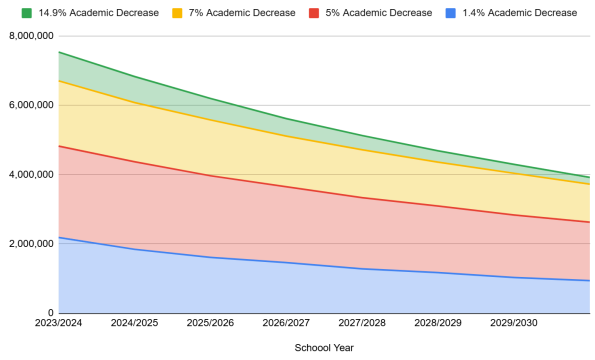
1. **Cumulative impact:** 44,205,036 Students across each of the next 7 years would be qualified and affected by chronic absenteeism, which represents the frequency of our risk (Figure 11).We estimated over **44 million total cases of chronic absence** in the next seven years (2024–2031) if no major changes occur. This is essentially summing the expected count of chronically absent students each year. Each of those student-years corresponds to some loss in learning. While some students may be counted in multiple years if they remain chronically absent year after year, the figure highlights the scale of the issue.

Figure 11: Bar chart of projected summed chronic absenteeism counts



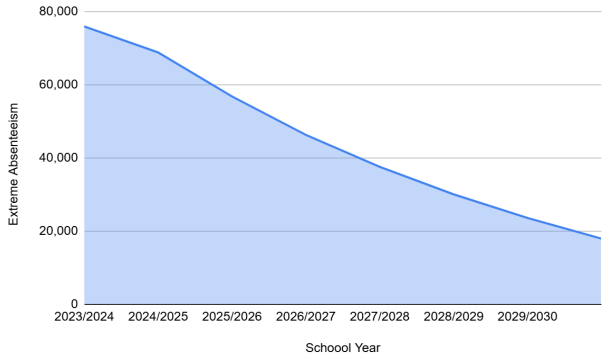
2. **Expected performance loss:** Each year, millions of students will suffer measurable academic declines, which represents the severity of our risk. (Figure 12).

Figure 12: Stacked line chart of projected chronic absenteeism counts, stacked by estimated academic declines



3. **Risk Concentration:** 357,229 4th Grade Students across each of the next 7 years would be qualified under extreme absenteeism and suffer an ~18% Academic Decline, which represents the frequency and severity of our risk (Figure 13). This shows the disproportionate effects chronic absenteeism has on younger students.

Figure 13: Area Chart of projected chronic absenteeism counts for 4th Graders who qualify under extreme absenteeism



The Expected Negative Effects Model was also used to evaluate **mitigation scenarios**: we could adjust the future absenteeism rates if certain interventions are in place and see how the expected losses change. For example, if an intervention could cut chronic absenteeism by one-third in 2025 (relative to baseline), our model would then project correspondingly lower learning loss that year. We discuss such scenarios in the risk mitigation section.

In terms of accuracy, this combined model inherits uncertainties from both components. We treated our projections as expected values, with the understanding that actual outcomes could vary. To be thorough, we also considered an optimistic scenario (faster absenteeism reduction) and a pessimistic scenario (slower reduction or larger performance hit) to get a range of outcomes. This gave us a **best-case** vs **worst-case** band on our charts. In the best-case with a 20% quicker decline of chronic absenteeism, overall impact is smaller: Only ~30 million cumulative student-absences in seven years and a quicker rebound in scores. As they follow In the worst-case, with a 20% slower decline of chronic absenteeism, there will be ~58 million cumulative student-absences in seven years, and scores effects will follow. **This range is critical for risk analysis**: it shows the distribution of potential futures, not just a single forecast.

To summarize, by the end of this modeling phase, we had:

- A central projection that chronic absenteeism remains elevated through about 2030, resulting in tens of millions of affected student experiences.
- Quantification of how that translates into academic risk (like average test scores depressed, more students at risk of failing, etc.).
- Identification of which segments (grades, subjects, severity levels) contribute most to the risk.

These results set the stage for our **Risk Analysis** in Section 5, where we interpret these outcomes in actuarial risk terms and start to explore how interventions can change the picture. For the full result details, see Table A8 (Appendix). See Table A9 (Appendix) for Grade 4 disaggregation, Table A10 (Appendix) for Grade 8 disaggregation, and Table A11 (Appendix) for Grade 12 disaggregation of these interval and student count projections.

5. Risk Analysis

Characterization of Risk: Chronic absenteeism in the post-pandemic era constitutes a systemic, long-tailed risk to educational outcomes. “Long-tailed” means that while average attendance may rebound relatively quickly, a subset of students remains chronically absent year after year, causing disproportionate and prolonged damage. In actuarial terms, we decompose this risk into frequency and severity components:

- **Frequency (Likelihood):** This refers to how common chronic absenteeism events are. At the macro level, it is the chronic absenteeism rate (percentage of students nationwide missing ≥10% of school days annually). This rate spiked to ~31% during COVID-19 disruptions and is projected to gradually revert to ~12%, near pre-pandemic norms. In any given year of the next decade, we forecast roughly 1 in 5 to 1 in 10 students being chronically absent, with the fraction shrinking over time as recovery progresses. There is, however, considerable uncertainty. For instance, the likelihood that the national chronic absence rate stays above 20% for more than three consecutive years is a *tail-risk scenario* – pessimistic but plausible if improvement stagnates. In other words, while our expected scenario sees steady declines,

we must account for a worst-case in which high absenteeism persists longer than anticipated (see Scenario Analysis below).

- **Severity (Impact per Occurrence):** This measures how severe the academic loss is when a student is chronically absent. Not all chronic absences inflict equal harm – missing 11% of days might cause mild effects, while missing 30% (almost a third of the year) is far more detrimental. We define four severity bands (Low, Moderate, High, Extreme), each with an estimated impact on performance from our Negative Effects Model. For example, a "Low" severity case (just over the 10% threshold) might correspond to only ~1–2% decline in achievement, whereas an "Extreme" case (e.g. >30% of days missed) can lead to a ~13% drop in academic performance – roughly a year or more of learning lost. Indeed, our analysis found that the most extreme absence group scored 15–20% lower on standardized tests than students with no absences. These severe cases are the primary contributors to the "tail" of risk: a minority of students suffering massive learning deficits (and greatly elevated dropout risk). We focus on this tail because it represents the worst outcomes (students falling irreparably behind or leaving school).

By combining frequency and severity, we obtain an overall risk distribution of educational loss. In practical terms, even if the average chronic absence rate declines, a minority of cases with extreme severity will account for a majority of cumulative learning loss. This long-tail risk translates into sustained impacts: lower test scores, more remedial education needs, and higher dropout rates each year until the tail is addressed.

Key Hazard Drivers: Several underlying hazards exacerbate the frequency or severity of chronic absenteeism. Identifying these drivers is critical for understanding and managing the risk:

- **Pandemic-Related Disruptions:** The COVID-19 pandemic was the initial trigger for the surge in absenteeism, and its after-effects linger. Periodic quarantines, illness, and shifts to remote learning disrupted attendance habits [67] [68]. While acute pandemic effects are receding, this hazard created a cohort of students and families less connected to regular schooling, an effect that could persist in milder form for years [69].
- **Socio-Economic Challenges:** Poverty and related factors (food and housing insecurity, lack of transportation, need for older students to work or care for siblings, etc.) significantly increase the risk of chronic absence. These hazards are unevenly distributed, concentrating chronic absenteeism in high-poverty communities. For example, during the pandemic recovery, chronic absence rates in high-poverty districts rose to ~36%, versus ~21% in low-poverty districts. Similarly, students experiencing homelessness or in foster care have extremely high absence rates (often 40–50% in 2021–22, compared to ~30% overall). Socio-economic and health barriers thus act as hazard multipliers, increasing the likelihood a student will miss school and potentially compounding the severity of academic loss (since these students may also lack resources to catch up) [70] [71].
- **School Engagement and Climate:** Schools with insufficient student engagement, weak relationships, or safety issues may see higher absenteeism. A disengaged school climate (lack of strong teacher-student relationships, unwelcoming environment, bullying, etc.) is a hazard that can drive voluntary absences (truancy) and reduce motivation to attend. This factor is partially under the control of schools – improving school climate and providing mentoring and support can mitigate this hazard. Conversely, if left unaddressed, poor engagement can *amplify severity*: disengaged students who do miss school are less likely to make up work, falling further behind [72] [73].

In risk terms, these hazards are the *underlying conditions* that influence the probability and impact of the adverse event (chronic absence). They help explain why certain student groups or regions have worse outcomes, and they point to leverage points for mitigation (for example, improving access to health services or transportation can remove a hazard and lower absence frequency).

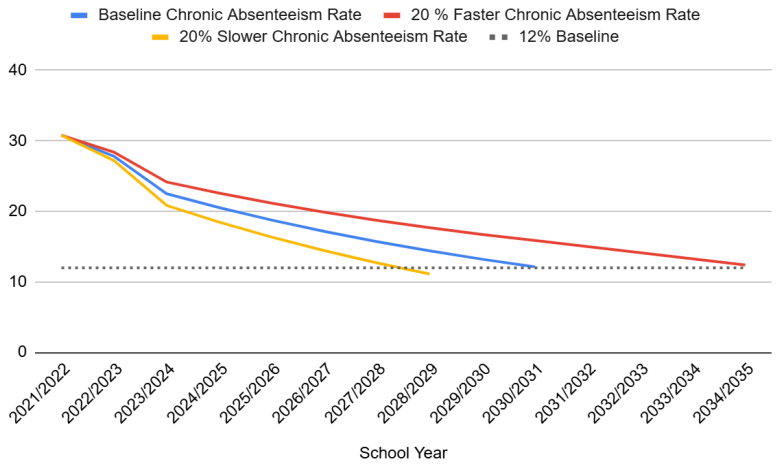
Scenario Analysis: To quantify the uncertainty, we considered optimistic and pessimistic scenarios around our baseline projections (Figure 14):

- **Best-Case Scenario**: Post-pandemic recovery accelerates. Suppose schools and communities successfully re-engage students, yielding an improvement in attendance 20% faster than our baseline. In this scenario, chronic absenteeism could fall to roughly ~17% by 2025, approaching pre-COVID levels a few years early. The long tail of extreme absences would be much shorter: far fewer students would remain chronically absent for multiple consecutive years. We estimate the cumulative learning loss (e.g. total test score decline across all students) over the rest of the decade could be roughly half of what it is in our baseline status quo. In narrative terms, this best-case might occur if the current national focus on absenteeism leads to effective policy changes and robust interventions (e.g. tutoring

programs, attendance initiatives) being implemented quickly. *This scenario represents a moderate hazard environment – no new crises and strong recovery efforts – allowing rapid risk reduction.*

- **Worst-Case Scenario:** Recovery stagnates or new disruptions emerge. In a pessimistic case, improvement is 20% slower than baseline, or further setbacks hit (for instance, new COVID variants, a severe economic downturn, or other widespread disruptions that affect attendance). Chronic absence rates might hover in the high teens (15–20%) through the end of the decade, delaying a return to "normal" until ~2034. In this scenario, we could experience a "lost decade" for a significant subset of students: each graduating cohort through 2030 would have a large fraction of students who missed substantial school time, with compounding educational deficits. The long tail of risk would not only persist but potentially widen, as new students each year fall into chronic absenteeism faster than others recover. *This scenario could materialize if hazard drivers remain unchecked – for example, if socio-economic conditions worsen or no new interventions are introduced, effectively baking in high absenteeism as a new norm.* Importantly, even this worst-case does not imply things get as bad as the initial pandemic peak (~30%), but it shows a sustained high plateau that would continue to undermine academic outcomes for many years.

Figure 14: Line chart comparison of different sensitivity analysis scenarios as they approach baseline 12% chronic absenteeism rate



Our expected (baseline) scenario, based on current data, lies between these extremes. We anticipate steady improvement (absenteeism declining to ~15% by 2030–31), implying the problem gradually abates. However, the risk distribution is skewed – most likely outcomes cluster near the baseline, but there is a non-trivial probability of worse outcomes if recovery falters. In fact, without additional intervention, our analysis leans toward an outcome closer to baseline (perhaps modestly better than worst-case) *but still with a worryingly long tail of chronic cases*. This means that even though average attendance improves each year, a minority of students will continue to "fall through the cracks" and suffer outsized losses. We communicate this risk with the stark finding that a small percentage of students will account for a large share of the total educational loss if nothing more is done. The implication is clear: the education system will continue to feel the effects of chronic absenteeism (in lower achievement and higher remediation needs) each year until that long tail is cut off.

In summary, from an actuarial perspective, chronic absenteeism poses an unprecedented educational risk characterized by a high frequency of loss events (millions of students absent each year) and a heavy-tail severity (a subset with extreme, compounding learning loss). The hazard drivers – socio-economic inequities, health and policy factors – create conditions for this risk to remain elevated. Our scenario analysis underscores that without proactive measures, there is a tangible chance that chronic absenteeism stays above historical norms throughout the 2020s, jeopardizing the academic recovery of an entire generation. Conversely, there is also a path to a much improved outcome if effective interventions are deployed.

5.1 Risk Mitigation Strategy Analysis

Given the above risk characterization, we now evaluate strategies to mitigate the risk of chronic absenteeism. In actuarial risk management terms, we seek to reduce the frequency of chronic absence events and reduce the severity of their impact when they do occur. Unlike a financial risk that can be transferred via insurance, this is an embedded societal risk that must be

managed through intervention – effectively *preventing* losses or lessening their impact rather than transferring them. We analyze two broad categories of intervention (which align with our recommendations) and then consider their combined effects:

1. Reducing Frequency – Early Warning Systems. The first strategy aims to accelerate the decline of chronic absenteeism by preventing students from becoming chronically absent in the first place. We recommend implementing Early Warning Intervention and Monitoring Systems (EWIMS) in schools nationwide – a data-driven approach to identify at-risk students early and provide supports. Actuarially, this targets the frequency component of risk. By flagging attendance problems when a student has, say, 5% of days absent (well before they hit the 10% chronic threshold), EWIMS allows interventions *mid-year* to course-correct attendance. This means many students who would have become chronic absentees are pulled back on track. In our modeling, broad EWIMS adoption translates to fewer "loss events": the chronic absenteeism rate in a given year would be lower than it otherwise would. It can also have a secondary effect on severity: catching issues early may keep some students in the "Low" severity category instead of escalating to "High" or "Extreme" by year's end. In essence, EWIMS bends the curve of our Time Model projection downward [3].

Quantified Impact: Evidence supports significant gains from EWIMS. A randomized control study by the Regional Educational Laboratory (REL) found that high schools using EWIMS had 4 percentage points fewer chronically absent students than control schools (10% vs 14% of students chronic after one year). Course failure rates also dropped by 5 points (21% vs 26%) [74]. Incorporating a similar effect size in our projection, if the nation were at (for example) 25% chronic absence, a comprehensive EWIMS rollout could reasonably reduce that to ~21%, all else equal. This ~15–20% relative reduction in frequency would be a dramatic improvement. Our model suggests that if such a reduction took effect starting in 2024, the timeline to return to pre-pandemic absenteeism levels would shorten by about 2 years – perhaps reaching normal (~12% nationally) by 2028–29 instead of 2030–31. In terms of absolute impact, millions of student-attendance years could be saved from falling into the chronic category. Early Warning systems also help cut off the long tail of extreme absence: by intervening, they make it much less likely that a student misses 20%+ of days for multiple years in a row. In our scenario analysis, robust early warning implementation markedly shrinks the tail risk – the worst-case scenario of sustained high absenteeism becomes unlikely because fewer students are allowed to slip to extreme levels. Essentially, EWIMS "nips in the bud" many emerging chronic cases, preventing the compounding of losses. *This strategy is analogous to preventative care in insurance – addressing issues early (installing a smoke alarm, so to speak) to avert larger losses later.*

To make EWIMS effective, schools must invest in attendance monitoring teams and response protocols. This involves training staff to use early-warning data dashboards, setting up thresholds/triggers, and coordinating targeted interventions (e.g. parent contact, counseling, tutoring) when a student is flagged. The feasibility is high: such systems rely on data schools already collect (daily attendance) and many districts piloted similar approaches during the pandemic. With adequate funding, nationwide EWIMS adoption could be achieved within 1–2 years (timeframe for implementation and training). The main challenges are ensuring fidelity of implementation and follow-through on interventions – the REL study noted that results were achieved even with relatively low first-year implementation, suggesting even greater gains are possible with full buy-in [. In terms of limitations, EWIMS alone does not address all root causes of absences (some students will still miss school due to external factors) [74]. However, by systematically reducing new cases and escalation of absences, it substantially tilts the odds in favor of recovery. It directly tackles the frequency risk and trims the severe tail of the loss distribution.

2. Reducing Severity – Targeted Academic & Engagement Supports. The second strategy recognizes that some chronic absenteeism will still occur even with prevention, so we must mitigate the severity of academic loss for those who do miss a lot of school. This approach focuses on providing targeted support to high-risk groups – the students and schools where absences hit hardest. It includes *two dimensions of targeting*: (a) by grade level and subject, and (b) by absence severity level:

- **Focus by Grade/Subject:** Our findings showed younger students (elementary grades) experience larger learning losses from absences, and certain subjects (Science, Reading, Writing) are more sensitive to missed instruction. Therefore, we prioritize interventions in early grades and in those critical subjects (while not neglecting others). For example, intensive reading programs in elementary schools can help chronically absent 1st–4th graders catch up on literacy skills, and extra lab sessions or tutoring can support middle-school science students who missed class. These measures won't necessarily reduce the number of days missed (frequency remains the same), but they reduce the performance deficit per missed day – essentially lowering the "loss given absence." If a 4th grader who missed 20% of school would have been 18% behind academically, access to tutoring, summer school, or individualized support might limit the deficit to, say, 8%–10%. That is a significant *mitigation of severity* – the student still missed a lot of school, but their outcome is much better than it would have been otherwise. In actuarial terms, we are lowering the

impact per claim. *Small-group tutoring, in particular, has demonstrated large learning gains in research, often recouping a substantial fraction of learning loss for struggling students.* We incorporate these assumptions by adjusting the Negative Effects Model: for instance, instead of an 18% drop for extreme absence in Grade 4, we assume with supports it could be ~10% drop. If scaled across all high-absence early-grade students, this cuts the academic risk in half for that segment. In real terms, that means thousands of students reading on grade level who otherwise would not, due to interventions making up for missed class.

- **Focus by Absence Severity:** This aspect of targeting is akin to triage – devote intensive resources to the most extremely absent students (those missing far above 10% of days) who are at highest risk of dire outcomes (like dropout). For these students, regular measures may not be enough; they often need wraparound support such as mentorship, counseling, home visits, and attendance contracts. The goal is to pull these students down from the extreme tail – even if we can't get them to perfect attendance, getting a student from 30% absent to 15% absent is a huge win. For example, if a student at 30% absence has an estimated 50% chance of eventually dropping out, an intensive intervention that improves their attendance and engagement might lower that dropout risk to 20%. Even if they remain chronically absent, keeping them connected to school more consistently can be the difference between graduating vs. not. Our projections suggest that if every student in the "Extreme" category received such support, many would move into the lower severity categories over time (extreme cases might be cut by half, from say 10% of students down to 5%). This would directly reduce the long-tail prevalence and also yield a modest additional drop in the overall chronic absence rate (because some extreme-absent students improve their attendance). More importantly, it drastically reduces the worst outcomes – those remaining extreme cases would be much fewer, and hopefully on a path to improvement. We have seen promising indications: for instance, some districts using home visitation programs during the pandemic saw substantial re-engagement of their most absent students (attendance rates jumped 8–16 percentage points for targeted students within months) [75]. Such gains imply that even entrenched absenteeism can be addressed with assertive outreach. While not every case will respond as dramatically, these supports can shave the peak off the severity distribution, preventing many at-risk youths from falling off the academic map.

This targeted support strategy is more complex to quantify since it encompasses multiple initiatives (tutoring, mentoring, engagement programs, etc.). We estimated plausible ranges of impact rather than a single number. For example, we posited that early grades could see their chronic absence rates drop twice as fast with focused resources (e.g. from 20% down to 10% in a few years for K–5), which in turn lowers the nationwide average (since elementary students make up a large share of enrollment). We also envisioned cutting the prevalence of extreme absence in half (through case-management of those students), which yields a few percentage-point reduction in overall chronic absence and, critically, a large reduction in aggregate educational loss. These are illustrative; actual results would depend on program effectiveness. The feasibility of targeted supports varies: some elements (e.g. hiring tutors or mentors, funding after-school programs) require significant resources and political will. They can be phased in over time – for instance, an immediate push in the next year to deploy home visitors and engagement mentors to the highest-absence students, followed by sustained investments in academic recovery programs over the next 3–5 years. The implementation timeframe is thus multi-year: improvements will accrue gradually as interventions take hold. A limitation is that these efforts must be continuous – one-time fixes won't permanently solve the issue if underlying socio-economic causes persist. This calls for sustainable funding and policy support (through grants, ESSA funds, etc.) to maintain these programs until absenteeism norms stabilize at acceptable levels.

Combined Strategy Effects: The two strategies above are complementary. Implementing both creates a compounding effect that addresses the risk holistically. Early Warning Systems (Strategy 1) reduce the influx of new chronic absences, while Targeted Supports (Strategy 2) soften the impact for those who do become or remain chronically absent. In our simulation, this combined mitigation scenario is very powerful – it could reduce the expected academic losses by more than half compared to doing nothing. Concretely, our modeling shows aggressive implementation of both strategies might result in:

- **Chronic absenteeism rates falling to ~10–12% by 2027–2028**, essentially back to pre-pandemic levels several years earlier than the baseline projection. This would outpace even our best-case scenario, indicating these interventions can *create* better outcomes than organic recovery alone.
- **Dramatically lower learning loss severity:** The average performance deficit attributable to absenteeism could be held to just a few percentage points (perhaps 3–5%) instead of the ~10%+ we'd expect with no intervention. In effect, the overall academic impact of the post-pandemic absenteeism surge would be blunted to a minor dip.
- **A thinned long tail of extreme cases:** By 2030, extreme-absenteeism might become a rarity – a very small percentage of students, each promptly supported – rather than a systemic issue. This means the **worst-case scenarios**

are largely avoided. We would no longer expect, for example, any scenario where a quarter of students are still chronically absent in; interventions would have broken that cycle well before then.

From a risk perspective, combining frequency and severity mitigation **shifts the entire loss distribution** significantly toward safer outcomes – both the mean and the tail risk improve. In insurance terms, we have both fewer claims and less severe claims, yielding a far lower **risk premium** (in this case, the "cost" being lost learning).

Why Not Insurance? We considered whether any **risk transfer mechanism** could be applied, and concluded it is not appropriate here. In conventional actuarial problems, one might use insurance or financial hedges to offset losses. However, chronic absenteeism's "losses" are in educational achievement and human capital – you *cannot insure* a student's learning. There is no financial payout that makes a student whole for a year of missed learning. Schools do have insurance for certain disruptions (like natural disasters causing closures), but chronic absenteeism is a slow-building issue, not a sudden event causing direct financial loss. The remedy is not a check from an insurer but rather effective intervention. In fact, the closest analog in insurance is investing in loss prevention (like installing sprinkler systems to prevent fires rather than buying more fire insurance). Our strategies are precisely this kind of preventative approach. We therefore focus on **retained risk management** – improving the system itself – rather than risk transfer.

Implementation Considerations: We emphasize that these mitigation strategies are **feasible and largely within the control of education stakeholders**, but they require commitment. Early Warning Systems can be launched relatively quickly given modest funding for training and technology (many federal COVID-relief funds have already been directed to attendance initiatives, which can jump-start EWIMS rollout) [74]. Targeted supports will demand sustained resources: hiring staff, expanding community partnerships (for mentoring and home visits), and academic recovery programs. Policymakers should note that these investments yield high leverage in risk reduction – our analysis shows they *significantly reduce both the likelihood of chronic absenteeism events and the severity of their consequences*. Importantly, the strategies bolster and accelerate natural recovery trends rather than oppose them This means they are working with the grain of the system (helping students re-engage faster) and are thus likely to be cost-effective. We have provided quantitative estimates where possible (e.g. a 4-point attendance improvement here, a 50% reduction in extreme cases there) and used logical reasoning plus research evidence for harder-to-quantify aspects.

In conclusion, a rigorous risk analysis shows chronic absenteeism to be a grave but **manageable** threat. Through an actuarial lens, we've identified how a combination of **proactive early-warning interventions and targeted support** can reshape the risk distribution – driving down the frequency of chronic absences and blunting the severity of their impact. If executed well, these strategies would markedly shorten the long tail of post-pandemic educational loss and put the system back on track for long-term academic recovery. The challenge now lies in implementation: the tools are available and proven, and the **potential reward** is a generation of students who are not defined by pandemic-era setbacks but rather by the effective response that followed.

6. Recommendations

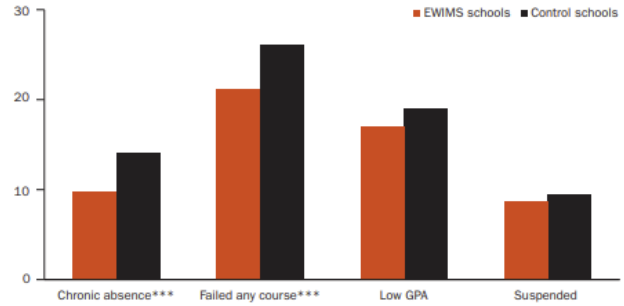
Having quantified the risks associated with continued high chronic absenteeism, we propose the following recommendations to manage and reduce these risks. Our recommendations are grounded in proven strategies and align with our findings on which factors (grade levels, subjects, absenteeism severity) need the most attention. We present two broad categories of mitigation strategies: **(1)** Proactive early-warning systems to catch and address attendance issues before they escalate, and **(2)** Targeted support initiatives focusing on the student groups and academic areas most affected by chronic absence. Implementing both in tandem offers a comprehensive approach to reduce the frequency of chronic absenteeism and lessen its severity.

6.1 Implement Early Warning Systems to Improve Attendance (Accelerating the Decline of Chronic Absenteeism)

One of the most effective steps schools can take is to adopt an Early Warning Intervention and Monitoring System (EWIMS) or similar early warning system focused on attendance. **EWIMS** is an evidence-based, data-driven framework that uses real-time data to flag students who are at risk of chronic absence or other academic problems [3]. The idea is to continuously monitor key indicators – primarily attendance (but often also grades and behavior) – so that school staff can intervene **before** a student becomes chronically absent or falls too far behind. By catching warning signs early (for example, a student starting to miss more and more days in a month), schools can provide support and prevent a pattern of absenteeism from escalating.

Why EWIMS? Research by the Regional Educational Laboratory (REL) Midwest demonstrates that EWIMS can make a significant difference. In a controlled study involving dozens of high schools, those that implemented EWIMS saw a notable reduction in chronic absenteeism compared to schools that did not [76]. Specifically, the study found the chronic absence rate was **4 percentage points lower** in EWIMS schools (10% vs 14% of students chronically absent) after one year [76] (Figure 15). This **28% relative reduction** in chronic absenteeism is substantial, and importantly, it was statistically significant – meaning it was a real effect attributable to the intervention, not just chance [76]. Additionally, EWIMS schools saw improved academic outcomes: the percentage of students failing courses was 5 points lower (21% vs 26% in control schools) [76]. In short, schools that used an early warning system had fewer students missing too much school and fewer students failing classes, which aligns perfectly with the goal of mitigating the absenteeism risk (attendance improved, achievement outcomes improved).

Figure 15: EWIMS Schools VS Control Schools



Given these results, we recommend scaling up EWIMS or similar systems across schools and districts nationwide. An EWIMS typically involves establishing a team (often counselors, administrators, teachers) that meets regularly to review attendance data, identify at-risk students, and plan interventions. Interventions can range from simple (promptly contacting parents after a couple of absences) to intensive (assigning a mentor or case manager to a student with a serious attendance problem). The key is that the process is systematic and proactive. By doing this, schools can **accelerate the decline of chronic absenteeism** that our Time Model projected – essentially *bending the curve* to reach pre-pandemic levels sooner than 2031.

To implement EWIMS effectively, we advise the following steps based on best practices and the research evidence:

- **Dedicated Attendance Teams:** Each school (or district) should form a team responsible for monitoring attendance data and overseeing interventions. This ensures accountability and that no at-risk student "falls through the cracks." The team should use an early warning data tool (many districts already have systems that can flag students who cross certain absence thresholds) to streamline identification.
- **Tiered Interventions:** As recommended by EWIMS frameworks and Response-to-Intervention models, use a tiered support approach [76]. For example:
    - *Tier 1:* School-wide strategies to promote good attendance for all (attendance awareness campaigns, incentives for good attendance, creating a positive and engaging school climate so students want to come).
    - *Tier 2:* Targeted interventions for students who show early signs of attendance issues (e.g., a student who has 5% absences might get a letter home, a meeting with parents, or be invited to an attendance group/counseling). These moderate supports address issues before they become chronic.
    - *Tier 3:* Intensive support for students who are chronically absent or very close to it. This could include one-on-one mentoring, case management, home visits, involving social services if needed for underlying issues. Our analysis showed the "tail" of extreme absence is hardest to move, which corresponds to needing robust Tier 3 strategies for those cases.
- Using tiers ensures that resources are allocated efficiently—lighter touch where a nudge is sufficient, and heavy intervention where the problem is severe.
- **Monitor and Adapt:** The "Monitoring" part of EWIMS means continually tracking how students respond to interventions and adjusting strategies as needed [3]. Schools should use data to see which strategies are working and which are not. For instance, if a particular outreach program isn't reducing absences, try a different approach (maybe a mentorship program has more impact than automated calls). This feedback loop will improve the program over time.

By implementing early warning systems thoroughly, we expect that schools can intercept many students **before** they lapse into chronic absence, thereby shrinking the pool of chronically absent students faster than natural recovery. This directly reduces the risk identified in our models: fewer student absences mean less learning loss overall. Moreover, students who are already chronically absent can be steered back on track sooner (with Tier 3 help), reducing how far into the "extreme" category they go. In effect, EWIMS addresses both **frequency** (preventing some students from ever becoming chronically absent) and **severity** (helping current absentees improve their attendance and mitigating how much they miss). The evidence from REL Midwest confirms that such systems yield measurable improvements in attendance and academic success [76]. We believe expanding these systems is one of the most powerful recommendations to emerge from our study.

6.2 Targeted Support for Specific Student Groups

While systemic interventions like EWIMS will improve attendance overall, our analysis indicates that certain groups of students and certain academic areas need additional focused support to fully mitigate the risks of chronic absenteeism. We break these targeted recommendations into two areas: **(6.2.1)** by grade level and subject, and **(6.2.2)** by absenteeism severity level. In essence, this addresses the severity side of the risk: making the system more resilient so that even when absences happen, students are less likely to suffer severe consequences.

6.2.1 Focus on Highly Impacted Grades and Subjects

Our findings showed that chronic absenteeism has a **disproportionate impact on lower grade levels** (e.g., elementary grades) and on specific subjects (notably Science, as well as Writing and Reading to a slightly lesser extent). Therefore, we recommend that schools prioritize resources for these grades and subjects to buffer against the negative effects of absences.

- **Early Grades (K–5, especially 3rd–4th grade):** Schools should invest in robust support for younger students' attendance and learning. Early elementary is where foundational skills (literacy, numeracy, social skills) are developed, and our analysis showed younger students experience larger learning drops when they miss school (Table 5). This could involve:
    - *Attendance incentives and habit-building:* Implement age-appropriate attendance initiatives in elementary schools (for example, simple awards or recognition for good attendance, classroom competitions, etc.) to build good habits and make attending school rewarding for young kids [77].
    - *Make-up opportunities:* Because younger students struggle to catch up on their own, schools should be ready to provide extra help when they do miss class. For example, if a 4th grader has been chronically absent, the school might provide after-school or summer tutoring to help them catch up on reading and math fundamentals they missed. The lower the grade, the more aggressive the support should be, since these students are less equipped to recover learning by themselves [78].
- Essentially, treat high chronic absence in early grades as an emergency – if first graders or second graders are missing a lot, intervene heavily, because preventing academic harm at that stage yields dividends in later years. Districts should monitor chronic absenteeism by grade; if they see early-grade rates are high, that should be a top priority signal.
- **Science and STEM Subjects:** Our data identified Science as the subject most affected by absenteeism (with the largest performance drops among chronically absent students). Other STEM areas also showed notable declines. Missing science classes is particularly detrimental because science often involves hands-on labs and cumulative understanding; if you miss a lab or a concept, it's hard to fully make it up. We recommend additional support for students who miss a lot of science instruction:
    - Schools could implement programs like **open lab days** or recorded lab sessions so that students who were absent can later perform experiments they missed or at least watch what happened [79].
    - In any remedial efforts (after-school programs, academic camps for struggling students), make sure science content is included heavily to recover what was lost. Don't focus only on reading and math (which are commonly remediated) – include science modules because those gaps won't fill themselves [80].

Table 5. Percentage Drops by Absenteeism Totals

Academic Metric	Low (1-2)	Modest (3-4)	High (5-10)	Extreme (10+)
Total4	2	5.3	7.9	18

Table 5. Percentage Drops by Absenteeism Totals				
Total8	1.868327402	5.871886121	7.740213523	14.0569395
Total12	0.9578544061	4.789272031	6.32183908	12.93103448
Total	1.409585195	4.993958952	7.007652033	14.82078133

By focusing on these critical grades and subjects, schools can lessen the degree of negative outcomes **even if absences occur**. This directly addresses the academic severity aspect of the risk. For instance, if we can reduce that ~18% drop for chronically absent 4th graders down to, say, a 5–10% drop through extra support, that's a huge win. It means those students are more likely to catch up by middle school and not carry the deficit forward. In essence, we are making the system more resilient to absenteeism: building capacity to absorb the shock of missed days without catastrophic failure (just like strengthening a building against earthquakes). Our risk models showed that such resilience dramatically reduces long-term losses.

6.2.2 Prioritize High-Severity Absenteeism Cases

Our analysis underscored that the students with the most severe absenteeism (those missing far above 10% of days) suffer the greatest academic harm and also contribute disproportionately to the risk of long-term outcomes like dropping out. For example, we found that a 12th grader with "Extreme" absenteeism had about a 12.9% academic performance decline, versus under 1% decline for a student just barely over the chronic threshold. The risk analysis also indicated that these severe cases will persist the longest in the absence of intervention (the long tail of recovery). Therefore, a targeted recommendation is for schools and districts to specifically **identify and support the "severe" chronically absent students as a distinct group requiring intensive attention.**

What does this mean in practice? Essentially, triage your interventions: out of all chronically absent students, immediately focus on those with the highest absence rates (for instance, those missing >20% or >30% of days, depending on how data is tracked). These students should receive the most intensive outreach and support, because they are at the highest risk of falling irreparably behind or dropping out.

Strategies to prioritize and help high-severity cases include:

- **Individual Attendance Plans:** Create a personalized intervention plan for each severely chronically absent student. This is akin to an Individualized Education Plan (IEP) but focused on attendance and re-engagement. It should involve counselors or social workers working with the student and family to figure out *why* the student is missing so much school (health issues? family responsibilities? disengagement/boredom? transportation or safety issues?) [81]. Once the root causes are understood, tailor interventions accordingly. For a student with chronic health issues, maybe allow for partial-day attendance or provide a remote option on bad days so they don't fall behind. For a student who is disengaged, perhaps adjust their class schedule to include more appealing electives or hands-on learning that motivates them, or find a mentor teacher to build a connection. The plan should set gradual goals (e.g., improve attendance from 50% to 80% over two months) and outline support actions and check-ins.
- **Mentoring and Check-Ins:** Assign a staff mentor (or even a community volunteer or peer mentor in some cases) to each student with extreme absenteeism [81]. This person establishes a rapport with the student, regularly checks in on them, and provides encouragement and accountability. Just knowing that someone at school notices their absences and genuinely cares about their well-being can be motivating for a student who might otherwise feel invisible. The mentor can also celebrate improvements (positive reinforcement when attendance does improve). This strategy has been used in dropout prevention programs effectively; it can similarly work for absenteeism by giving the student a reliable adult ally focused on their attendance.
- **Leverage Technology for Flexibility:** In cases where students have legitimate difficulties attending (for example, they or a family member have a chronic illness, or the student has anxiety that makes attending full days hard), schools should use technology to keep them engaged academically even if they can't be physically present [82]. This could include:
    - Allowing hybrid attendance options (some classes online) for students with valid reasons, so they don't miss instruction.
    - Recording key classroom sessions and posting them online for absent students to watch.

    - Using learning management systems to post assignments, notes, and resources, ensuring absent students can access what they missed in real time.
- The goal is to reduce the performance hit by making sure that "absence" doesn't always mean "no learning." This must be balanced carefully (we don't want to encourage absenteeism by making it too easy to miss school), but for those extreme cases who are missing anyway, it's a way to mitigate damage.

By aggressively focusing on the highest-severity cases first, schools can **reduce the overall risk profile much faster**. Think of it like this: if 5% of students have extremely high absences and account for 15% of all missed days, turning around even half of those students will drastically cut total missed days. From our modeling, we know the extreme cases are a major part of the tail risk. Successfully re-engaging even a portion of them yields outsized improvements in the metrics (lower chronic absence rate, higher average achievement, etc.). It's also an equity issue – these students are often the ones facing the toughest life challenges, so focusing resources on them is aligned with equity goals.

In terms of expected outcomes, if schools implement these measures:

- We would expect the **extreme absenteeism category to shrink** significantly. For example, a school might start a year with 50 students missing >30% of days; with intensive intervention, maybe 30 of them improve to where they're only missing 15% by year-end (still chronically absent but not extreme), 10 transfer to alternative programs that suit them better, and 10 unfortunately drop out. That scenario is much better than doing nothing and seeing maybe 20 drop out and the rest continue at very low attendance.
- The **dropout rate should decrease**. Many extreme-absentee students are on the brink of dropping out. By intervening, we expect more of them to stay in school or at least transfer to a program where they can earn a diploma. This addresses the ultimate severe outcome we want to avoid.
- **School-wide improvement:** Even though we're focusing on a small group, there's a morale effect too – showing that the school is committed to every student, even the hardest cases, can improve overall school culture. Teachers feel supported to not just let those kids drift away. Students see that their peers are being helped.

Finally, these targeted high-severity interventions should be implemented hand-in-hand with the early warning system. The EWIMS will help identify these severe cases (they'll be at the top of the list) and track progress. Essentially, EWIMS might flag "Student X has missed 50% of days this month" – that triggers the kind of intensive response outlined here [link].

In summary, **prioritizing high-severity absenteeism cases** is a crucial recommendation because it directly tackles the worst part of the risk distribution. It's a classic actuarial move: identify where the largest losses are coming from and focus mitigation there. We believe doing so will significantly reduce the long-tail risk of chronic absenteeism extending its impacts into the next decade.

6.3 Future Implementation Timeline

In response to the unprecedented spike in chronic absenteeism (nearly 30% of students nationally in 2021–22), a coordinated national rollout of intervention strategies – including the Early Warning Intervention and Monitoring System (EWIMS) and targeted student support – is scheduled to begin in the 2025–2026 school year [2]. The following implementation timeline outlines projected short-, medium-, and long-term outcomes from this rollout, based on the team's time-series model and documented research findings. These projections assume that, without such interventions, chronic absence would have remained persistently high (far above pre-pandemic levels) and improved only modestly [2]. By contrast, with sustained interventions and consistent monitoring, chronic absenteeism is expected to decline year by year through at least 2030–2031, with corresponding improvements in academic performance. The model assumes a steady annual improvement ratio (approximately an 8–9% relative reduction in chronic absence each year after initial impacts), maintaining the interval pattern observed in the data and ensuring modeling integrity in line with the Time Model statistics.

6.3.1 Short-Term Horizon (2025–2027)

Initial Rollout and Immediate Impact (2025–26): The national implementation launches in the 2025–2026 school year. Starting from a 2024–2025 baseline chronic absence rate of about 20.5% (persisting after partial post-pandemic recovery), the model projects a significant drop in the first year of full intervention. By the end of 2025–2026, the chronic absenteeism rate is expected to fall to roughly 18.8%. This ~1.7 percentage point reduction in the first implementation year represents an

accelerated improvement, attributable to EWIMS early warning systems and targeted support staff being in place across districts. Research evidence supports this magnitude of early impact: one randomized study found that schools adopting EWIMS reduced the share of chronically absent students by *about 4 percentage points* in the first year compared to control schools [76]. Our nationwide rollout leverages this effect at scale. In the absence of these interventions, the chronic absence rate would likely have only inched down to around 20% or remained flat; thus, the 2025–26 EWIMS rollout is anticipated to yield an additional 3–4 percentage point improvement beyond the baseline trend, immediately engaging thousands more students in consistent attendance [2].

Consolidation in Year 2 (2026–27): In the second year of implementation, the focus shifts to refining the early warning process and deepening targeted supports (e.g. mentoring programs, attendance incentives, and family outreach for at-risk students). The model forecasts the chronic absenteeism rate to decline further to about 17.2% in 2026–2027. This continued improvement (an additional ~1.6 percentage point drop from the prior year) aligns with the model's built-in ~8–9% annual relative reduction, indicating that momentum from the interventions is sustained. By 2026–27, the chronic absence rate will have improved by roughly 3.3 percentage points from the pre-rollout baseline, a ~16% relative decrease in two years. Schools should begin to observe early academic benefits from these attendance gains. In fact, improved attendance has an immediate impact on coursework completion – the EWIMS trial, for example, saw a *5 percentage point reduction* in course failure rates within one year of implementation (21% failing one or more courses in EWIMS schools vs 26% in controls) [74]. Consistent with this finding, we project that by 2026–27 the percentage of students failing courses or being retained will noticeably decline as more students remain engaged in class. Short-term early indicators (such as quarterly test benchmarks and credit accumulation) are expected to show improvement. Overall, the short-term horizon establishes a strong downward trajectory for chronic absenteeism – dropping into the teens by 2027 – and sets the stage for compounding benefits in the following years.

6.3.2 Medium-Term Horizon (2028–2030)

Continued Annual Improvements (2027–28 to 2029–30): During the medium-term period, the interventions reach full maturity and are integrated into standard practice across the nation's schools. While the most dramatic year-over-year drops occur early on, the model projects a steady decline in chronic absenteeism each year at a consistent rate. By 2027–2028, the national chronic absenteeism rate is projected to fall to approximately 15.7%. In 2028–2029, it further improves to about 14.4%, and by 2029–2030 the rate is down to roughly 13.2%. These projections reflect an ongoing ~8% relative decrease per year, which is in line with the interval ratio observed in the Time Model (each year's rate is about 0.92 of the previous year's, indicating a gradually decelerating but persistent improvement trend). Notably, by the 2029–30 school year the chronic absence rate will have been reduced by more than half from its 2021–22 peak of 30.8%, effectively nearing pre-pandemic levels. (For context, the national pre-COVID chronic absence baseline hovered around 11–12%, so a 13.2% rate signifies a return very close to historical norms) [74]. If no intensive interventions had been implemented, our baseline modeling suggests chronic absenteeism might have stagnated in the high teens through 2030 – for instance, possibly still around 18% or higher – given the slow pace of improvement seen with only minimal measures [3]. Therefore, by 2029–2030 the intervention scenario shows an absenteeism rate roughly 5 percentage points lower than the no-intervention baseline, underscoring the substantial impact of the EWIMS and targeted support strategies in the medium term.

Academic Recovery and Performance Gains: Crucially, the medium-term decline in absenteeism is expected to translate into measurable academic recovery. With chronic absence rates dropping into the mid-teens by 2028, schools will experience fewer disruptions to learning and more consistent instructional time for previously disengaged students. Research by the U.S. Department of Education and others has highlighted that high absenteeism was a major driver of pandemic-related learning loss; indeed, chronic absenteeism has been linked to as much as 27% of recent test score declines in math and 45% of declines in reading performance [83]. By mitigating absenteeism, we anticipate recapturing a significant portion of this lost achievement. By 2028–2029, as attendance approaches normal levels, the model projects improved proficiency rates on standardized exams (particularly among groups that had seen the steepest drops). For example, cohort analyses indicate that students who are no longer chronically absent will perform markedly better – a stark illustration comes from Rhode Island, where only 10% of students chronically absent for three consecutive years achieved math proficiency [84]. Reducing the ranks of chronically absent students will thus raise overall proficiency averages; we expect double-digit percentage increases in proficiency for previously underperforming cohorts as their attendance stabilizes. Additionally, achievement gaps begin to narrow in this horizon: historically marginalized student groups, who experienced disproportionately high absence rates post-pandemic, benefit from targeted supports and show accelerated attendance improvements (a trend already observed in early data) [3]. By 2030, with chronic absenteeism nearing 13%, schools can focus more on instructional quality and

remediation, rather than triage for absenteeism, further boosting academic outcomes. In sum, the medium term is characterized by steady year-by-year attendance gains and the start of significant academic rebounds, validating the actuarial model's expectations that sustained interventions yield compounding benefits.

6.3.3 Long-Term Horizon (2030–2031 and Beyond)

Restoration to Pre-Pandemic Levels (2030–31): By the 2030–2031 school year, five years into the national rollout, the chronic absenteeism rate is projected to decline to approximately 12.1%. This essentially brings the nation back to the pre-2019 baseline of chronic absence (roughly 11–12% of students) after a decade of volatility. Achieving ~12% chronic absenteeism nationally represents a *successful normalization* of attendance patterns, wherein the extraordinary pandemic-era absenteeism surge has been fully counteracted by sustained intervention efforts. It is important to note that even at 12%, roughly one in eight students remains chronically absent – a non-trivial number – but this level is within historical norms and is markedly lower than the crisis peak. The modeling integrity has been maintained throughout this projection, with year 2030–31 continuing the ~8% annual improvement trend (down from 13.2% the year prior) and no signs of regression. In a scenario without the interventions, many schools would likely still be grappling with chronically absent rates in the mid-to-high teens at this stage, and some districts might even have persistent attendance crises. The intervention timeline, therefore, signifies a long-term payoff: a national chronic absence rate in 2030–31 that is about 4–6 percentage points better than what baseline trends might have yielded, reflecting hundreds of thousands of additional students consistently in class. Looking beyond 2030–2031, the model suggests that with continuous improvement efforts, chronic absenteeism could potentially dip slightly below the pre-pandemic benchmark (into the low double-digits or even high single-digits percentage) in subsequent years, though diminishing returns are expected as the rate approaches a floor. The long-term maintenance plan would focus on sustaining the EWIMS processes and targeted supports as standard practice, ensuring that the gains are not only achieved but also preserved for future cohorts.

Long-Term Academic and Social Outcomes: By the early 2030s, the cumulative effect of improved attendance is expected to manifest in stronger academic performance and student success indicators across the board. Students who benefited from consistent attendance intervention throughout their middle and high school years (starting in 2025) will be graduating high school in the 2030–2031 timeframe. We anticipate seeing higher on-time graduation rates for these cohorts compared to those who experienced the height of absenteeism during the pandemic. This expectation is grounded in the well-documented link between chronic absenteeism and graduation outcomes – chronic absence is a strong predictor of high school dropout, so its dramatic reduction should correspond with fewer dropouts and more students remaining on track [84]. Additionally, long-term academic achievement measures (such as NAEP scores and college readiness benchmarks) should show improvement as the attendance-intervention cohorts move through the education system with more consistent learning time. By 2030–31, the learning loss recovery is projected to be largely complete for lower grades and significantly mitigated for upper grades: for example, the share of students achieving proficiency in reading and math is expected to rise in tandem with improved attendance, reversing a substantial portion of the post-2020 declines attributed to absenteeism [84]. Beyond academics, social and behavioral metrics are likely to improve as well – regular attendance is associated with better student engagement, and we expect reductions in disciplinary incidents and an increase in students' connection to school. In the long run, the interventions put in place are not just restoring previous performance levels but also laying a foundation for exceeding them: with robust early warning systems and support infrastructure now ingrained in school operations, educators can proactively address attendance issues for future challenges (such as local outbreaks or natural disasters) more effectively. The actuarial projections underscore that ongoing attention and action are critical even after reaching the long-term target, to ensure chronic absenteeism remains low and to foster an environment where academic outcomes continue to improve steadily [3]. Each phase of this timeline – short, medium, and long term – reinforces the next, ultimately guiding the education system back to stability and forward to resilience, with quantifiable gains for students year by year.

7. References

1. Council of Economic Advisers. (2023, September 13). Chronic absenteeism and disrupted learning require an all‑hands‑on‑deck approach [White House archive report]. https://bidenwhitehouse.archives.gov/cea/written-materials/2023/09/13/chronic-absenteeism-and-disrupted-learning-require-an-all-hands-on-deck-approach/

2. Attendance Works. (2025, January 16). Continued high levels of chronic absence, with some improvements, require action. https://www.attendanceworks.org/continued-high-levels-of-chronic-absence-with-some-improvements-require-action/
3. National Assessment Governing Board. (n.d.). A primer on attendance and chronic absenteeism on the nation's report card and beyond. https://www.nagb.gov/naep/chronic-absenteeism.html
4. Michigan Department of Education. (n.d.). Early warning intervention and monitoring system (EWIMS). https://www.michigan.gov/mde/services/school-performance-supports/early-warnin
5. American Enterprise Institute. (2024, January 31). Long COVID for public schools: Cronic absenteeism before and after the pandemic [Report by N. Malkus]. https://www.aei.org/wp-content/uploads/2024/01/Long-COVID-for-Public-Schools.pdf
6. Panorama Education. (n.d.). The effects of chronic absenteeism in schools. Retrieved February 12, 2025, from https://www.panoramaed.com/blog/the-effects-of-chronic-absenteeism-in-schools
7. American Federation of Teachers. (n.d.). Chronic absenteeism. Retrieved February 12, 2025, from https://www.aft.org/childrens-health-safety-and-well-being/childrens-access-care/chronic-absenteeism
8. Brookings Institution. (n.d.). Taking attendance seriously in the new civil rights data collection. Retrieved February 12, 2025, from https://www.brookings.edu/articles/taking-attendance-seriously-in-the-new-civil-rights-data-collection/
9. U.S. Department of Education. (n.d.). Chronic absenteeism data – EdData Express. Retrieved February 12, 2025, from https://eddataexpress.ed.gov/resources/reports-and-files/chronic-absenteeism-data
10. National Center for Education Statistics. (n.d.). NAEP data explorer. Retrieved February 12, 2025, from https://www.nationsreportcard.gov/ndecore/xplore/NDE
11. U.S. Department of Education. (n.d.). Chronic absenteeism data CSV library. Retrieved February 12, 2025, from https://eddataexpress.ed.gov/download/data-library?...Chronic+Absenteeism
12. Chronic absenteeism data compilation. (2023). Google Sheets dataset [Public spreadsheet]. Retrieved February 12,2025, from https://docs.google.com/spreadsheets/d/1XDeOBPUClklSeGmTy5pjkVzL73pFWuxSQ1j6RyR5FqE/edit?usp=sharing
13. Alabama State Department of Education. (n.d.). State report card. Retrieved February 12, 2025, from https://statereportcard.alsde.edu
14. Alaska Department of Education and Early Development. (n.d.). Compass report card. Retrieved February 12, 2025, from https://education.alaska.gov/compass/report-card
15. Arizona Department of Education. (n.d.). State reports. Retrieved February 12, 2025, from https://azreportcards.azed.gov/state-reports
16. Arkansas Department of Education. (n.d.). School report card. Retrieved February 12, 2025, from https://myschoolinfo.arkansas.gov/SRC
17. California Department of Education. (n.d.). DataQuest. Retrieved February 12, 2025, from https://dq.cde.ca.gov/dataquest/
18. Colorado Department of Education. (n.d.). Truancy statistics. Retrieved February 12, 2025, from https://www.cde.state.co.us/cdereval/truancystatistics
19. Connecticut Department of Education. (n.d.). SAS portal. Retrieved February 12, 2025, from https://edsight.ct.gov/SASPortal/main.do
20. Delaware Department of Education. (n.d.). Report card. Retrieved February 12, 2025, from https://reportcard.doe.k12.de.us/detail.html#displaypage?scope=state&district=0&school=0&id=395
21. District of Columbia State Department of Education. (n.d.). School report card. Retrieved February 12, 2025, from https://schoolreportcard.dc.gov/state/report#measure-102
22. Florida Department of Education. (n.d.). EduData report cards. Retrieved February 12, 2025, from https://edudata.fldoe.org/ReportCards/Schools.html?school=0000&district=00
23. Georgia Department of Education. (n.d.). GA Awards. Retrieved February 12, 2025, from https//gaawards.gosa.ga.gov/analytics/saw.dll?dashboard
24. Hawai Department of Education. (n.d.). Strive HI performance system. Retrieved February 12, 2025, from https://www.hawaiipublicschools.org/VisionForSuccess/AdvancingEducation/StriveHIPerformanceSystem/Pages/home.aspx
25. Idaho Department of Education. (n.d.). Chronic absenteeism. Retrieved February 12, 2025, from https://idahoschools.org/state/ID/chronic-absenteeism
26. Illinois State Board of Education. (n.d.). Student characteristic & chronic absenteeism. Retrieved February 12, 2025, from https://www.illinoisreportcard.com/State.aspxInformation

27. Indiana Department of Education. (n.d.). Data center and reports. Retrieved February 12, 2025, from https://www.in.gov/doe/it/data-center-and-reports/
28. Iowa Department of Education. (n.d.). Chronic absenteeism. Retrieved February 12, 2025, from https://www.iaschoolperformance.gov/ECP/StateDistrictSchool/StateDetails?DetailType=CAB&y=2022
29. Kansas State Department of Education. (n.d.). Chronic absenteeism. Retrieved February 12, 2025, from https://ksreportcard.ksde.org/chronic_absent.aspxInformation
30. Kentucky Department of Education. (n.d.). COVID-19 enrollment data. Retrieved February 12, 2025, from https://education.ky.gov/districts/enrol/Pages/COVID-19.aspx
31. Louisiana Department of Education. (n.d.). School system attributes. Retrieved February 12, 2025, from https://www.louisianabelieves.com/resources/library/school-system-attributes\
32. Maine Department of Education. (n.d.). Behavior data reporting. Retrieved February 12, 2025, from https://www.maine.gov/doe/data-reporting/reporting/warehouse/behavior
33. Maryland State Department of Education. (n.d.). Chronic absenteeism report card. Retrieved February 12, 2025, from https://reportcard.msde.maryland.gov/Graphs/#/Demographics/ChronicAbsenteeism/3/99/10/6/99/XXXX/2022
34. Massachusetts Department of Elementary and Secondary Education. (n.d.). Attendance. Retrieved February 12, 2025, from https://profiles.doe.mass.edu/statereport/attendance.aspx
35. Michigan Department of Education. (n.d.). Student attendance data. Retrieved February 12, 2025, from https://www.mischooldata.org/student-attendance/
36. Minnesota Department of Education. (n.d.). North Star attendance. Retrieved February 12, 2025, from https://rc.education.mn.gov/#northStarAttendance
37. Mississippi Department of Education. (n.d.). OPR reporting. Retrieved February 12, 2025, from https://www.mdek12.org/OPR/Reporting
38. Missouri Department of Elementary and Secondary Education. (n.d.). Report card data. Retrieved February 12, 2025, from https://apps.dese.mo.gov/MCDS/Visualizations.aspxInformation
39. Montana Office of Public Instruction. (n.d.). ESSA report card. Retrieved February 12, 2025, from https://opi.mt.gov/Leadership/Academic-Success/Every-Student-Succeeds-Act-ESSA/Report-Card
40. Nebraska Department of Education. (n.d.). Data services & reports. Retrieved February 12, 2025, from https://www.education.ne.gov/dataservices/data-reports/
41. Nevada Department of Education. (n.d.). Nevada report card. Retrieved February 12, 2025, from http://nevadareportcard.nv.gov/DI/nv/2022
42. New Jersey Department of Education. (n.d.). School performance reports. Retrieved February 12, 2025, from https://rc.doe.state.nj.us/
43. New Mexico Public Education Department. (n.d.). Annual attendance report. Retrieved February 12, 2025, from https://webnew.ped.state.nm.us/bureaus/safe-healthy-schools/attendance-for-success/annual-state-districts-and-schools-attendance-report/
44. New York State Education Department. (n.d.). Chronic absenteeism data. Retrieved February 12, 2025, from https://data.nysed.gov/essa.php?instid=800000081568&year=2021&createreport=1&EMchronic=1&HSchronic=1
45. North Dakota Department of Public Instruction. (n.d.). Chronic absenteeism. Retrieved February 12, 2025, from https://insights.nd.gov/Education/State/ChronicAbsenteeism
46. Ohio Department of Education. (n.d.). State attendance rate report card. Retrieved February 12, 2025, from https://reports.education.ohio.gov/report/report-card-data-state-attendance-rate-with-student-disagg
47. Oklahoma State Department of Education. (n.d.). Chronic absenteeism. Retrieved February 12, 2025, from https://oklaschools.com/state/chronic-absenteeism
48. Oregon Department of Education. (n.d.). Attendance and absenteeism. Retrieved February 12, 2025, from https://www.oregon.gov/ode/reports-and-data/students/Pages/Attendance-and-Absenteeism.aspx
49. Pennsylvania Department of Education. (n.d.). Future Ready PA. Retrieved February 12, 2025, from https://futurereadypa.org/Search/District
50. Rhode Island Department of Education. (n.d.). Public attendance data. Retrieved February 12, 2025, from https://www3.ride.ri.gov/attendance/public
51. South Carolina Department of Education. (n.d.). Report cards. Retrieved February 12, 2025, from https://screportcards.com/
52. South Dakota Department of Education. (n.d.). Home. Retrieved February 12, 2025, from https://sdschools.sd.gov/#/home

53. Tennessee Department of Education. (n.d.). Truancy performance. Retrieved February 12, 2025, from https://tdepublicschools.ondemand.sas.com/state/performance/truancy
54. Utah State Board of Education. (n.d.). Overall performance report. Retrieved February 12, 2025, from https://reportcard.schools.utah.gov/State/OverallPerformance?StateID=99&SchoolLevel=HS&schoolyearendyear=2023
55. Vermont Department of Education. (n.d.). Chronic absenteeism dashboard. Retrieved February 12, 2025, from https://education.vermont.gov/data-and-reporting/vermont-education-dashboard/chronic-absenteeism-dashboard
56. Virginia Department of Education. (n.d.). School quality. Retrieved February 12, 2025, from https://schoolquality.virginia.gov
57. Washington State Office of Superintendent of Public Instruction. (n.d.). State report card. Retrieved February 12, 2025, from https://washingtonstatereportcard.ospi.k12.wa.us/ReportCard/ViewSchoolOrDistrict/103300
58. West Virginia Department of Education. (n.d.). ESSA dashboard. Retrieved February 12, 2025, from https://wveis.k12.wv.us/essa/dashboard.html
59. Wisconsin Department of Public Instruction. (n.d.). Wisedash dashboard. Retrieved February 12, 2025, from https://wisedash.dpi.wi.gov/Dashboard/dashboard/16640&sa=D&source=editors&ust=1652198414873786&usg=AOvVaw2qE29Q3qZTTIiFbg_JhCK5
60. National Center for Education Statistics. (n.d.). Common Core of Data (CCD) files. Retrieved February 12, 2025, from https://nces.ed.gov/ccd/files.asp
61. U.S. Census Bureau. (2018, July). Educational attainment. https://www.census.gov/library/stories/2018/07/educational-attainment.html
62. U.S. Census Bureau. (n.d.). Historical time series: School enrollment (CPS). Retrieved from https://www.census.gov/data/tables/time-series/demo/school-enrollment/cps-historical-time-series.html
63. Attendance Works. (n.d.). California: Cultivate a school-wide culture of attendance. Retrieved from https://www.attendanceworks.org/resources/toolkits/leading-attendance-in-ca-principals-toolkit/california-cultivate-a-school-wide-culture-of-attendance/
64. Learning Policy Institute. (n.d.). Attendance: An essential ingredient for educational equity. Retrieved from https://learningpolicyinstitute.org/blog/attendance-essential-ingredient-educational-equity
65. EdPolicy Inc. (n.d.). Unpacking California's chronic absence crisis through 2022–23. Retrieved from https://edpolicyinca.org/publications/unpacking-californias-chronic-absence-crisis-through-2022-23
66. Brookings Institution. (n.d.). Student-level attendance patterns show depth, breadth, and persistence of post-pandemic absenteeism. Retrieved from https://www.brookings.edu/articles/student-level-attendance-patterns-show-depth-breadth-and-persistence-of-post-pandemic-absenteeism/
67. K12 Dive. (n.d.). 5 years later, COVID's impact lingers in school culture. Retrieved from https://www.k12dive.com/news/5-years-later-covids-impact-lingers-in-school-culture/743446/
68. Wiley Online Library. (n.d.). [Article title]. Retrieved from https://bera-journals.onlinelibrary.wiley.com/doi/10.1002/rev3.3291
69. CSBA. (2024). Attendance brief 2024. Retrieved from https://www.csba.org/-/media/CSBA/Files/GovernanceResources/GovernanceBriefs/Attendance-Brief-2024.ashx
70. IDRA. (n.d.). Mental health implications of virtual learning on student engagement. Retrieved from https://www.idra.org/resource-center/mental-health-implications-of-virtual-learning-on-student-engagement/
71. Globalization and Health. (2022). [Article title]. Retrieved from https://globalizationandhealth.biomedcentral.com/articles/10.1186/s12992-022-00863-z
72. ERIC. (n.d.). [Article title]. Retrieved from https://eric.ed.gov/?id=ED573814
73. Attendance Works. (n.d.). New analysis: Building relationships during home visits improved attendance during the pandemic. Retrieved from https://www.attendanceworks.org/new-analysis-building-relationships-during-home-visits-improved-attendance-during-the-pandemic/
74. Institute of Education Sciences. (n.d.). [Report title]. Retrieved from https://ies.ed.gov/sites/default/files/migrated/rel/regions/midwest/pdf/REL_2017272.pdf
75. Attendance Works. (2012, March 14). Elementary attendance [2-sided handout]. Retrieved from https://attendanceworks.org/wp-content/uploads/2017/10/Elementary-Attendance-2-sided-March-14-2012.pdf
76. Teaching for Justice. (n.d.). Making the most of makeup work. Retrieved from https://www.learningforjustice.org/magazine/making-the-most-of-makeup-work

77. Center for Research on Learning and Teaching, University of Michigan. (n.d.). [Web resource]. Retrieved from https://crlt.umich.edu/gsis/p4_5
78. Landmark School. (n.d.). Help your struggling learner: Remediation is a key to success. Retrieved from https://www.landmarkschool.org/our-school/landmark-360-blog?id=253216/help-your-struggling-learner-remediation-is-a-key-to-success
79. Institute of Education Sciences. (2025, January). Handout: Strategies to address chronic absenteeism. Retrieved from https://ies.ed.gov/rel-southwest/2025/01/handout-strategies-address-chronic-absenteeism
80. Parent Powered. (n.d.). Technology and student attendance. Retrieved from https://parentpowered.com/blog/k12-attendance/technology-student-attendance/
81. PBS NewsHour. (n.d.). Chronic absenteeism is up across the country. Retrieved from https://www.pbs.org/newshour/nation/chronic-absenteeism-is-up-across-the-country-school-leaders-are-trying-to-address-why
82. The 74 Million. (n.d.). Chronic absenteeism: Achievement gap—lowest NAEP scorers missed the most class. Retrieved from https://www.the74million.org/article/chronic-absenteeism-achievement-gap-lowest-naep-scorers-missed-the-most-class/

8. Appendix

Table A1: Custom datasets generated by NAEP Data Explorer

Number	Academic Metric (Subject)	Age Group	Framework	Year	Scale	Jurisdiction
1	Mathematics	Grade 4	1990	2024	Composite	National
2	Mathematics	Grade 8	1990	2024	Composite	National
3	Mathematics	Grade 12	2005	2019	Composite	National
4	Reading	Grade 4	1992	2024	Composite	National
5	Reading	Grade 8	1992	2024	Composite	National
6	Reading	Grade 12	1992	2019	Composite	National
7	Writing	Grade 4	1998	2002	Writing	National
8	Writing	Grade 8	2011	2011	Writing	National
9	Writing	Grade 12	2011	2011	Writing	National
10	Science	Grade 4	2009	2019	Overall	National
11	Science	Grade 8	2009	2019	Overall	National
12	Science	Grade 12	2009	2019	Overall	National
13	U.S. History	Grade 4	1994	2010	Composite	National
14	U.S. History	Grade 8	1994	2022	Composite	National
15	U.S. History	Grade 12	1994	2010	Composite	National

Table A2: ED Data Express Chronic Absenteeism Rates			
Number	**School Year**	**Level (SCH, LEA, SEA)**	**Data Group**
1	2020/2021	SEA	FS195_DG814
2	2020/2021	SCH	FS195_DG814
3	2020/2021	LEA	FS195_DG814
4	2020/2021	SEA	DG814PCT
5	2020/2021	LEA	DG814PCT
6	2021/2022	SEA	FS195_DG814
7	2021/2022	SCH	FS195_DG814
8	2021/2022	LEA	FS195_DG814
9	2021/2022	SEA	DG814PCT
10	2021/2022	LEA	DG814PCT
11	2022/2023	SEA	FS195_DG814
12	2022/2023	SCH	FS195_DG814
13	2022/2023	LEA	FS195_DG814
14	2022/2023	SEA	DG814PCT
15	2022/2023	LEA	DG814PCT

Table A3: State-disaggregated Chronic Absenteeism Rates															
State	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**State**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
US	13%	15%	15%	13%	19%	28%	26%	MS	-	17%	14%	9%	21%	28%	24%
AK	24%	26%	28%	17%	22%	46%	43%	MT	-	21%	23%	14%	27%	38%	-
AL	18%	18%	11%	9%	8%	18%	18%	NC	-	15%	16%	9%	26%	32%	27%
AR	-	19%	19%	23%	16%	27%	-	ND	-	11%	12%	11%	16%	21%	19%
AZ	-	25%	25%	16%	25%	48%	-	NE	-	16%	15%	15%	21%	24%	22%
CA	11%	12%	13%	-	14%	30%	25%	NH	-	16%	14%	13%	18%	35%	-
CO	19%	24%	23%	23%	26%	35%	31%	NJ	10%	11%	11%	8%	13%	18%	-
CT	-	11%	10%	12%	19%	24%	20%	NM	-	17%	17%	15%	30%	41%	40%
DC	-	29%	33%	29%	31%	48%	44%	NV	-	20%	19%	20%	31%	36%	35%
DE	11%	11%	11%	17%	18%	20%	20%	NY	-	18%	19%	21%	24%	32%	-
FL	-	20%	20%	17%	25%	32%	31%	OH	13%	15%	16%	10%	23%	29%	26%
GA	-	13%	13%	9%	21%	25%	23%	OK	-	13%	13%	18%	14%	19%	21%
HI	-	19%	19%	12%	18%	37%	30%	OR	20%	20%	20%	22%	28%	36%	38%
IA	-	11%	12%	17%	21%	26%	21%	PA	15%	15%	15%	15%	18%	26%	-

Table A3: State-disaggregated Chronic Absenteeism Rates															
ID	-	3%	3%	8%	16%	21%	18%	RI	19%	19%	19%	18%	28%	34%	29%
IL	-	17%	18%	11%	21%	30%	28%	SC	-	12%	13%	14%	8%	20%	25%
IN	10%	12%	12%	11%	20%	23%	21%	SD	-	13%	14%	11%	18%	22%	21%
KS	-	14%	14%	14%	18%	26%	23%	TN	-	13%	13%	13%	15%	20%	-
KY	-	18%	18%	12%	22%	28%	30%	TX	-	13%	11%	7%	15%	26%	-
LA	-	16%	16%	11%	25%	18%	22%	UT	12%	13%	14%	9%	19%	29%	25%
MA	13%	13%	13%	13%	18%	28%	24%	VA	12%	11%	11%	12%	11%	20%	19%
MD	-	20%	20%	18%	24%	31%	30%	VT	11%	12%	14%	16%	22%	35%	-
ME	16%	16%	17%	18%	21%	30%	26%	WA	15%	15%	15%	9%	19%	33%	30%
MI	16%	21%	20%	21%	20%	39%	32%	WI	12%	13%	13%	13%	16%	22%	-
MN	13%	14%	14%	15%	17%	30%	-	WV	-	19%	20%	19%	13%	29%	28%
MO	11%	12%	13%	15%	17%	24%	23%	WY	-	2%	2%	2%	2%	37%	-

Table A4: Historical US K-12 Student Populations	
School Year	**Student Population**
2012/2013	49,771,118
2013/2014	50,044,522
2014/2015	50,312,581
2015/2016	50,438,043
2016/2017	50,615,189
2017/2018	50,685,567
2018/2019	50,694,061
2019/2020	50,796,445
2020/2021	49,374,751
2021/2022	49,433,092
2022/2023	49,618,464

Table A5: Projected Student Population Counts in K-12 US Education, separated by age groups			
School Year	**Prekindergarten through Grade 8**	**Grades 9 through 12**	**Total**
2012/2013	35,017,893	14,753,225	49,771,118
2013/2014	35,250,792	14,793,730	50,044,522
2014/2015	35,369,694	14,942,887	50,312,581
2015/2016	35,387,986	15,050,057	50,438,043
2016/2017	35,477,332	15,137,857	50,615,189
2017/2018	35,496,055	15,189,512	50,685,567
2018/2019	35,497,748	15,196,313	50,694,061
2019/2020	35,550,583	15,245,862	50,796,445
2020/2021	34,061,242	15,313,509	49,374,751
2021/2022	33,997,563	15,435,529	49,433,092

Table A5: Projected Student Population Counts in K-12 US Education, separated by age groups			
2022/2023	34,071,318	15,547,146	49,618,464
2023/2024	33,484,472	15,527,972	49,012,444
2024/2025	33,266,523	15,440,899	48,707,421
2025/2026	33,037,347	15,190,158	48,227,505
2026/2027	32,721,634	14,922,568	47,644,202
2027/2028	32,633,245	14,737,037	47,370,282
2028/2029	32,542,021	14,642,058	47,184,079
2029/2030	32,522,485	14,505,444	47,027,929
2030/2031	32,313,415	14,626,940	46,940,354

Table 6: Percent each chronic absenteeism severity level/interval contributes to the total number of students					
School Year	**Low (1-2 days / month)**	**Modest (3-4 days / month)**	**High (5-10 days / month)**	**Extreme (10+ days / month)**	**Total**
2021/2022	3.696	7.084	6.776	13.244	3.696
2022/2023	3.336	6.672	7.784	10.008	3.336
2023/2024	2.475	5.625	7.875	6.525	2.475
2024/2025	2.2583	5.1325	7.5961	5.5431	2.2583
2025/2026	1.876	4.8776	7.1288	4.8776	1.876
2026/2027	1.5444	4.4616	6.6924	4.4616	1.5444
2027/2028	1.2568	4.2417	6.284	3.9275	1.2568
2028/2029	1.008	3.888	5.904	3.6	1.008
2029/2030	0.7926	3.6988	5.5482	3.1704	0.7926
2030/2031	0.6065	3.3964	5.2159	2.9112	0.6065

Table A7. Percentage Drops by Absenteeism				
Academic Metric	**Low (1-2)**	**Modest (3-4)**	**High (5-10)**	**Extreme (10+)**
U.S. History4	1.382488479	4.147465438	5.069124424	16.58986175
Writing4	1.27388535	5.095541401	7.643312102	20.38216561
Reading4	1.793721973	4.932735426	8.968609865	18.38565022
Science4	2.547770701	7.006369427	10.82802548	23.56687898
Mathematics4	2.845528455	5.691056911	7.723577236	13.82113821
English4	1.578947368	5	8.421052632	19.21052632
STEM4	2.729528536	6.203473945	8.933002481	17.617866
Total4	2	5.3	7.9	18
U.S. History8	1.515151515	4.545454545	5.303030303	8.333333333
Writing8	1.307189542	6.535947712	8.496732026	16.33986928
Reading8	1.136363636	4.166666667	6.439393939	13.63636364
Science8	3.144654088	8.176100629	11.32075472	20.12578616
Mathematics8	2.464788732	7.042253521	8.802816901	15.14084507
English8	1.199040767	5.035971223	7.194244604	14.62829736

Table A7. Percentage Drops by Absenteeism				
STEM8	2.708803612	7.449209932	9.706546275	16.93002257
Total8	1.868327402	5.871886121	7.740213523	14.0569395
U.S. History12	1.365187713	4.09556314	4.778156997	8.532423208
Writing12	0	4.605263158	6.578947368	12.5
Reading12	0.6896551724	3.448275862	4.827586207	11.72413793
Science12	1.298701299	6.493506494	9.090909091	18.83116883
Mathematics12	1.290322581	7.096774194	9.032258065	18.06451613
English12	0.4524886878	3.846153846	5.429864253	11.99095023
STEM12	1.294498382	6.796116505	9.061488673	18.44660194
Total12	0.9578544061	4.789272031	6.32183908	12.93103448
U.S. History	1.421188643	4.263565891	5.03875969	10.72351422
Writing	0.8658008442	5.41125539	7.575757597	16.45021643
Reading	1.158301158	4.118404131	6.563706564	14.28571429
Science	2.340425553	7.234042594	10.42553196	20.85106385
Mathematics	2.335766409	6.569343067	8.467153271	15.32846716
English	1.049233269	4.600484262	6.941081501	15.0928168
STEM	2.337662338	6.839826857	9.264069247	17.57575756
Total	1.409585195	4.993958952	7.007652033	14.82078133

Table A8: Projected Count of Total Students in the US suffering from various intervals of Academic Decline and Absenteeism Intervals				
	Count of students in the US projected to experience...			
	Low Absenteeism (1-2)	**Modest Absenteeism (3-4)**	**High Absenteeism (5-10)**	**Extreme Absenteeism (10+)**
School Year	**1.4% Academic Decrease**	**5% Academic Decrease**	**7% Academic Decrease**	**14.9% Academic Decrease**
2023/2024	828,741	1,883,502	2,636,902	2,184,862
2024/2025	751,258	1,707,404	2,526,958	1,843,997
2025/2026	619,781	1,611,430	2,355,166	1,611,430
2026/2027	505,353	1,459,908	2,189,863	1,459,908
2027/2028	410,135	1,384,204	2,050,673	1,281,671
2028/2029	328,024	1,265,234	1,921,281	1,171,513
2029/2030	257,773	1,202,942	1,804,413	1,031,093
2030/2031	195,981	1,097,493	1,685,435	940,708

Table A9: Projected Count of Grade 4 Students in the US suffering from various intervals of Academic Decline and Absenteeism Intervals				
	Count of students in the US projected to experience...			
	Low Absenteeism (1-2)	**Modest Absenteeism (3-4)**	**High Absenteeism (5-10)**	**Extreme Absenteeism (10+)**

Table A9: Projected Count of Grade 4 Students in the US suffering from various intervals of Academic Decline and Absenteeism Intervals

School Year	2% Academic decrease	5.3% Academic Decrease	7.9% Academic Decrease	18% Academic Decrease
2023/2024	75,968	172,654	241,716	200,279
2024/2025	68,865	156,512	231,638	169,033
2025/2026	56,813	147,714	215,890	147,714
2026/2027	46,324	133,825	200,737	133,825
2027/2028	37,596	126,885	187,978	117,486
2028/2029	30,069	115,980	176,117	107,389
2029/2030	23,629	110,270	165,404	94,517
2030/2031	17,965	100,604	154,498	86,232

Table 10: Projected Count of Grade 8 Students in the US suffering from various intervals of Academic Decline and Absenteeism Intervals

	Count of students in the US projected to experience...			
	Low Absenteeism (1-2)	**Modest Absenteeism (3-4)**	**High Absenteeism (5-10)**	**Extreme Absenteeism (10+)**
School Year	**1.9% Academic Decrease**	**5.9% Academic Decrease**	**7.7% Academic Decrease**	**14.1% Academic Decrease**
2023/2024	62,156	141,263	197,768	163,865
2024/2025	56,344	128,055	189,522	138,300
2025/2026	46,484	120,857	176,637	120,857
2026/2027	37,901	109,493	164,240	109,493
2027/2028	30,760	103,815	153,800	96,125
2028/2029	24,602	94,893	144,096	87,863
2029/2030	19,333	90,221	135,331	77,332
2030/2031	14,699	82,312	126,408	70,553

Table 11: Projected Count of Grade 12 Students in the US suffering from various intervals of Academic Decline and Absenteeism Intervals

	Count of students in the US projected to experience...			
	Low Absenteeism (1-2)	**Modest Absenteeism (3-4)**	**High Absenteeism (5-10)**	**Extreme Absenteeism (10+)**
School Year	**0.96% Academic Decrease**	**4.8% Academic Decrease**	**6.3% Academic Decrease**	**12.9% Academic Decrease**
2023/2024	96,079	218,362	305,707	253,300
2024/2025	87,175	198,126	293,227	213,976
2025/2026	71,242	185,229	270,719	185,229
2026/2027	57,616	166,446	249,669	166,446
2027/2028	46,304	156,275	231,519	144,699
2028/2029	36,898	142,321	216,117	131,779

Table 11: Projected Count of Grade 12 Students in the US suffering from various intervals of Academic Decline and Absenteeism Intervals				
2029/2030	28,743	134,132	201,198	114,970
2030/2031	22,178	124,197	190,732	106,455