Impact of Connected Chromebooks on Tukwila School District Student Achievement

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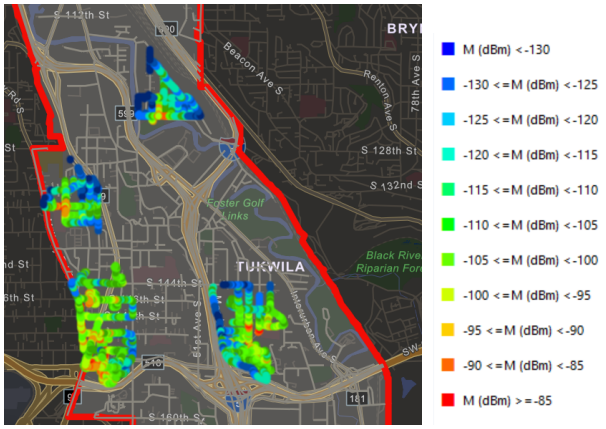
***Abstract*—During the COVID-19 pandemic, the Tukwila School District (TSD) partnered with the City of Tukwila to provide Chromebooks with City-run private LTE network access to low-income middle and high school students. This paper presents a case study of the student Chromebook program and its impact on academic performance. We use inverse probability weighting and coarsened exact matching to control for confounds and isolate the Chromebooks' effect on students' cumulative GPAs. We find a consistent, positive impact of Chromebook receipt on GPA, with a larger positive impact for the second cohort of students selected by teachers. Network usage analysis reveals low overall activity concentrated outside of City business hours, suggesting that the program has low impact on City bandwidth. However, the majority of usage is dominated by a handful of users. We identify some preliminary usability issues with the LTE deployment to inform better student onboarding and facilitate increased network adoption.**

***Index Terms*—internet access, municipal networks, educational technology, statistical analysis, digital divide, socioeconomics**

I. Introduction

During the Covid-19 pandemic, when Internet access became critical infrastructure for students attending school, many local governments and school districts across the United States sought to deploy network connectivity and distribute devices such as laptops, Chromebooks, or hotspots to improve their students' classroom access [1]–[3], especially in unserved and underserved areas. Thanks to the rapid deployment of government funding for these projects [4]–[6], the reach of connectivity throughout low-income and rural communities has improved since the pandemic [7]. However, it has been difficult to assess the impact of school-based technology interventions on students' academic performance due to factors such as a lack of systematic data collection in emergency conditions, as well as ambiguities and confounds in student performance data correlating with students' eligibility for connectivity interventions for low-resource populations. As availability of federal funding for these interventions decreases, school districts must decide whether they have sufficient justification and resources to continue sustaining these interventions into the future.

In partnership with the Tukwila School District (TSD), a small city in the Seattle metro area of around 22,000 residents including 2,167 students, we present a case study of the TSD's



(a) Coverage map. (b) Signal strength key.

Fig. 1: TSD LTE network deployment: signal strength heat map from managed service provider Federated Wireless's drive test, measured from within a vehicle (8 dB loss compared to outside). Warmer shades correspond to stronger signals, cooler shades to weaker signals.

4G LTE broadband and Chromebook program. The broadband network was deployed and supported since 2021 by the City of Tukwila's IT department, sharing upstream bandwidth with the City of Tukwila network, and targeting low-income neighborhoods where students lived that were shown to have limited high-speed internet penetration and poor cellular coverage. The program initially provided all middle and high school students qualifying for free or reduced price lunch and living within the network coverage area with a school Chromebook to take home, which included a SIM card to access the network. After the first year of the program, teachers continued to provide Chromebooks to students who demonstrated need. We sought to analyze the relationship between students' grades and whether they had received a Chromebook as part of this program.

We also measured bandwidth consumption patterns by the student Chromebooks on the City of Tukwila network, to understand whether or not the students' home usage of the City bandwidth would impact its overall capacity needs. These

findings have implications for the sustainability and costs to local governments engaging in similar bandwidth sharing programs with students at home. Our findings contribute:

- A positive correlation between middle and high school students' GPAs and receipt of a Chromebook.
- Measurement of student-used bandwidth showing overall low usage, with peak data consumption occurring outside of working hours for the City.

This case study suggests positive impacts on student performance of school-provided networked computing devices, as well as a beneficial use case for excess City bandwidth during non-work hours.

II. Related Work

A. Previous Broadband and Device Program Studies

Prior work on the effects of broadband and device deployment on student outcomes provide mixed results, and there is a gap in the literature on measurement of network usage in such programs. A 2014 study of student broadband access in Portugal schools found broadband access to have a negative impact on grades. However, school districts participating in the study did not have standardized content filtering systems, and the broadband access posed a high risk of distracting students [8]. A 2019 study on broadband subsidies in North Carolina found no relationship between dollars per student spent on broadband subsidies and SAT scores [9], and a post-COVID 2024 study in Norway on broadband access for adolescents found effects on academic outcomes to vary by socioeconomic status and gender [10].

In contrast, studies on the effects of 1:1 Chromebook deployment programs on student performance consistently report increased student engagement, assessed via anecdotal evidence from teachers [11]–[15]. However, these studies had small sample sizes and either unmeasured or inconclusive findings on the effect of Chromebook receipt on GPA or test scores. The scarcity of post-COVID literature on the effects of broadband and device access on educational outcomes highlights the need to reevaluate their impact on student achievement. Prior studies have relied only on pre- and post-treatment GPA and test scores or self-reported assessments from teachers to infer these programs' impact on student achievement. No during- or post-COVID study has used within-school control groups to isolate causal effects of Chromebook and broadband deployment programs on GPA and test scores.

B. Models for Educational Achievement

An important theoretical framework for a causal model of educational achievement is found in the education production function [16], which considers GPA and test scores as outcomes representing educational achievement, with socioeconomic status (SES), lagged test scores (representing previous achievement), and demographic background as inputs.

$$Y_{ijt} = \beta X_{ijt} + \gamma a_{ijt} + \mu a_{ijt} \quad (1)$$

Y_{ijt} represents student i's standardized test score in subject j in year t. X includes lagged test scores, demographics, English language learner (ELL) and special education status, and controls for socioeconomic status. a represents absences and μ represents unobserved inputs for academic achievement.

We note that short-term attendance or absenteeism is considered an input, but acts as an output in the long-term, serving as a proxy for educational achievement. Liu, Lee & Gershenson [16] provide causal evidence that missing 10 classes reduces course grades by approximately 17–18% of a standard deviation, using within-student between-subject variation to address endogeneity. Gershenson, Jacknowitz & Brannegan [17] found that these effects are amplified for low-income and multilingual students, the population targeted in the Tukwila School District's Chromebook program. Because absenteeism both mediates the Chromebooks' effect on educational attainment and is itself strongly predicted by socioeconomic status, we treat absence rate within our dataset as a covariate rather than an outcome.

Socioeconomic status (SES) is documented as a confounding variable in education research. Sirin [18] finds a strong correlation (r=0.28) between SES and academic achievement, which is why SES must be controlled for in study design rather than treated as a direct covariate. Song, Liu & Tan [19] state that when causal rather than correlational models are used to control for SES, SES's impact on students' outcomes is minimal. Thus, our study design uses the methods described in Sec. III to control for SES as a confounding variable. Sirin also notes that Free/Reduced Lunch (FRL)[1] eligibility correlates more weakly with achievement as grade level rises, since older students are responsible for FRL self-enrollment. This poses a potential limitation for our study, since we use FRL status as a proxy for SES. However, with their Chromebook eligibility at stake, we posit that most eligible students interested in receiving a Chromebook through the program would pursue the required FRL enrollment, leaving out primarily students who were not interested.

Our paper uses Grade Point Average (GPA) as a measure of student achievement rather than standardized test scores. Allensworth & Clark [21] found that high school GPAs are consistent in comparing students' achievement within schools, while inconsistent across schools. Standardized test scores also carry less information per student than GPA and are a worse measurement for comparing individual students' outcomes within the same school, though they do provide a signal at the school level.

In summary, our observational study provides methodological improvements over existing quantitative work on broadband and device deployments' effects on academic achievement. Informed by prior studies, we use GPA as the primary outcome, control and treatment groups within the same schools, and account for student SES, absence rate, and demographics as confounding variables.

[1]USA policy National School Lunch Program [20]

III. Methodology and Proposed Methods

The following procedures were approved by a University of Washington IRB, with data access through a data sharing agreement between the Tukwila School District and the University of Washington.

A. Chromebook Distribution Program

1) Data: Our dataset included 2,167 total middle and high school students in the Tukwila School District, which has only one middle and one high school. Of these, 1,190 students were at Showalter Middle School and 977 were at Foster High School. 1,705 students in the District (79%) qualified for free/reduced lunch (FRL) in total. 226 (13%) of these students participated in the Chromebook distribution program, with 139 receiving a Chromebook in Phase I at the start of the 2023-2024 school year, and the other 87 receiving one in Phase II at the start of the 2024-2025 school year. The 139 Phase I students had to meet the selection criteria of speaking a second language at home and living within the coverage area of the TSD LTE network deployment, while Phase II students did not.

TABLE I: Demographic Composition of Treated (n=226) and Control (n=1,923) Groups

	Chromebook	**No Chromebook**
Male	47.1%	49.8%
Special Education	6.1%	5.0%
English Language Learning (ELL) [2]	76.6%	31.8%
Asian	18.9%	20.1%
Black (Non-Hispanic)	29.1%	26.8%
Hawaiian/Pacific Islander	3.7%	4.4%
Hispanic	39.3%	30.8%
Multiracial	1.6%	9.4%
White (Non-Hispanic)	5.7%	7.8%
American Indian/Alaskan Native	0.4%	0.6%
Race Not Provided	1.2%	0.3%

TABLE II: Variable Descriptions

Variable	**Type**	**Notes**
2023-24 Chromebook	Binary	n=139 for Phase I
2024-25 Chromebook	Binary	n=87 for Phase II
Cumulative GPA	Continuous	
Absence Rate 2023-24	Continuous	∼30% missing
Absence Rate 2024-25	Continuous	∼30% missing
Test Scores	Continuous	∼70% missing
Race/Ethnicity	Categorical	8 categories
Gender	Binary[3]	
Graduation Year	Continuous	Proxy for grade level
Special Education	Binary	
Free Reduced Lunch	Binary	Proxy for SES
Multilingual 2023-24	Binary	Enrolled in ELL program
Multilingual 2024-25	Binary	Enrolled in ELL program

Cumulative GPA for each student was collected at the time of the data export on December 19, 2025, and reflects a student's performance throughout their enrollment in the Tukwila School District system rather than just the treatment year. Cumulative GPA thus incorporates both pre- and post-treatment performance, since it incorporates a student's performance across their entire enrollment. Ideally, we would compare GPA pre- and post-treatment, but the dataset provided by the school district only included a snapshot of the cumulative GPA when the data was exported, rather than annual or semester-level records. The absence of separate pre- and post-treatment GPA scores in the dataset limits our study, diluting our estimates of the treatment effect. Similar programs in the future should collect granular records of GPA for cleaner pre/post comparisons.

We decided to rely solely on GPA as an outcome variable, omitting test scores available in our dataset. Approximately 70% of test scores were missing across the 8 state-level standardized Math and English/Language Arts (ELA) exams[4] in the dataset, with missingness likely related to students' enrollment date in the Tukwila School District as well as absence rate. Attempts to account for the missing data with Multivariate Imputation by Chained Equations (MICE) violated the assumptions that the data was missing at random, and could not be used.

B. Analysis

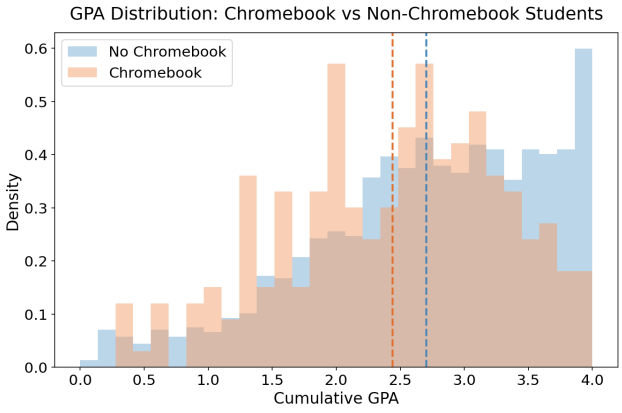


Fig. 2: Distribution of cumulative GPA across Chromebook recipients and non-recipients. Students assigned a GPA of "0," including all students below 9th grade and those in 9th-12th grade who have not earned any credits, are not displayed.

To isolate the effect of receiving a Chromebook on students' GPAs, our initial methods used partial regression on students' demographic variables and test scores to predict GPA. These methods yielded insignificant results ($p > 0.05$), likely due to confounds from socioeconomic status (SES) on baseline academic performance. Since the Chromebook distribution program targeted low-income minority students, eligibility criteria for the program included qualifying for Free/Reduced Lunch and speaking a second language at home. Due to these

[2]Student receives services through the Washington State Multilingual Education Program to achieve English proficiency [22]

[3]Gender identity was noted as binary in the school data, though we acknowledge the presence of other genders

[4]Scores were from the Smarter Balanced Assessment (SBA) Math/ELA [23] and i-Ready Math/Reading exams [24].

qualifying requirements, the treatment and control groups had significantly different characteristics that may have affected their academic performance.

To account for these confounds, we adopted two frameworks that restricted the control group to a population comparable to the treated group: Inverse Probability Weighting (IPW) and Coarsened Exact Matching (CEM). Both frameworks ensured valid comparison of academic performance across two different groups with the same demographic profiles [25]. Under both frameworks, we estimated the treatment effect, representing the effect of receiving a Chromebook on GPA. This is specified as the Average Treatment Effect on the Treated (ATT) under IPW, and it is specified as the Sample Average Treatment Effect on the Treated (SATT) under CEM.

1) Inverse Probability Weighting: Inverse Probability Weighting (IPW) reweights each observation in both the control group and the treated group by its propensity score, the probability of receiving the treatment based on its covariates. The resulting weighted sample approximates a sample where treatment is independent of all covariates. We estimate propensity scores using logistic regression, with receipt of the Chromebook as the outcome variable and the following as predictors: GPA, absence rate, free/reduced price lunch eligibility, grade level, and school. We then apply the estimated propensity score weights to run weighted ordinary least squares (WLS) regression predicting cumulative GPA as a function of Chromebook status to estimate the ATT.

TABLE III: IPW Demographic Distributions

Variable	Treated	Control	Control (IPW)
Multilingual (ELL)	77.0%	38.0%	76.3%
Male	47.3%	49.2%	46.5%
Special Education	6.6%	5.1%	6.4%
Averaged Graduation Year	2027.04	2027.61	2027.11
Race: Asian	19.0%	17.6%	18.0%
Race: Black/Non-Hispanic	27.9%	28.5%	29.5%
Race: Hawaiian/Pacific Islander	3.1%	5.0%	3.0%
Race: Hispanic	40.7%	32.9%	39.7%
Race: Multiracial	1.8%	8.7%	1.7%
Race: Not Provided	1.3%	0.3%	1.9%
Race: White/Non-Hispanic	5.8%	6.4%	5.7%

2) Coarsened Exact Matching: Coarsened Exact Matching (CEM) establishes sets of matched data points in treatment and control groups by creating discrete bins for continuous covariates and matching individual data points to those bins. Students without an exact match in the other group are removed from the analysis. For every treated student, we find one or more control students with a similar profile across the binned covariates. For our dataset, we coarsened and matched on the following covariates: GPA, absence rate, free/reduced price lunch eligibility, grade level, and school. The control sample is reweighted so that the control and treated groups have matching distributions across bins. We estimated the Sample Average Treatment Effect on the Treated (SATT) as a weighted difference in means.

C. Network Usage Measurements

Each student Chromebook included a SIM card with access to the LTE broadband network deployed for TSD students by the City of Tukwila. To measure student use of these broadband connections, we examined network data usage from the IP Detail Records (IPDR) logged by the Druid Raemis [26] LTE network core. The IPDR logs session timestamps, transmitted and received packet counts, and unique International Mobile Subscriber Identity (IMSI), which was used to identify individual users. 97 unique devices appeared in the usage records, and 78 of these were mapped to students in the Chromebook deployment records. The remaining devices are kept as standby units registered in the system, ready to replace broken devices or distribute to new recipients who enroll in the program.

To answer the question of whether and how much the student usage of City bandwidth would overlap with the City's working hours, we collected the historical times and counts of transmitted (uploaded) and received (downloaded) packets for each user based on the IPDR logs, and multiplied these by the standard IP packet size of 1500 bytes to estimate the total data consumption, since the system did not provide raw data usage counts. We aggregated this estimate over all students and produced plots of average hourly usage over the course of a day. Expecting students' usage patterns to vary based on day of week and time of year, we partitioned the data between school year weekdays, school year weekends, summer weekdays, and summer weekends using the TSD academic calendar.

IV. Results and Discussion

A. Receiving a Chromebook Shows Positive Impact on GPA

TABLE IV: Estimates of Sample Average Treatment Effect on the Treated (SATT) or Average Treatment Effect on the Treated (ATT) for Chromebook recipients (See Sec. III-B for method and test details.)

Specification	**Method**	**(S)ATT**	**SE**	**p**
Phase I, II → GPA	CEM	+0.210	0.099	0.034*
Phase I, II → GPA	IPW	+0.183	0.073	0.012*
Phase I, II → GPA (trimmed)	IPW	+0.204	0.078	0.009**
Phase I → GPA	IPW	+0.158	0.098	0.105
Phase II → GPA	IPW	+0.340	0.168	0.043*

* $p<0.05$, ** $p<0.01$

Both IPW and CEM yielded significant positive estimates of the effect of receiving a Chromebook on GPA, as shown in Table IV. Under CEM, the Sample Average Treatment Effect on the Treated (SATT) was +0.21 GPA points, with a standard error of 0.099 and p-value of 0.034. Under IPW, the ATT was +0.183 GPA points with a standard error of 0.073 and a p-value of 0.012. Using propensity score trimming—removing observations with a propensity score below the 5th percentile or above the 95th percentile—yielded an ATT of +0.204 GPA points with Standard Error (SE) = 0.078 and p-value of 0.009, confirming that the estimate is not driven by high-leverage

outliers with extreme propensity scores. The consistency of estimates across both methods provides confidence in the positive association between receiving a Chromebook and GPA.

We acknowledge that our results identify the effect of Chromebook receipt on GPA, not the unobserved factors impacting the relationship between Chromebook receipt and GPA. Given the low rate of observed network usage, connectivity access is unlikely to be the sole or even primary mechanism. Possible alternative factors facilitating the effect of Chromebook receipt on GPA could be offline schoolwork, schoolwork on school or home networks, or unobserved household factors.

B. Robustness Checks

We report two robustness checks of our findings in Table V. The first check is a placebo test where we randomly assigned the treatment label to 266 control students and re-ran both inverse probability weighting and coarsened exact matching. This yields two non-significant ATTs of +0.034 (p = 0.704) and -0.07 (p = 0.939), confirming that the matching methods in the two model implementations do not produce spurious effects.

TABLE V: Robustness Checks

Specification	**ATT**	**SE**	**p**
Placebo Test			
IPW Placebo treatment (control only)	+0.034	0.090	0.704
CEM Placebo treatment (control only)	-0.007	0.093	0.939
Covariate Sensitivity			
Full model (baseline)	+0.183	0.073	0.012*
Drop Multilingual Status	+0.032	0.068	0.635
Drop Special Education	+0.189	0.073	0.009**
Drop Gender	+0.192	0.072	0.008**
Drop Grade Level	+0.239	0.073	0.001**
Drop Race/Ethnicity	+0.214	0.072	0.003**

* $p<0.05$, ** $p<0.01$. Placebo test assigns treatment randomly among control students (n=226). Covariate sensitivity reruns IPW dropping one covariate group at a time.

Covariate sensitivity analysis was conducted for IPW only. Since CEM matches directly on covariate bins rather than estimating a propensity model, dropping individual covariates would change which observations are pruned rather than identifying the influence of each covariate. Covariate sensitivity analysis shows the ATT estimate remains close to +0.2 when dropping gender, special education status, grade level, or race/ethnicity as covariates from the model. However, the estimate is not stable when multilingual status is dropped (ATT = +0.032, p = 0.635), which is expected. Multilingual status is the strongest predictor of treatment assignment, and excluding it from the propensity model introduces severe confounding.

C. Effect of Teacher Selection

Dividing the Chromebook recipients into Phase I and Phase II cohorts reveals asymmetry in the Chromebook's effect on GPA. The ATT for students in the first cohort (who received Chromebooks at the start of the 2023-2024 school year) was +0.158 GPA points, but was insignificant with a p-value of 0.105. As described in Sec. III-A1, these students had been selected based on FRL and multilingual status, as well as living within the TSD network coverage area. In contrast, the ATT for students in the second cohort (who received Chromebooks at the start of the 2024-2025 school year) was +0.340 GPA points, with a standard error of 0.168, and significant p-value of 0.043.

The students in the second cohort did not have the multilingual status or home address requirements, and were instead identified on a case-by-case basis by teachers as those who would benefit from the program based on their knowledge of students' circumstances. One interpretation is that this intentional selection of students by teachers is more effective than using standardized eligibility filters to identify situations where Chromebooks will improve students' academic outcomes. This suggests that teacher selection would be the more resource-efficient way to allocate Chromebooks when devices in a school district are scarce. At the same time, we consider that teacher biases could affect the allocation of devices to students, causing some students who need Chromebooks to be missed. We also acknowledge that academic achievement as measured by GPA is not the only meaningful benefit to a student's household that a take-home device could provide, which should potentially be considered when designing a school district Chromebook program.

D. Effects of Network Usage on GPA were Inconclusive

We investigated whether network usage predicted GPA and standardized test scores, but our results were inconclusive and data-limited. Only 78 of the 226 recipients could be matched to network usage records, implying that most Chromebook recipients had not used the internet service provided with the device. We divided the 78 identified students into bins of low, medium, and high cumulative data usage, and compared mean outcomes across usage groups using Analysis of Variance (ANOVA). However, the p-values for the F-statistics were insignificant for all tests.

E. Possible Barriers to Network Adoption

The network consumption was extremely right skewed with four devices driving the majority of the network usage, indicating that only a few students were able to make significant use of their connection. The median device only consumed 7.83 MB over the entire observation period, though the mean usage was 1,709 MB and the maximum was 54,596 MB. In future work, we hope to further investigate the reasons for low network adoption. We hypothesize that the true network coverage area and instructions for connecting may not have been publicized adequately. Students may also have encountered significant usability barriers, as revealed through initial exploratory usability testing with a sample student Chromebook in one of the highlighted areas in Fig. 1.

We found that the practically usable coverage area (within which Chromebooks could attach to the LTE network and run an Internet speed test) was limited to the spots shown in red on the map, corresponding to a Reference Signal Received

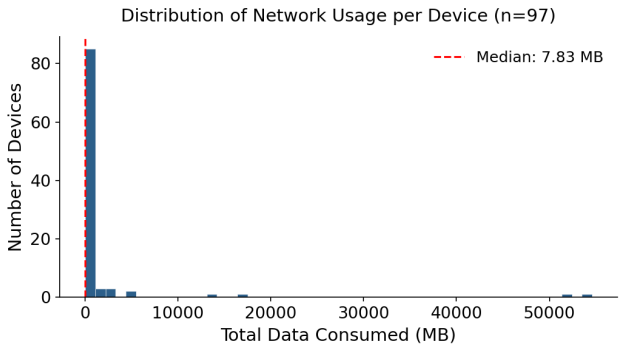


Fig. 3: Distribution of total cellular data in Megabytes (MB) transmitted or received per device across all 97 Chromebook devices, from July 2024 through November 2025.

Power (RSRP) above -85 dBm according to the the installation contractor's drive test measurements. The hardware guide for the Chromebook's LTE modem specifies a receive sensitivity for LTE Band 48 (CBRS) of -102 dBm [27]. However, Fig. 1 shows a large portion of the advertised coverage area to have weaker signal strength than the modem's minimum requirement, placing many students outside coverage in practice. Outside TSD's coverage, the Chromebooks would incorrectly report the SIM as belonging to "T-mobile" (Fig. 4a)[5], and attempting to connect would result in failure, perhaps causing users to think the network was unavailable.

Even when the TSD network had good signal strength and could be connected to with a click, we noted that a "X" icon above the signal bars in the user interface suggested unavailability (Fig. 4b), and the network name "315 010" did not identify the school district. Further, the Chromebooks would first attempt to connect to WiFi if it was enabled and known SSIDs were seen, requiring manual intervention to connect to LTE. We hypothesize that only a few students living in stronger coverage areas were reliably able to overcome these confusing user signals to eventually access the network.

We emphasize that our initial usability testing was anecdotal and performed on a single device, not a systematic or structured analysis with real users. Further qualitative work would be needed to confirm these suspected barriers. However, we were unable to obtain this data within the scope of this work due to limited TSD capacity for study coordination as well as privacy concerns around contacting students.

F. Network Use So Far Has Low Impact During City Hours

For the student network use we did observe (Figures 5-6), the bulk of weekday usage occurred outside of school or workday hours, making a case for sustainable bandwidth-sharing between student home and City use. To produce these graphs, we collected the IP sessions logged in the LTE network core over one full year of the deployment, from September 2024 to September 2025, and partitioned them by hour of day, weekday vs. weekend, and school year vs. summer. We looked for differences between summer and school year usage, as well as differences in usage between weekdays and weekends. We ultimately decided to focus on usage over weekdays throughout the entire year to determine whether bandwidth sharing during working hours with the City of Tukwila's LTE network is a viable option.

The majority of data usage occurred in the evening and late-night. On school year weekdays, the highest session counts and data use were between 8 PM and 6 AM. We speculate that this nighttime traffic could be related to recreation, learning goals, or both, from occasional gaming to high-volume media downloads scheduled at night for when the Chromebooks are not otherwise occupied. The impact of these infrequent high-volume outliers can be observed in the difference between height and location of peaks in Fig. 5 (aggregate data averaged over all days) vs. Fig. 6 (data averaged over all individual user sessions). We note that summer break usage was slightly higher in volume, with peaks occurring earlier in the evening.

On the other hand, Fig. 6, which shows hourly data use averaged over all sessions, reveals local peaks in the mid to late afternoon within City working hours. Further study is needed to confirm whether these usage patterns hold when the student population is better onboarded to the network and potentially producing a higher traffic load, or whether students' onboarding would influence traffic patterns at all given other modes of internet access available to them.

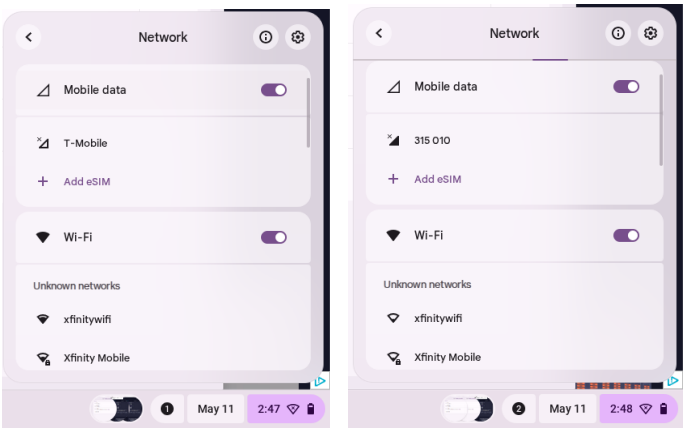
We note that weekend traffic during both the school year and summer is both lower-volume and more cleanly outside of working hours, ideal for City bandwidth sharing. City net-

[5]This is possibly based on an outdated database entry in ChromeOS for the operator of the Public Land Mobile Network (PLMN) "315-010," which is now commonly used for CBRS private LTE deployments [28] like TSD's.

Fig. 4: Usability issues in the Chromebook user interface for connecting to TSD's LTE. Shows the pop-up element for network connections in the lower right corner of the screen.

(a) When out of TSD's coverage range, the Chromebook wrongly identifies the SIM as T-mobile and tries to connect to their towers, which reject the SIM.

(b) Even when within TSD's coverage range, the network name "315 010" is unintuitive. The X above the signal strength bars may also be misleading.



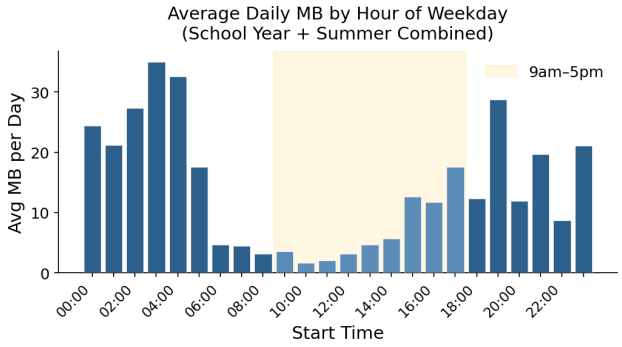


Fig. 5: Average cellular data consumption (transmitted and received megabytes of data) by hour of day on summer break weekdays. Usage occurs both inside and outside working hours, but the bulk of usage is outside working hours. Usage was grouped by hour, and the aggregate sum by hour was averaged over 250 weekdays in the school year and 85 weekdays in the summer.

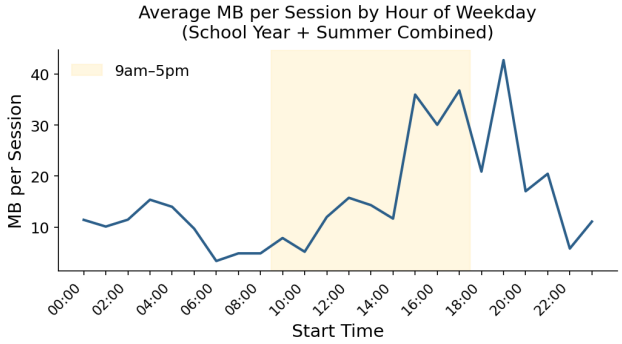


Fig. 6: Average cellular data consumption (transmitted and received megabytes of data) per session by hour of day on weekdays. Peak usage has very low volume but overlaps with early afternoon working hours, suggesting that future addition of many more users could create a spike during that time. The mean data volume consumed for all sessions with nonzero usage were calculated for each hour.

work resources are largely unused during weekends including workday hours, making weekend network access for students at home an easy choice.

V. Conclusion and Recommendations

In this paper, we present a case study of the Tukwila School District's Chromebook distribution program and LTE broadband network deployment. We establish a positive relationship between receipt of a Chromebook and middle and high schoolers' GPAs, using inverse probability weighting and coarsened exact matching to control for demographic confounds. We find that teacher selection of Chromebook recipients maximizes positive academic impacts for students and recommend this approach for lower-resourced school Chromebook programs, while highly-resourced programs could achieve more equitable impacts for target demographics through broader distribution.

We also measure the student Chromebooks' bandwidth consumption on the network, showing low usage with the bulk of data consumption occurring outside of City working hours. However, we also identify some usability issues in connecting to the TSD private LTE network from student Chromebooks which could explain the low usage. We note that broader outreach and instruction for students on how to access the network could result in heavier network traffic load, for example during the late afternoon working hours.

Having a network deployment is somewhat uncommon for school districts with device distribution programs, and we do not yet know how common the particular features of this case such as the lack of student awareness and confusing UI are among such networks, limiting generalizability. Since Phase I students were required to live in the network coverage zone, there were possible neighborhood effects between the treatment and control group that were unaccounted for. Multilingual program enrollment was also an eligibility criterion for Phase I, but since the TSD has a particularly high rate (77%) of multilingual enrollment status, school districts without this diversity may not have the same effects from this variable. Additionally, the teacher selection effects in Phase II may not replicate consistently since its effects are person-dependent.

We recommend further study with more detailed qualitative and quantitative data collection to understand the circumstances around students' current use or non-use of the deployed network, as well as their general Internet needs at home. We strongly recommend that researchers evaluating similar programs collect annual or semester-level GPA. The absence of pre- and post-treatment scores was our most significant constraint in this study. We also recommend documenting program eligibility criteria carefully, as the eligibility rules shape the populations within the treatment and control groups.

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