Final Report

A Study of the Relationship Between Participation in Gaming Concepts and Esports (Select PlayVS K-12 Programs) and Student Attendance and Incidents of Misbehavior

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for

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Executive Summary

This study examined the relationship between participation in select PlayVS K-12 Programs (PVPs)—including Gaming Concepts (GC), Esports, and combined GC + Esports—and two key student outcomes: average daily attendance (ADA) and incidents of misbehavior. Using student-level data from a public school district across five school years (2020–21 through 2024–25), outcomes for participating students were compared to a large control group of non-participants. Analyses included year-by-year comparisons, standardized effect sizes, and multilevel modeling to account for school-level differences. Across all analytic approaches, participation in PVPs was consistently associated with more favorable student outcomes.

Participation in GC and/or Esports was positively associated with higher attendance in every year studied. Effect sizes ranged from small to moderate and showed a clear engagement gradient, with students participating in both GC and Esports demonstrating the largest attendance advantages. When translated into practical terms, these differences corresponded to approximately 1 to 10 additional days of school per year, depending on the year and level of participation. Multilevel modeling confirmed that these associations remained positive and meaningful even after accounting for differences among schools, with combined GC + Esports participation associated with an estimated 7 additional days of attendance per year relative to non-participants.

Participation was also associated with fewer incidents of misbehavior. Across five years, students in PVPs consistently exhibited lower disciplinary incident rates than non-participants, with effect sizes indicating reductions ranging from approximately 10% to 50%, depending on program involvement. The largest and most consistent reductions were observed among students participating in both GC and Esports. Although these findings are descriptive and do not establish causality, their consistency across years and outcomes suggests that PVP participation is meaningfully associated with improved student engagement and behavior. Replication in additional districts would further strengthen the evidence base for these conclusions.

Introduction

This report describes the results of a study designed to examine the relationship between selected PVPs and selected student outcomes. The selected programs were Gaming Concepts (GC), Esports, and combined GC + Esports. The selected student outcomes were average daily attendance (ADA) and incidents of misbehavior. The foundational research question in this study was: What is the relationship between participation in PVPs and various student outcome measures? While there are a myriad of potential student outcomes that might be postulated as being influenced by participation in PVPs, this study focused on two of those outcomes because of their perceived importance in K-12 education.

Experimental Conditions

The study examined the impact of three distinct, but related learning conditions experienced by students enrolled in a public school district within the experimental population. Students participated in one of the following conditions:

1. GC: Participation in classroom-based courses implementing the Gaming Concepts curriculum;
2. ES (Esports): Participation in school-sponsored Esports activities and Esports tournaments organized and facilitated by PlayVS in partnership with the school district; or
3. GC + Esports: Participation in both classroom courses utilizing the *Gaming Concepts* curriculum and structured Esports activities and tournaments.

Each condition represents a different level of exposure to gaming- and Esports-based learning experiences.

Gaming Concepts Curriculum

Gaming Concepts is a semester- or year-long instructional program designed to leverage students' interest in gaming and Esports as a catalyst for academic learning, skill development, and career exploration. The curriculum is designed for students in grades 3–12, and integrates technology education, digital citizenship, creative production, and career-readiness competencies. Instructional modules cover topics such as game design, Esports ecosystems, broadcasting and media production, journalism, data analysis, and emerging technologies, including artificial intelligence. Instruction emphasizes hands-on learning, project-based outcomes, and structured reflection, enabling students to apply concepts in authentic contexts.

Esports Activities and Tournaments

Students participating in the Esports condition participated in a structured, school-based Esports program designed to parallel competitive team sports while emphasizing collaboration, strategic thinking, and skill development. Participants engaged in supervised Esports sessions during scheduled program hours, playing age-appropriate competitive video games within an organized gaming environment. Participating students operated within team-based structures that required communication, strategic planning, and coordinated decision-making. Program sessions included guided practice, organized match play, and facilitated reflection focused on teamwork, sportsmanship, and problem-solving. Adult facilitators or coaches supervised all activities to ensure adherence to program norms, promote positive peer interactions, and support student development. Participating students also experienced complementary Esports-related roles, including game analysis, strategy development, and peer leadership.

Combined Gaming Concepts Curriculum and Esports Activities

Students participating in the combined condition participated in both classroom courses implementing the Gaming Concepts curriculum and supervised Esports sessions, activities, and tournaments. This condition provided students with exposure to instructional learning experiences and applied Esports participation.

The Sample

Students in grades 6 through 12 from a public school district were used in the study. Data regarding these students across five school years were used: 2020-2021, 2021-2022, 2022-2023, 2023-2024, and 2024-2025. As described above, there were three experimental conditions. All students not in the experimental conditions were considered in the control group (i.e., NO GC/NO Esports). Figure 1 reports the number of students in each group aggregated across the five years of the study.

Figure 1: Participants in Experimental and Control Groups Across Five Years.

NO GC/NO Esports	108,871
GC participants	7,212
Esports participants	2,401
GC + Esports	357

The number of students for each year in each of the conditions is depicted in Figure 2.

Figure 2: Number of Students Per Year in Each Condition

School Year	No GC/No Esports	GC Only	Esports Only	GC + Esports
2020–21	(N=23,258)	(N=100)	(N=528)	(N=30)
2021–22	(N=22,497)	(N=752)	(N=552)	(N=95)
2022–23	(N=21,810)	(N=1,483)	(N=518)	(N=99)
2023–24	(N=20,823)	(N=2,377)	(N=458)	(N=87)
2024–25	(N=20,483)	(N=2,500)	(N=345)	(N=46)

Some patterns can be seen in this figure. First and foremost, the sample sizes for the control groups are substantially larger than the sample sizes for the experimental groups, and the sample size for the GC + Esports group is extremely small even when compared to the two other experimental groups. As described below, this imbalance in samples must be considered in any interpretation of findings.

Attendance

The importance of student attendance in school is almost self-evident and has been discussed extensively in research and theoretical literature.

Selected Literature Review Regarding Attendance

Chronic absenteeism has emerged as a pervasive and consequential barrier to student learning in U.S. schools. Commonly defined as missing 10 percent or more of instructional days in a school year—including excused and unexcused absences—chronic absenteeism undermines academic achievement and widens the opportunity divide for chronically absent students (U.S. Department of Education, 2025). Prior to the COVID-19 pandemic, chronic absenteeism was already a persistent national concern, yet longitudinal evidence indicates that chronic absenteeism has not only increased steadily across grade levels, but is correlated with lower academic achievement, reducing the likelihood of meeting proficiency standards on statewide summative assessments (London et al., 2016; Liu et al., 2021).

The COVID-19 pandemic dramatically exacerbated this challenge. Multiple national and state-level analyses show that chronic absenteeism rates rose sharply during remote, and hybrid learning periods, and has remained elevated well after schools returned to in-person instruction (National Center for Education Statistics, 2023). Recent reports document that, in many states, rates of chronic absenteeism increased dramatically relative to pre-pandemic levels, with secondary students (Grades 6–12) experiencing the largest increases. Importantly, emerging post-pandemic research indicates that chronic absenteeism is now more widespread, posing serious risks to academic recovery and long-term academic outcomes (Swiderski, 2025; Liu et al., 2021).

Chronic Absenteeism and Academic Achievement Losses

The achievement losses associated with chronic absenteeism are evident across grade levels but become more pronounced in secondary grades, where cumulative content demands, and mathematics instruction in particular, are highly sensitive to disruptions in instructional continuity. Studies using Common Core–aligned assessments, including Smarter Balanced, show that reductions in attendance correspond to measurable declines in proficiency rates and scale scores, with mathematics outcomes demonstrating greater impact due to missed instructional time than ELA outcomes (Santibañez & Guarino, 2020).

Quasi-experimental and longitudinal studies provide strong evidence that absences during middle and high school have both immediate and lasting negative effects on academic achievement. Using statewide administrative data, Liu, et al. (2021) found that secondary school absences significantly reduced students' standardized test scores in math and reading, even after controlling for student fixed effects and prior achievement. Notably, these effects persisted beyond the year of the absence, indicating cumulative academic harm over time.

Kirksey (2019) further demonstrated that missing instructional time in high school—even below conventional chronic absenteeism thresholds—was associated with statistically significant declines in standardized assessment outcomes. Importantly, this work also suggests that incremental gains in ADA can yield measurable improvements in academic performance on summative exams.

Timing, Intensity, and Spillover Effects

The timing and concentration of absences also seem to matter. London, Sánchez, and Castrechini (2016) showed that chronic absenteeism during secondary grades was strongly associated with lower academic achievement and that these effects intensified when absences occurred during critical instructional periods leading up to statewide assessments. Complementary evidence from Gottfried (2010) demonstrated that absences exert a measurable negative effect on standardized test scores, reinforcing an argument of causality.

Beyond individual student impacts, attendance has classroom-level implications. Research on peer effects suggests that higher concentrations of absenteeism within classrooms depress overall academic performance, including standardized test outcomes, even for students with strong individual attendance records (London et al., 2016). This finding reinforces the importance of schoolwide and district-level attendance strategies aimed at increasing ADA.

Increasing Average Daily Attendance and Academic Achievement

Together, these trends position chronic absenteeism—and by extension, efforts to improve ADA—as a central leverage point for restoring instructional time and improving student performance on high-stakes summative assessments.

A growing body of empirical research demonstrates a consistent and statistically significant relationship between student attendance and academic achievement on statewide summative assessments in English Language Arts (ELA) and mathematics at the secondary level. While attendance is often framed as student absences, or chronic absenteeism, the inverse interpretation has also been established: Higher ADA—achieved through reduced absences—is associated with higher performance on high-stakes standardized exams.

After analyzing nearly a decade of North Carolina administrative data spanning Grades 6–12, Swiderski (2025), reported that increased attendance was strongly associated with higher ELA and mathematics test performance. The study found that even modest improvements in attendance corresponded with meaningful gains in standardized test scores, particularly in mathematics—an outcome consistent with prior secondary-level research.

From this perspective, chronic absenteeism functions as a powerful mediator between schooling conditions and academic performance: When students are not present, they are systematically denied access to grade-level instruction, feedback, and practice opportunities that summative assessments are explicitly designed to measure.

Synthesis and Implications

Multiple strands of evidence seem to converge on a reasonable inference: Increasing student ADA yields measurable gains on statewide summative assessments in ELA and mathematics. Consequently, efforts to reduce chronic absenteeism and increase ADA represent not only an engagement strategy, but a research-supported pathway for improving student performance on high-stakes ELA and mathematics assessments.

Taken at face value, compounding evidence strongly establishes attendance as a critical leverage point for improving secondary academic achievement and provide a strong empirical foundation for interventions and research designs that examine attendance improvements as a mechanism for raising summative assessment performance.

Prior Attendance Study Findings

The literature reviewed establishes a robust theoretical and empirical foundation linking student engagement and attendance to participation in structured, interest-aligned learning experiences. Research on extracurricular and co-curricular participation consistently demonstrates that when students experience a sense of belonging, relevance, and competence, measurable gains in attendance and engagement follow (Mahoney, et al., 2003; Fredricks, et al., 2004).

However, despite the exponential growth of gaming and Esports as dominant elements in youth cultures, comparatively few studies have examined these contexts as formal educational interventions. This gap represents an opportunity to further examine whether gaming-based instructional and activity models function similarly to established co-curricular programs by influencing key mediating variables such as motivation, school attachment, and persistence.

Russell’s (2021) mixed-methods doctoral study provides a critical empirical anchor for this line of inquiry. Using a convergent design, Russell examined the effects of the Gaming Concepts curriculum on high school students’ perceptions of engagement and their attendance outcomes in a small Alternative School setting. Qualitative findings revealed increased engagement among participating students, with themes related to relevance, belonging, and sustained interest in school (Russell, 2021).

Quantitative analyses conducted across two consecutive academic years revealed statistically significant attendance advantages for students enrolled in the gaming curriculum when compared to their non-enrolled peers. Russell’s (2021) findings demonstrated consistent treatment effects across both the 2017–2018 and 2018–2019 school years, indicating that participation in the Gaming Concepts course was associated with meaningful improvements in student attendance. Specifically, students enrolled in the course during the 2017–2018 academic year exhibited an average attendance rate that was 7.44 percentage points higher than that of students who did not participate in the course. Similarly, during the 2018–2019 academic year, enrolled students demonstrated an average attendance advantage of 7.71 percentage points over their non-enrolled counterparts.

Participants in the ADA Study

The research question for the ADA study was: What is the relationship between average daily attendance (ADA) and students’ participation in PVPs. The average daily attendance by year and conditions is reported in Figure 3.

Figure 3: Average Daily Attendance by Condition and Year

School Year	No GC/No Esports	GC Only	Esports Only	GC + Esports
2020–21	0.9401 (N=23,258)	0.9843 (N=100)	0.9752 (N=528)	0.9924 (N=30)
2021–22	0.8990 (N=22,497)	0.9259 (N=752)	0.9315 (N=552)	0.9394 (N=95)
2022–23	0.8869 (N=21,810)	0.9115 (N=1,483)	0.9129 (N=518)	0.9398 (N=99)
2023–24	0.8897 (N=20,823)	0.9042 (N=2,377)	0.9113 (N=458)	0.9094 (N=87)
2024–25	0.9007 (N=20,483)	0.9070 (N=2,500)	0.9164 (N=345)	0.9424 (N=46)

A number of patterns are observable in these data. Summing over the data across all four groups, the highest attendance was in 2020–21, which is common in districts that:

- Shifted to hybrid/remote models
- Had altered attendance accounting rules

Attendance declined sharply post-2020–21, reaching a low in 2022–23. A modest rebound appears in 2023–24 and 2024–25, though levels remain below pre-decline norms.

This pattern is consistent with post-pandemic attendance recovery trends. Additionally:

- GC participants show consistently higher attendance in every school year
- The largest gap appears in 2020–21
- Attendance for GC participants declines post-2020–21 (mirroring district trends) but remains above non-participants

Some generalizations that can be made given these data include:

- GC + Esports students have the highest attendance in every year
- The attendance advantage persists even through post-2020–21 declines
- The 2023–24 dip mirrors system-wide trends, followed by a strong rebound in 2024–25
- All groups experience a decline after 2020–21
- GC + Esports shows the strongest recovery by 2024–25
- Non-participants recover the least

Effect Size Computation

To determine the relationship between the experimental conditions and average daily attendance, effect sizes were calculated comparing the average daily attendance for the three experimental groups. Therefore, there are three effect sizes for each of the five school years, with No GC / No Esports serving as the control group and each participation group treated as a separate experimental comparison. Figure 4 reports the effect sizes computed using Cohen's d.

Figure 4: Effect Sizes (Cohen's *d*) with 95% Confidence Intervals Outcome: Average Daily Attendance Control Group: No GC / No Esports

School Year	GC Only vs Control	Esports Only vs Control	GC + Esports vs Control
2020–21	0.39 [0.19, 0.59]	0.31 [0.22, 0.40]	0.46 [0.10, 0.82]
2021–22	0.22 [0.14, 0.29]	0.26 [0.18, 0.35]	0.32 [0.12, 0.53]
2022–23	0.19 [0.14, 0.24]	0.20 [0.11, 0.29]	0.40 [0.21, 0.60]
2023–24	0.12 [0.07, 0.16]	0.17 [0.08, 0.26]	0.15 [−0.06, 0.36]
2024–25	0.06 [0.01, 0.10]	0.14 [0.03, 0.24]	0.36 [0.07, 0.65]

Figure 4 lists the effect sizes for the comparison of each of the three experimental groups with the control group for each of the five school years. In general, the following benchmarks are used to interpret effect sizes:

- 0.20 ≈ small
- 0.50 ≈ moderate
- 0.80 ≈ large

Using these benchmarks, one might refer to the effect sizes in figure 4 as small to moderate in favor of the experimental groups across the five school years. Key patterns that are discernable in these findings include:

All effect sizes are positive, implying that participation is associated with higher attendance relative to non-participation in every year. There also appears to be a dosage or engagement gradient. Specifically, across most years:

- GC + Esports → largest effects
- GC only / Esports only → smaller but still positive effects

Taken at face value, this pattern strengthens the construct validity of participation as an engagement proxy. Trends over time include the following:

- Strongest effects appear in 2020–21
- Effects attenuate in 2023–24
- GC + Esports rebounds strongly in 2024–25, despite small N

This is consistent with:

- System-wide post-pandemic normalization
- Participation becoming less “selective” as programs scale

Cautionary Notes:

- Unequal sample sizes
    - Control group Ns are very large
    - GC + Esports Ns are small in some years
      → Cohen’s d is still interpretable, but precision varies
- Selection bias
    - These are descriptive effect sizes
    - They do not imply causal effects
- Experiment-wise context

- 15 effect sizes represent a family of comparisons
- Reporting effect sizes (not p-values) is appropriate here, but experiment-wise error should be acknowledged (see discussion below)

How Effect Sizes Were Calculated

It is important to note that effect sizes can be computed in many ways. In this study, Cohen's d with a pooled standard deviation was employed. Each effect size compares a particular experimental group to the NO GC / No Esports control group within the same school year. The following formula was used to calculate Cohen's d.

$$\boxed{d = \frac{\bar{X}_{\text{exp}} - \bar{X}_{\text{ctrl}}}{s_p}}$$

where:

$$\boxed{s_p = \sqrt{\frac{(n_{\text{ctrl}} - 1)s_{\text{ctrl}}^2 + (n_{\text{exp}} - 1)s_{\text{exp}}^2}{n_{\text{ctrl}} + n_{\text{exp}} - 2}}}$$

Symbol	Meaning
$\bar{X}_{\text{ctrl}}$	Mean attendance of NO GC / No Esports group
$\bar{X}_{\text{exp}}$	Mean attendance of the participation group
s_{ctrl}	Sample standard deviation of control group
s_{exp}	Sample standard deviation of experimental group
n_{ctrl}	Sample size of control group
n_{exp}	Sample size of experimental group

Use of Cohen's d is justified for a number of reasons that include the following:

- Groups are independent
- Outcome variable (attendance proportion) is continuous
- This form of *d*:
    - Handles unequal group sizes
    - Is standard in education and behavioral research
- Focuses on magnitude of difference, not statistical significance

Cautionary Notes:

The findings regarding effect sizes should be interpreted with the following issues in mind:

- No small-sample correction was applied.
    - The reported values are Cohen's *d*, not Hedges' *g* which is sometimes used when some groups have small sample sizes
    - For small-N groups (especially GC + Esports), *g* would be slightly smaller
- Selection bias was not addressed.
    - These are descriptive effect sizes
    - They do not imply causal impact
- The outcome was bounded.
    - Attendance is bounded [0, 1]
    - This can slightly compress SDs and inflate *d* relative to unbounded outcomes

Interpretation of Confidence Intervals

It is important to note that figure 4 also reports the 95% confidence interval for each effect size. A 95% confidence interval identifies the interval of scores for which one can be 95% confident that the true effect size lies. In effect, a confidence interval acknowledges the error that a reported effect size might contain due to sampling and other random or systematic factors. If the 95% confidence interval does not include zero, then one can say that the effect size is significant at the .05 level.

An examination of the confidence intervals indicates that all effect sizes except one were significant at the .05 level. The non-significant effect size is for the 2023-2024 comparison between the control group and the GC + Esports experimental group (0.15).

Generalizations regarding these data include:

- GC Only and Esports Only confidence intervals are relatively narrow due to larger Ns
- GC + Esports CIs are wider, reflecting small sample sizes
- Most effects have CIs entirely above 0, indicating reliable positive differences
- One exception:
    - GC + Esports in 2023–24 crosses 0 → effect direction is positive but statistically uncertain

It is also important to note that even when effects are "small" statistically:

- Attendance gains of this magnitude often translate into several additional days of school per year
- Consistency across years strengthens practical significance

Cautionary Notes:

With four participation groups times five years there are 20 group–year means. Thus, there are 15 separate inferential tests. This increases the possibility of experiment-wise error. Stated differently, experiment-wise error (also called family-wise error) refers to the overall probability of making at least one Type I error (false positive) across a set of statistical tests that belong to the same experiment or analysis family. More specifically, if a researcher runs one statistical test at $\alpha = .05$, you accept a 5% chance of a false positive. If a researcher runs many tests in the same study and treats each as $\alpha = .05$, the chance that at least one result is falsely significant increases, sometimes dramatically.

That inflated risk is the experiment-wise error rate. In more technical terms, experiment-wise error rate (EWER) is the probability of committing one or more Type I errors across all hypothesis tests conducted within an experiment or family of comparisons.

Mathematically:

$$\text{EWER} = 1 - (1 - \alpha)^k$$

where

- α= per-test significance level
- k= number of tests

To illustrate, assume a researcher conducts 10 independent hypothesis tests, each at $\alpha = .05$.

$$\text{EWER} = 1 - (0.95)^{10} \approx 0.40$$

This means that there is a 40% chance of at least one false positive even though each test is "only" 5% risk.

Comparison with Glass's Delta

As noted above, Cohen's d is not the only way to compute an effect size. In this situation a case can be made that Glass's Delta should be used because it employs the standard deviation of the control as the denominator for the effect size calculation. When a control group is much larger than the experimental groups, this is quite reasonable.

Below is a full comparison table, recalculating all effect sizes using Glass's Δ (control-group SD) and directly comparing them to the original Cohen's d, with N and 95% confidence intervals for each. It is important to note that for ease of comparison effect sizes in this figure are reported to the third decimal point.

Figure 5: Comparison of Effect Sizes

Control = Group C
Outcome = Average Daily Attendance (%)

Note: Glass's Δ uses the SD of group C as the denominator; Cohen's d uses the pooled SD.

2020–21

Group	N	Cohen's *d* (95% CI)	Glass's Δ (95% CI)
GC	100	0.389 [0.19, 0.59]	0.388 [0.19, 0.58]
ES	528	0.311 [0.22, 0.40]	0.308 [0.22, 0.39]
GC+ES	30	0.460 [0.10, 0.82]	0.459 [0.10, 0.82]

2021–22

Group	N	Cohen's *d* (95% CI)	Glass's Δ (95% CI)
GC	752	0.218 [0.14, 0.29]	0.216 [0.14, 0.29]
ES	552	0.263 [0.18, 0.35]	0.261 [0.18, 0.35]
GC+ES	95	0.324 [0.12, 0.53]	0.324 [0.12, 0.53]

2022–23

Group	N	Cohen's *d* (95% CI)	Glass's Δ (95% CI)
GC	1,483	0.190 [0.14, 0.24]	0.188 [0.14, 0.24]
ES	518	0.199 [0.11, 0.29]	0.199 [0.11, 0.29]
GC+ES	99	0.404 [0.21, 0.60]	0.404 [0.21, 0.60]

2023–24

Group	N	Cohen's *d* (95% CI)	Glass's Δ (95% CI)
GC	2,377	0.115 [0.07, 0.16]	0.113 [0.07, 0.16]
ES	458	0.169 [0.08, 0.26]	0.169 [0.08, 0.26]
GC+ES	87	0.154 [−0.06, 0.36]	0.154 [−0.06, 0.36]

2024–25

Group	N	Cohen's *d* (95% CI)	Glass's Δ (95% CI)
GC	2,500	0.055 [0.01, 0.10]	0.054 [0.01, 0.10]
ES	345	0.135 [0.03, 0.24]	0.135 [0.03, 0.24]
GC+ES	46	0.359 [0.07, 0.65]	0.359 [0.07, 0.65]

An examination of this figure indicates the following:

- Glass's Δ is slightly smaller, as expected
- Differences are at the third decimal place
- Rankings and significance do not change

The reasons for this include the following:

- Control-group SD ≈ pooled SD
- Control group dominates the pooled estimate (large *N*)
- Experimental groups have similar or slightly smaller variance

Incorporating the findings regarding Glass's delta, one might conclude that the initial effect sizes are robust to alternative standardization methods. Effect sizes computed using Glass's Δ (control-group SD) were nearly identical to those obtained using Cohen's d (pooled SD). Stated more technically, one might conclude that because the control-group variance closely matched the pooled variance, standardized mean differences using Glass's Δ and Cohen's d differed only trivially.

Effect Sizes Interpreted as Added Attendance Days

A very concrete way to interpret effect sizes that employ average daily attendance as the outcome measure is to translate them into expected days gained or lost in the context of a school year. Figure 6 provides an interpretation of each effect size translated into added attendance days, assuming a 180-day school year.

Figure 6: Effect Sizes Interpreted as Days Gained
School Year Length: 180 days

School Year	GC Only	Esports Only	GC + Esports
2020–21	+8.0 days	+6.3 days	+9.4 days
2021–22	+4.8 days	+5.9 days	+7.3 days
2022–23	+4.4 days	+4.7 days	+9.5 days
2023–24	+2.6 days	+3.9 days	+3.6 days
2024–25	+1.1 days	+2.8 days	+7.5 days

The first column in this figure is the school year. The second, third and fourth columns are the anticipated days gained or lost for students in the GC only, Esports only, and GC + Esports groups respectively. Before discussing findings, it is useful to examine how they were calculated.

The "added days" estimates translate differences in average attendance rates into a concrete number of additional days a student is expected to attend school over a standard 180-day school year. Instead of relying on standardized units (standard deviations), this approach uses actual attendance proportions, making the results directly interpretable and policy relevant. The calculation of added days involved the following steps:

Step 1: Compute Mean Attendance Rates

For each school year and group, compute the mean Average Daily Attendance (ADA):

$$\bar{A}_{\text{group, year}}$$

where attendance is expressed as a proportion (e.g., 0.91 = 91% attendance).

Step 2: Define the Control Group

The NO GC / No Esports group is treated as the control condition:

$$\bar{A}_{\text{control, year}}$$

All comparisons are made within the same school year to avoid confounding with year-to-year attendance shifts.

Step 3: Compute the Attendance Difference

For each participation group, compute the difference in attendance proportions relative to the control group:

$$\Delta A_{\text{year}} = \bar{A}_{\text{experimental, year}} - \bar{A}_{\text{control, year}}$$

Example:

- Control mean = 0.899
- GC mean = 0.926

$$\Delta A = 0.926 - 0.899 = 0.027$$

This means the participation group attended school 2.7 percentage points more often than non-participants.

Step 4: Convert Proportion Differences to Days

Assuming a 180-day school year, convert the proportion difference into days:

$$\boxed{\text{Added Attendance Days} = \Delta A_{\text{year}} \times 180}$$

Continuing the example:

$$0.027 \times 180 = 4.86 \text{ days}$$

In short, added attendance days were calculated by subtracting the mean attendance rate of non-participants from that of each participation group within the same school year and multiplying the resulting difference by 180 instructional days. On average, students in the participation group attended about 5 more days of school that year than comparable non-participants. More granular generalizations one might make include the following:

The added days attributed to experimental groups appear to be meaningful educationally. Even the smallest effects correspond to:

- 1–3 additional days of school per student per year

The largest effects correspond to:

- 7–10 additional days, which is:
    - ~1–2 full weeks of school
    - Often larger than effects seen in many attendance interventions

There appears to be an engagement gradient across nearly all years in that students involved in both GC and Esports consistently show the largest attendance advantages.

Time trends appear to matter:

- Largest gains appear in 2020–21 to 2022–23
- Effects shrink in 2023–24 as attendance normalizes
- GC + Esports rebounds strongly in 2024–25, despite small sample sizes

This pattern suggests the interpretation that participation:

- May be most impactful during periods of disruption or disengagement
- Remains beneficial even as systems stabilize

In summary, across five school years, participation in GC and/or Esports was associated with attendance gains ranging from approximately 1 to 10 additional days per year relative to non-participants, with the largest gains observed among students participating in both activities.

Cautionary Notes:

The cautionary concepts one should consider when interpreting these findings include:

- These are descriptive translations, and do not necessarily demonstrate causality
- Attendance is bounded, so gains should not be extrapolated indefinitely
- Small-N groups (especially GC + Esports) yield less precise estimates, but magnitudes remain substantively large

Multi-Level Modeling

Multi-level modeling is commonly used when data is nested. That is the case in this study. More specifically, the outcome of ADA is being compared across four groups: a control group and three experimental groups. However, the participants in each group are embedded (i.e., nested) in a number of different schools. Theoretically, it might be the case that students in a particular group (let's say one of the experimental groups) all came from schools where the average daily attendance was high because of factors attributable to the school as opposed to factors attributable to the intervention. Thus, the average daily attendance for students in this experimental group might be high but not because of their participation in the intervention. The common way to examine this possibility is to use multi-level modeling. In this study a two-level multi-level linear model was employed:

Level 1 (Student level)

- Outcome: Average Daily Attendance (proportion) ADA
- Predictors:
  - Participation group (GC, Esports, GC + Esports)
  - School year (modeled as a linear time trend)

Level 2 (School level)

- Random intercept for school, allowing each school to have its own baseline attendance level

The equation that was used to model this level is:

$$\text{Attendance}_{ij} = \beta_0 + \beta_1(\text{GC}_{ij}) + \beta_2(\text{Esports}_{ij}) + \beta_3(\text{GC+Esports}_{ij}) + \beta_4(\text{Year}) + u_{0j} + e_{ij}$$

Where:

- u_{0j}= school-level random effect
- Control group = No GC / No Esports (reference category)

In nontechnical terms, this equation predicts the average daily attendance for an individual student while controlling for the difference in attendance due to the school the student attends. The effects of the various interventions (i.e., the type of PVPs the student participated in) are depicted in figure 7.

Figure 7: Fixed Effect Coefficients

Key Fixed Effects Results (Attendance Proportion Units)

Predictor	Coefficient	Interpretation
GC Only	+0.012	+1.2 percentage points
Esports Only	+0.029	+2.9 percentage points
GC + Esports	+0.041	+4.1 percentage points
School Year (trend)	−0.009	Overall post-pandemic decline

Figure 7 indicates that all participation effects are positive and statistically reliable after accounting for school clustering. The coefficients represent the predicted increase or decrease in ADA for each of the fixed factors. For example, a student in the GC Only group is predicted to have a gain of 0.012 in the ADA reported as a proportion. This translated into a 1.2 percentage point gain in ADA.

These coefficients can be translated into added attendance days assuming a 180-day school year. Since the coefficients represent proportion differences, one can convert them directly:

$$\text{Added Days} = \beta \times 180$$

Figure 8 depicts the attendance gains adjusted for the multi-level analysis.

Figure 8: Multilevel-Adjusted Attendance Gains

Participation Group	Attendance Gain	Added Days per Year
GC Only	+0.012	≈ 2.2 days
Esports Only	+0.029	≈ 5.2 days
GC + Esports	+0.041	≈ 7.4 days

These attendance gains are different from those reported above in the discussion of effect sizes. One reason is that they answer different questions. The multi-level results answer the question: What remains after accounting for school context? The year-by-year effect calculations answers the question: What differences do we observe?

Key insight from this analysis includes the following:

- The magnitude shrinks, as expected
- Direction and ordering remain intact
- GC + Esports remains the strongest association

In effect, considering school differences does change the magnitude of the anticipated effect, but the pattern of effects remains the same.

Finally, another way to quantify the influence of individual schools is to compute an intraclass correlation coefficient (ICC). Using the random-intercept-for-school model, the school-level random intercept can be quantified via the following formula:

$$\text{ICC} = \frac{\sigma^2_{\text{school}}}{\sigma^2_{\text{school}} + \sigma^2_{\text{residual}}}$$

Using the full student-level attendance data across all schools and the five school years, the estimated variance components were:

- Between-school variance σ^2_{school}= 0.000677
- Within-school (residual) variance $\sigma^2_{\text{residual}}$= 0.014406

Therefore,

$$\text{ICC} = \frac{0.000677}{0.000677 + 0.014406} = 0.0449$$

An interpretation of an ICC ≈ 0.045 is that about 4.5% of the total variation in student attendance is between schools, and about 95.5% is within schools (between students in the same school). This means that a one-SD school difference in attendance is approximately:

$$\sqrt{0.000677} \approx 0.026$$
$$0.026 \times 180 \approx 4.7 \text{ days}$$

In short, the ICC indicates that schools typically differ by roughly ±5 days around the district's mean (before controlling for other predictors).

In summary, after accounting for school-level differences using a multilevel model, participation in GC and Esports remained positively associated with attendance. Estimated gains ranged from approximately 2 additional days per year for GC participation, to over 7 additional days per year for students participating in both GC and Esports, relative to non-participants.

Incidents of Misbehavior

The second outcome examined in this study was incidents of misbehavior. One can make the case that this outcome might be influenced by participation in PVPs. Therefore, the second research question in this study was: What is the relationship between participation in PVPs and incidents of misbehavior.

Selected Literature Review for Behavioral Incidents

Attendance must be considered as a foundational precursor to learning as it determines the amount of time students actually spend engaged in classroom instruction. When behavior problems escalate, attendance patterns often suffer. Behavioral incidents in schools—ranging from classroom disruptions to exclusionary disciplinary practices such as suspensions and expulsions—are more than momentary lapses in learning continuity. Classroom behavioral incidents that result in lost instructional access may also signal deeper issues between students, teachers, and classroom contexts that negatively impact attendance and academic achievement. A growing body of research suggests that these behaviors often serve as early indicators of educational disengagement, predicting not only declines in daily attendance, but also measurable academic setbacks across subjects and grade levels.

Gregory et al. (2010) found that disciplinary exclusions, particularly suspensions, are associated with both lower attendance rates and a diminished sense of school belonging. The authors argue further that the academic achievement gap and the discipline gap are mutually reinforcing phenomena rooted in systemic inequities rather than individual student deficits. Their synthesis of national discipline and achievement data demonstrates that exclusionary disciplinary practices—particularly suspensions—disproportionately affect students of color and are associated with reduced instructional access, weakened school engagement, and lower academic outcomes Gregory et al. (2010).

More recently, Valdebenito et al. (2025) also emphasized that exclusionary disciplinary actions correlate not only with lower attendance rates and reductions in academic achievement, but also with weaker connections to school communities and increasing disengagement from learning.

Notably, even single disciplinary actions can undermine a student's sense of belonging—a psychological mechanism that appears to be linked to attendance. When students feel alienated or stigmatized by disciplinary events, their motivation to attend regularly diminishes, particularly in elementary settings where school attachment is formative (Kim, Gong Liu, Davison, Bi, & Penner, 2025).

The Impact of Behavioral Incidents on Academic Achievement

Beyond attendance, behavior incidents influence the quality of learning experiences and academic outcomes both directly and indirectly. A strand of longitudinal research shows that suspension experiences serve to depress students' academic achievement.

Hattie's (Hattie, n.d.) synthesis of over 2,000 meta-analyses confirms that classroom management and positive student behavior are significant predictors of academic performance, with disruptive behavior contributing negatively to learning outcomes (Hattie, n.d.). A recent meta-analysis listed on the MetaX searchable website indicates that the effect of suspending and expelling students has a weighted effect size of -.20, denoting a negative impact on student achievement (Hattie, n.d.).

At the school level, higher suspension rates correlate with lower aggregate test scores even after adjusting for school demographics, suggesting that punitive climates may suppress overall academic performance. Examining the academic consequences of suspension and expulsion using large-scale longitudinal data, Zhu (2025), found that “Out of School Suspension” (OSS) practices produce statistically significant negative effects on student achievement. Zhu’s (2025) analyses shows that students who experience OSSs demonstrate lower standardized test performance in both mathematics and reading, even after controlling for prior achievement and demographic factors.

Importantly, Zhu (2025) also discovered spillover effects: Higher school-level suspension rates are associated with reduced academic performance among non-suspended peers, suggesting that exclusionary discipline—such as OSS—depresses overall instructional quality and learning conditions. This finding suggests that exclusionary discipline practices operate not only as an individual punishment but as a systemic mechanism that undermines academic outcomes schoolwide.

The review emphasizes that disciplinary exclusion functions as a mechanism of opportunity loss—reducing both access to instruction and the relational conditions necessary for sustained attendance and academic success. Across developmental stages and contexts, behavioral incidents exert a negative influence on student attendance and academic achievement, particularly for students who experience repeated exclusions. Exclusionary discipline interrupts instructional continuity, erodes psychological belonging, and predicts lower test performance; even when controlling for confounders, suspended students demonstrate weaker outcomes. Moreover, punitive climates negatively affect peers and classroom cultures, reinforcing disengagement and learning loss.

Effect Sizes

As with the case of ADA as an outcome, the relationship between participation in PVPs and incidents of misbehavior was examined using Cohen’s d effect sizes. Figure 9 depicts these results.

Figure 9: Year-Specific Effect Sizes (Cohen's d) + 95% CIs

Effect sizes are negative when groups have fewer incidents than controls
(i.e., lower is better)

2020–21

Group	N	d	95% CI	P
GC	100	−0.41	[−0.62, −0.20]	< .001
ES	528	−0.36	[−0.44, −0.28]	< .001
GC + ES	30	−0.52	[−0.89, −0.15]	.006

2021–22

Group	N	d	95% CI	p
GC	752	−0.24	[−0.31, −0.17]	< .001
ES	552	−0.29	[−0.37, −0.21]	< .001
GC + ES	95	−0.34	[−0.54, −0.14]	.001

2022–23

Group	N	d	95% CI	p
GC	1,483	−0.18	[−0.23, −0.13]	< .001
ES	518	−0.22	[−0.31, −0.13]	< .001
GC + ES	99	−0.41	[−0.61, −0.22]	< .001

2023–24

Group	N	d	95% CI	p
GC	2,377	−0.11	[−0.15, −0.07]	< .001
ES	458	−0.18	[−0.27, −0.09]	< .001
GC + ES	87	−0.16	[−0.38, 0.06]	.15 *(ns)*

2024–25

Group	N	d	95% CI	p
GC	2,500	−0.06	[−0.10, −0.02]	.01
ES	345	−0.15	[−0.26, −0.04]	.008
GC + ES	46	−0.39	[−0.68, −0.10]	.01

Examining the pattern of effect sizes across the five years, one finds the following ranges of score values:

- GC: −0.06 to −0.41
- ES: −0.15 to −0.36
- GC + ES: −0.16 to −0.52

When interpreting these values, it is important to remember that negative values mean fewer incidents than control (C). As indicated in figure 9, all effect sizes were negative, indicating that experimental groups had fewer incidents than the control group. Additionally, all effect sizes were statistically significant at the .05 level except for one.

The formula used to compute these effect sizes was:

$$d_t = \frac{I\bar{N}C_{E,t} - I\bar{N}C_{C,t}}{s_{p,t}}$$

Where t stands for the school year

INC $_{E,t}$ Stands for the average number of incidents for the experimental group

INC $_{C,t}$ Stands for the average number of incidents for the control group

S $_{p,t}$ stands for the pooled standard deviation

The effect size analysis reported above estimates year-specific standardized mean differences using Cohen's d, computed from the full set of student records with valid outcome and participation data within each year. As was the case with analyses for the attendance outcome, a robustness check was conducted using Glass's Δ (control-group standard deviation). This alternative approach yielded effect sizes that were directionally consistent but sometimes smaller in magnitude, reflecting the sensitivity of standardized mean differences to variance structures and sample restrictions when applied to skewed count data. This noted, substantive conclusions were unchanged across specifications.

Cautionary Notes:

- When interpreting these effect sizes, it is important to note that disciplinary incidents are highly skewed count outcomes characterized by substantial zero inflation (i.e., the majority of scores were zero). This creates a situation (called heteroscedasticity) where the variance of error scores is not stable.

- Because standardized mean differences are not ideal summaries for zero-inflated count outcomes, results for the outcome of incidents should be interpreted primarily in terms of direction, relative magnitude, and consistency across years**.**

Interpretation in Terms of Expected Incidents

As was the case with ADA, effect sizes were translated into expected incidents of misbehavior. To do this, control group values for means and standard deviations for incidents were computed across the five years of the study producing the following results

- Typical mean incidents (control) ≈ 0.8–1.2 incidents/year
- Typical SD (control) ≈ 1.1–1.3 incidents

These values were then used to compute expected values for incidents. To stay conservative the following value was used as the estimate of the population standard deviation for the control group:

$$\boxed{s_C \approx 1.2 \text{ incidents}}$$

The following formula was then used to compute expected difference in incidents:

$$\text{Expected difference in incidents} = d \times s_C$$

Figure 10 depicts expected differences in incidents for different values of Cohen's *d.*

Figure 10: Expected Fewer Incidents for Values of Cohen's *d*

Cohen's *d*	Fewer incidents per student per year
−0.05	~0.06 fewer incidents
−0.10	~0.12 fewer incidents
−0.20	~0.24 fewer incidents
−0.30	~0.36 fewer incidents
−0.40	~0.48 fewer incidents
−0.50	~0.60 fewer incidents

Using the range of mean incidents reported above, the baseline value for the control group mean was ~1 incident per student per year (on average). This is the reference point for interpreting expected decreases in incidents per experimental group. To illustrate, consider the GC group comparison with the control group. Observed effects ranged roughly from −0.06 to −0.41, but most years were −0.10 to −0.25.

Interpretation:

- GC students experience about 0.1–0.3 fewer incidents per student per year
- That corresponds to roughly a 10–25% reduction
- Effects diminish over time, consistent with selection rather than sustained behavior change

In general, then, GC participation is associated with small but measurable reductions in incidents — roughly one fewer incident for every 4–10 students per year.

Next, consider the ES group. Effect sizes were typically in the −0.15 to −0.36 range. Translating the effects to expectations about incidents results in the interpretations:

- ES students experience about 0.2–0.4 fewer incidents per student per year
- Roughly a 20–35% reduction
- Consistent across years

In general, then, students participating in Esports average about one-third fewer disciplinary incidents than comparable non-participants.

Finally, consider the GC + Esports group. Effect sizes were typically in the -0.35 to -0.52 range. Translating these effects to expectations about incidents results in the interpretations:

- GC + Esports students experience about 0.4–0.6 fewer incidents per student per year
- Roughly a 35–50% reduction
- Largest and most consistent effect (with wider uncertainty due to small N)

In general, then, Students participating in both GC and Esports experience roughly half as many disciplinary incidents as non-participants.

In summary, when translated into expected incident counts, the observed standardized effects correspond to meaningful behavioral differences. GC participation was associated with approximately 0.1–0.3 fewer incidents per student per year, Esports participation with approximately 0.2–0.4 fewer incidents, and combined GC and Esports participation with approximately 0.4–0.6 fewer incidents relative to non-participants. Given baseline incident rates near one per student per year, these effects represent reductions on the order of 10–50 percent.

Multi-Level Modeling

Relative to the research question regarding the effects of participation in PVPs on incidents of misbehavior, a multi-level model was not fitted to the data for technical reasons. Such an analysis was not possible for the outcome variable of incidents. This is because the distribution of incidents of misbehavior across schools, years, and group status was highly skewed in that the majority of entries for individual student misbehavior was zero. To conduct a valid and mathematically viable multi-level analysis, critical variables in the equation cannot have such extreme skewing in their distributions.

General Recommendations

The studies described in this report present a reasonable case as to the positive effects of participation in select PVPs on important student outcomes. Students participating in both Gaming Concepts and Esports showed the strongest and most consistent advantages across both attendance and behavior outcomes, suggesting a cumulative engagement effect. Findings for the combined GC + Esports group should be interpreted as promising but preliminary due to methodological challenges (such as small N size for experimental groups). That case would be substantially strengthened if it were replicated in one or more other districts. If resources and data are available, PlayVS should strongly consider such replication studies.

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