Insights from Implementation of Free Internet Program in Low-income Households Through Private LTE and Commercial 5G Networks

Aryo Yarahmadi
University of Houston
Houston, Texas, USA
ayarahma@cougarnt.uh.edu

Alireza Ansaripour
University of Houston
Houston, Texas, USA
aansarip@cougarnet.uh.edu

Omprakash Gnawali
University of Houston
Houston, Texas, USA
odgnawal@central.uh.edu

ABSTRACT

Digital inclusion remains a critical challenge for low-income households, who often lack reliable and affordable access to the Internet. Although policymakers and service providers are paying more attention to connectivity solutions for low-income families, there is limited real-world evidence on how these solutions perform. Also, traditional survey-based analysis methods used by most programs and research often fall short of capturing shifts in user behavior due to their brief, isolated view of usage. Furthermore, surveys rely on qualitative self-reports from users, who may have varying perspectives and interpretations. In this work, we present the first large-scale, real-world deployment and evaluation of a private LTE network, using actual network data, as a solution for providing free Internet access in underserved urban areas. We also compare its potential with commercial 5G networks as alternative solutions for free connectivity. Our program provided Internet connectivity for over 3580 households using the private LTE network and 935 households using the commercial 5G network. We collected network usage data for one year, speed tests, and information about devices used by users for one month. By categorizing the users based on their download volume, we found that the lack of usage is not necessarily due to lower service quality. Low-income households also have the same traffic patterns as the general public. We also analyzed the types of devices commonly used by low-income households and how these findings can be used to shape digital inclusion programs.

CCS CONCEPTS

• **Networks** → **Mobile networks**; • **General and reference** → *Measurement*; *Empirical studies*; • **Social and professional topics** → **Computing literacy**.

KEYWORDS

Digital Inclusion, Mobile Networks, Measurement

1 INTRODUCTION

In recent years, digital inclusion has gained more meaning than just connecting individuals to the Internet and providing suitable devices. Digital literacy and acceptance ensure that users have the skills to engage effectively in the digital world. Internet access in developed countries like the United States affects nearly every aspect of daily life, including education, employment, healthcare, communication, and civic engagement. Without an Internet connection, low-income households face multiple challenges in improving their life. Despite the growing importance of digital inclusion, many low-income families remain disconnected or do not use their Internet effectively. According to the National Telecommunications and Information Administration (NTIA), 20% of U.S. residents still lack a broadband Internet connection [14].

Therefore, there is a need to find a technical solution for Internet access that is cost effective and good enough for residential use. The efficacy of these solutions can only be properly evaluated in the real world, which presents environment complexities, unpredictable user behaviors, and situations that can not be created in a controlled testing environment. Beyond access, the evaluation must also give some insights about how and to what extent is the service is used, including aspects covering usage habits, user device ecosystems, and access pattern changes. Most of the digital inclusion programs rely on surveys and crowd-source-based methods to gather data about their users. However, these methods do not provide fine-grained and real-time data. Also, these methods depend on self-reported data, which can be biased, incomplete, or outdated.

In this paper, we describe two different types of technical systems that were used to provide free Internet access to low-income households. The first system is a privately owned LTE network in an urban area with low-income households in the United States. The second system uses a commercial 5G network available in the cities. We provided free Internet access to over 3580 low-income households via the private LTE network and 935 low-income households via the commercial 5G network, thus providing service to a total of 4515 households. Over one year, we collected detailed usage data and device metrics. Furthermore, in the last month of data gathering, we performed speed tests on the user modems and gathered detailed data about the connected devices to the modem.

Our analysis of Internet use in these 4515 households show that low-income households have the similar usage patterns as other households. Furthermore, within our user population, despite users having access to the same Internet quality, they generated significantly different traffic volumes. Also, we analyzed the type and number of devices that households use during the different hours of the day and their relation to generated traffic volumes. The key takeaways from this work are as follows:

- Despite low digital literacy and limited device access among low-income households, usage patterns in this population follow a similar pattern to those in the general population.
- Network-based data analysis provides fine-grained insights about how the usage patterns change over time. Such fine-grained temporal insights are not possible to infer from snapshot surveys typically used by digital inclusion ecosystem.
- It is feasible to run subsidized Internet program either through private LTE networks or commercial 5G networks. These two networks provide different economic and technical tradeoffs in deployments.
- The overall traffic volume in a household influences the mix of devices connected to the Internet.

2 RELATED WORK

Connectivity among low-income households: Studies commonly collect surveys from participants to understand different aspects of Internet usage among low-income households. Surveys have pointed out that low-income households have lower rates of Internet use due to a lack of exposure to the Internet and financial difficulties [3]. nationwide survey by the American Community Survey (ACS) also highlighted a gap between low-income and high-income households in device distribution and broadband connectivity [11]. Researchers have also noted that providing broadband connections to underserved communities increased the use of bandwidth-intensive applications in these households and enabled them to connect multiple devices simultaneously [16]. Most of the research in this area focuses on using survey results gathered from low-income households.

Understanding Internet use with network instruction: Although surveys provide valuable insights, they often do not provide real-time data or cover user interactions over time. Surveys are also prone to human errors caused by survey collectors and participants. Researchers have relied on network data to measure Internet usage among subscribers to tackle these challenges. In these studies, researchers have suggested using traffic volume to measure user engagement and Internet usage [4, 15]. During the COVID pandemic, a study conducted across multiple ISPs in the USA and Europe cited that traffic volume increased 15-20% after lockdown [4]. Another study in UC San Diego campus cited an average of 50% increase in traffic volume per device as students shifted toward using online tools [15]. Also another study studied the mobile network users mobility patterns and data volume usage[17].

As initial works in network measurement studies mainly focused on reporting aggregated data in the network [7], researchers have also emphasized the importance of categorizing the network users as each group may behave differently depending on the country of users [5]. Studies have also cited different trends in connectivity between international and domestic students [15]. To fill this knowledge gap for Internet subscribers of low-income households, our work utilizes network data to provide insights into traffic volume and user devices.

Digital divide and digital inclusion: For the connectivity aspect of the digital divide, researchers explored different means of providing access to the Internet[6], such as using Starlink as a backhaul for a private LTE network[13]. However, this research still lacks real-world deployment. Furthermore, researchers also explored the effectiveness of federal funding, such as the Connect America Fund (CAF)[10], and infrastructure deployment in more rural areas or ACP.One of the similar projects that provided free internet access for low-income households is Project OVERCOME[1]. To assess this project's effectiveness, researchers used surveys.

Studies showed a changing trend in low-income households, where users use more IoT [8]and entertainment devices like smart TVs[12]. They also asked the participants about their skills in using different IoT devices. This method has two main drawbacks. The first is that asking users about their perception of their skills can raise bias issues, and it is hard to compare two individuals. Second, this method will not show device usage dynamics over time. To address both the issues, we used DHCP table data in addition to surveys to get more granular data about what devices users use.

3 DATA AND METHODS

3.1 Target Population and Survey

For device distribution, potential users filled out an application for the free Internet service. The eligibility criteria for receiving free Internet service were to be a low-income household and be eligible for the National School Lunch Program (NSLP). After checking the eligibility of the user, the modem was provided. Furthermore, since the target population of all programs is the same, we used device distribution surveys to find out about community members' demographics and their current Internet use profile.

Result: In total 9484 responders, 64.6% of the population had an income per household of below $30k and 33.5% between $30k and $75k. The average household size was 4.1.

3.2 Private LTE network Dataset

The CBRS-based private LTE network is deployed in the urban area of a major city in a US state. We used LTE modems from two vendors: 1- Cradlepoint R500-PLTE and 2- Sierra Wireless RV55.

The Cradlepoint R500-PLTE (N=383) can monitor and report traffic volumes and radio connectivity metrics and perform speed and ping tests. We collected the traffic and radio connectivity data from the Cradlepoint devices from November 2023 until October 2024. Furthermore, to perform the OOKLA speed and ping tests, we used browser automation on the admin dashboard and then scraped data from the dashboard. We performed the ping and speed test on 180 devices from September 2024 to October 2024 to minimize the bandwidth-intensive speed test and minimize interaction with user modems. Over two months, we performed 13852 speed tests. Furthermore, using the ping test capability, we analyzed the 13339 ping tests. Also, gathering data about the connected user devices happened only in October 2024 from all Cradlepoint devices with hourly frequency.

The Sierra wireless RV55 (N=3200) does not support speed test, ping, or connected device query capabilities. However, it provides the upload and download volume, radio connectivity metrics, board, and radio module temperature hourly. We collected the traffic and device data from these modems from October 2023 to October 2024.

In total, the Private LTE dataset consists of more than 34 million data points and 270 GB of raw data.

3.3 Commercial 5G Network Dataset

The commercial 5G network uses the Tmobile network to connect to the Internet. The Inseego FX2000 and FX3100 modems (N=939) report daily download and upload volume, which we collected from July 2023 to October 2024. We used browser automation to get a list of connected devices, daily connectivity metrics, device version, and location for two months. This dataset consists of 562,000 data points.

3.4 Usage Categorization

Due to the significant difference in traffic between different users, following the tradition in this literature, we categorize the users into different data-volume classes: heavy, medium, moderate, light, and near-zero users, to have a meaningful analysis of user behaviors and digital acceptance.

Due to the active distribution of modems during the data gathering period in private LTE and commercial 5G networks, we needed to filter out test devices. We consider a device to be *deployed* when we receive at least 7 days of data points from a modem. Only the deployed modems are included in the analysis.

Before sorting the users and assigning heavy, medium, moderate, or light groups to them, we put the users under a certain amount of daily downloads into a near-zero category. Then, we sort users by their daily download volume and categorize them as heavy, medium, moderate, or light based on their relative position within the overall distribution. To determine the final category, we count how often each user falls into each group across all observed days and normalize these counts by the number of days the user appears in the ranking. Finally, we sort users by priority ranking, giving the highest priority to those most frequently labeled as heavy and the lowest to those mainly classified as light.

We employed relative ranking of users for all groups except near-zero rather than relying on absolute download volume across all groups. This decision was motivated by the observation that most applications, such as streaming, primarily affect the total download volume without altering the underlying application category. Streaming applications, for example, can adjust the bandwidth use depending on the bandwidth availability. Consequently, grouping users solely based on absolute volume could result in clustering users with different Internet usage patterns into the same group. Therefore, we use relative ranking if we establish that the user uses the Internet and is not in the near zero category.

3.5 Devices Connected to the Internet

Two types of data were collected to understand the devices connected to the Internet: surveys and network data.

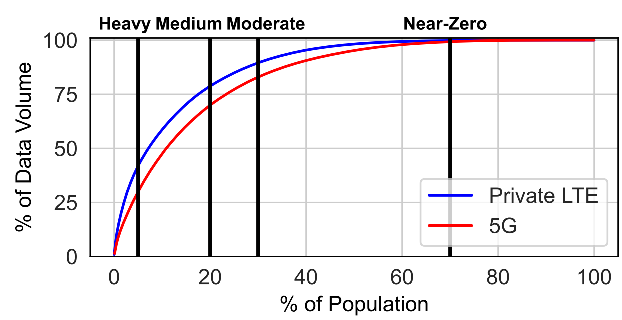

Figure 1: Population and data volume share relation. 7% of the Population contributed to 50% of the data volume in our LTE network and 40% in the 5G network.

The survey (N=8863) asked how often (in a 0-5 scale) the users used these devices at home: cell phones, tablets, laptops, and PCs.

We also obtained the device list from the routers' DHCP table. In total, we gathered 5844 distinct MAC addresses from 1627 households. In addition to MAC addresses and host names, we extracted the DHCP lease duration and update times of each MAC address with hourly frequency from the DHCP tables. We categorized the user devices into cell phones, tablets, laptops, and PCs. Entertainment devices, including smart TVs, streaming sticks, and gaming consoles. IoT devices, including CCTV cameras, smart lighting, and different types of sensors. Next, to categorize connected devices, we performed three levels of analysis. In the first level, we matched the MAC addresses with OUI (Organizationally Unique Identifier) assigned by the IEEE to manufacturers to identify the device manufacturer. If the device is not identifiable by the manufacturer or the device uses MAC randomization, we combine the MAC address with the hostname to identify devices. However, 20 % of devices did not report hostnames when they use MAC randomization. To identify these devices, we compared the DHCP leases of different categories and the device counts of each category over households. According to Figure 3, we see similarities in the DHCP lease behavior of unknown devices and phones and tables category. Furthermore, we compared the 848 households without any unknown devices with 779 households with unknown devices. According to Figure 2, we found that households with unknown devices had a lower count of phones and tablets, while the composition of other devices remained unchanged.

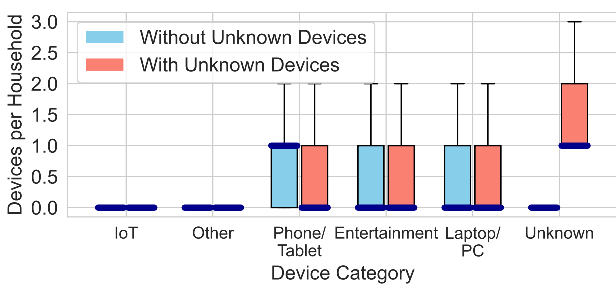

Figure 2: Average Number of devices per household. We can see a decrease in the phone and tablet category's mean and median in households with unknown devices and no change in other categories

Therefore, by analyzing the household device composition and DHCP lease characteristics, we can assume the unknown devices are phone/tablet categories that used MAC randomization.

3.6 Connection Quality Assessment

To maintain consistency in connection quality assessments, we used the OOKLA speed test, a known tool for measuring Internet quality for both networks.

The Cradlepoint modems connected to the Private LTE network provide the speed test functionality, and we use them as a proxy for the speed experienced by all the users in the private LTE network. Furthermore, we used the onboard ping test on the Cradlepoint modems to assess the connection stability of the private LTE network.

The commercial 5G network modems do not have speed test functionality. We estimate their connection speed by using the available third-party mobile speed test database, assuming that our devices experience similar speeds as third-party mobile devices on commercial networks in the same geographical area (bounded by 600mx600m polygon in the dataset) as the location of our modems. In total, 151 of our modems resided in the speed test polygons where collectively 15207 third-party mobile test results are available from the Q3 2024 dataset[2].

4 RESULTS

Because the data volume used by many applications primarily increases with higher connection speeds, while the nature and functionality of the applications themselves remain unchanged, we analyze each network separately. This is necessary because the two networks use different technologies and exhibit significant differences in performance.

Table 1: Total data volume transmitted during data gathering period

Network Metric	5G	Private LTE
Total Download (TB)	2355	1505
Total Upload (TB)	158	79
Download per User (GB)	2580	429
Upload per User (GB)	173	23

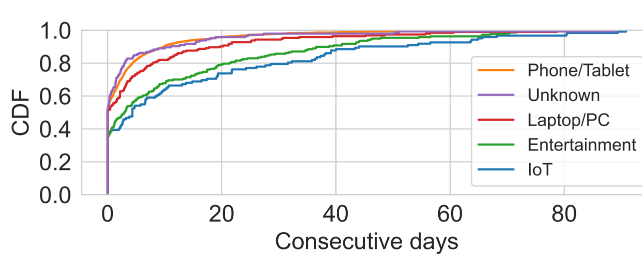

Figure 3: Number of consecutive days the connected devices used the same IP address.

Table 2: User categories population and data share of each category in different networks.

Category	Private LTE (N=3587)		5G (N=935)	
	N	Data Share (%)	N	Data Share (%)
Heavy	132	35.45	43	28.22
Medium	528	40.89	174	46.59
Moderate	660	17.54	217	18.97
Light	1321	5.98	434	6.21
Near Zero	946	0.14	67	0.01

4.1 Data Volume Overview

Table 1 shows that users transmitted 2.45 petabytes of data using the commercial 5G network over 15 months. For the private LTE network, the transmitted data was 1.54 petabytes over 10 months. Although the private LTE network had many more users, less data was transmitted than the commercial 5G network because the commercial 5G network had higher download speed. The download-to-upload ratio for the commercial 5G network was 14.9, and the private LTE network was 19. According to the National Cable & Telecommunications Association (NCTA), the average download-to-upload ratio grew from 3 in 2010 to 16 in 2020. This similarity shows that our user group is also mostly consumers of data.

4.2 User Categorization

We experimented with different thresholds that provides the most contrast between user groups. First, we select the near-zero users with less than 150 MB of downloads daily. After separating the near-zero users from the rest of the distributed devices, we categorize the remaining users (See Table2). The results show that in the private LTE network, the top 5% of households use more than 42% of the total data, and in the 5G network, they use more than 30% of the total download traffic. Although we had different demographics and target users, our data and population share were similar to previous research that covered different areas of the world[9]. Each category's population is shown in Table 2. Also, Figure 1 shows a significant difference between the download volume of different users in both datasets. For example, we can see that 10% of the users contributed to more than 50% of the total download volume in our network.

4.3 Connection Quality

Connection Speed: Table 4 shows the download speeds and Table 5 shows the upload speeds of the different user groups for both the private and commercial networks. The average download speed for the private LTE network was 46.09 Mbps (σ=51.79), and the upload speed was 4.80 Mbps (σ=5.3). The average download speed for the commercial 5G network was 279.20 Mbps (σ=77.66), and the average upload speed was 26.00 Mbps (σ=8.04). Our results show that the private LTE met the standards of the first generation of FCC standard on braodband Internet (25 Mbps up / 1 Mbps down). The private LTE was subsequently upgraded to meet the latest broadband standards (100 Mbps down / 25 Mbps up). Overall, both the networks provided broadband-level connection speeds to the households.

Latency: Table 3 shows the results for latency measurements. The average latency for the private LTE network was 63 ms (σ=42). The 5G network's average latency was 28 ms (σ=7). Although the private LTE network experienced higher latencies, the latency is still within an acceptable margin for most applications. The 5G network latency was better than most DSL services and close to cable services. We also see the same pattern mentioned in the connection speed that different user groups experienced the same connection quality.

Packet loss: We analyzed the ping tests for the private LTE network. 4.8% of ping tests aborted with a timeout. The average packet loss for all the devices was 0.9%. We found evidence of bursty loss at the time scale of 1-hr: 28 % of the devices experienced at least 5% packet loss during one 1-hr timeslot in one week. Most of these time slots were between 9 PM and 12 AM, which is the high data use period. We could not perform the tests on 5G network due to limitations of the user modems.

Takeaway: Both private LTE and commercial 5G networks provided acceptable broadband-grade service for users, which shows that both deployments are viable options for providing subsidized Internet access. Also, the service quality was consistent among all user groups, but the usage by users of different groups was inconsistent. Therefore, as long as the service can cover the requirements of the applications, further improving the service will not affect user usage.

4.4 Growth in Network Use Across Different Types of Users

In this section, we try to find out if the users change from one category (e.g., light user) to another (e.g., heavy user) over time. To this end, we assign the groups to the users twice: first and last month of deployment and compare their

Table 3: Latency (ms) experienced by the users of private LTE network and commercial 5G network.

User Group	Private-LTE μ / σ	5G Network μ / σ
Heavy	69.63 / 65.34	27.48 / 5.58
Medium	62.65 / 40.39	28.54 / 6.74
Moderate	65.18 / 40.39	28.54 / 6.34
Light	65.18 / 32.51	29.03 / 9.19
Zero	59.30 / 17.47	28.61 / 6.22

Table 4: Download speed (Mbps) of private LTE network and commercial 5G network.

User Group	Private-LTE μ / σ	5G Network μ / σ
Heavy	42.64 / 26.86	265.56 / 79.91
Medium	49.79 / 36.39	272.36 / 81.96
Moderate	42.79 / 28.16	283.11 / 76.49
Light	50.04 / 90.70	276.76 / 76.20
Zero	42.41 / 30.51	283.71 / 76.11

starting (first month) and ending (last month) group and the dynamics in-between.

Figure 5 and Figure 6 show the data on how the user categories changed over time. Most of the non-zero category users did not become zero category users. This absence of abandonment may indicate a higher probability that the provided service is enough for the users. The results also show a good chance for medium, moderate, and light users to increase their traffic volume. This upward move could be due to the users finding more applications or getting better devices that generate more traffic. However, near-zero users did not experience a significant shift in their traffic volume. Although it is hard to tell why these Zero cateogry users did not increase their data use, it is unlikely that it is due to bad service because results from prior section showed the overall good quality service to all the categories of users.

Table 5: Upload speed (Mbps) of private LTE network and commercial 5G network.

User Group	Private-LTE μ / σ	5G Network μ / σ
Heavy	4.19 / 3.05	25.39 / 9.04
Medium	5.99 / 3.71	25.71 / 9.14
Moderate	4.27 / 3.25	26.19 / 7.76
Light	4.61 / 8.91	25.81 / 7.65
Zero	4.62 / 3.66	26.0 / 7.43

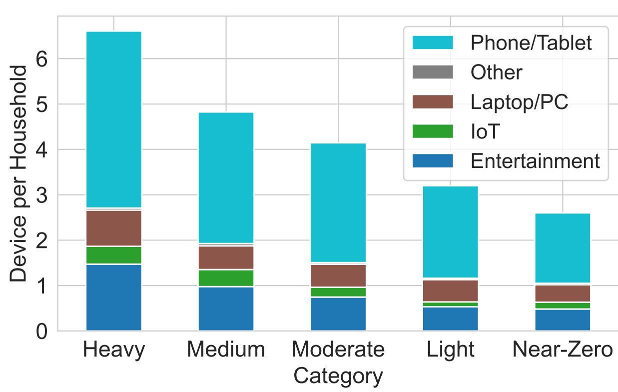

Figure 4: Average Devices per household. Heavy users have more IoT and entertainment devices

Table 6: Users' usage frequency of each device to connect to the Internet, according to the survey. The highest score for each group is 5.

Device Group	Score μ / σ
Phone	4.38 / 1.33
Tablet	1.88 / 2.1
Laptop	1.51 / 2.09
PC	1.11 / 1.85

Takeaway: Non-zero users used more data over time. This change may indicate that they find more use cases or better devices that consume more traffic. The zero category users not increasing their data use is an opportunity to develop more intensive interventions related to digital divide.

Figure 5: 5G network users grouping over the first month and the last month of their presence.

4.5 Usage Patterns

Figure 7 shows the hourly usage pattern in the Cradlepoint devices. The pattern was the same for the Sierra wireless devices too. All user groups have the same usage pattern in one day, and the main difference between these user groups is the amount of data transmission. Furthermore, although the number of connected devices decreases in the evening, the overall data usage still increases. The reason could be that in the evening, more entertainment devices are being used compared to the other times of the day, which can significantly increase household data usage.

Takeaway: Our observation shows the same usage patterns as most previous research that studied the general population (e.g., Fig 3 in [17]). This finding shows that although these users have less access to more up-to-date devices and are less digitally literate compared to the general population, they have the same usage patterns.

4.6 User Device Population

The survey (N=8863) results are shown in Table 6, indicating that phones and tablets are the most common way for users to access the Internet. We analyzed the DHCP table on private LTE networks and commercial 5G network modems to get more detailed data about users' devices.

Table 7 shows that phones and tablets are the most common Internet-connected devices. Entertainment devices are the second most popular, indicating that streaming services and gaming consoles are becoming part of every household, independent of household income. Also, the emergence of IoT devices, such as sensors and CCTV cameras, in lower-income households shows the utility of these devices. According to Figure 7, users with higher download volume have more connected devices, and heavy users have more IoT and entertainment devices. Combining high data usage with less popular devices shows that these users are more digitally literate than other users. We also noticed that the number of connected devices decreased during the peak hours of download traffic. This pattern may indicate that most generated traffic is from streaming services.

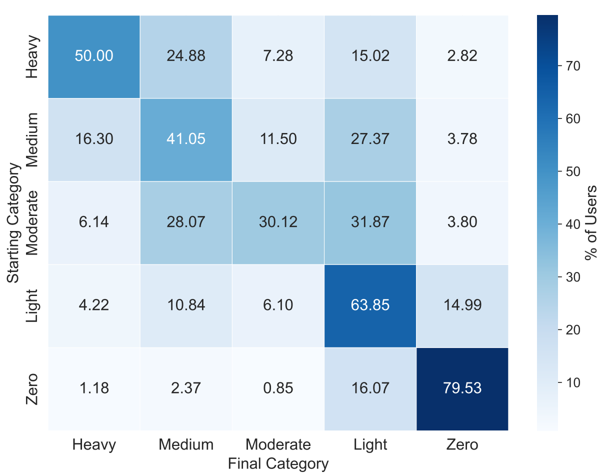

Figure 6: Private LTE network users grouping over the first month and the last month of their presence.

Takeaway: Peak data use is in the late evenings. The relation between the number of connected devices and download traffic volume shows that most users use the Internet in the evening for streaming and entertainment regardless of the number of connected devices during that period.

Table 7: Population of devices connected to the routers. Data from 1627 households.

Device Group	Count	%	Per Household
Phone or Tablet	3005	57.63	1.84
Entertainment	1076	20.63	0.66
Laptop or PC	789	15.13	0.48
IoT	288	5.52	0.17
Other	56	1.07	0.03
Total	5214	100	3.20

4.7 Evolution of signal strength

Figure 8 shows a slight RSRP degradation over time in the private LTE network. This RSRP degradation is related to environmental damage, such as antenna misalignment. At around the 300th day, the nonprofit performed maintenance and optimization of the cell towers, and we can see the improvement in the RSRP of private LTE network modems. Although we see a slight difference in the RSRP of different user groups, even after maintenance and optimization, we did not see any difference in connection quality regarding speed, latency, and packet loss.

Regarding signal quality, the commercial 5G network is much more stable. Commercial networks usually have more periodic maintenance and optimizations. Furthermore, since the coverage for these networks in urban areas is more consistent than the private LTE network, we see much less difference between different user groups' signal quality. However,

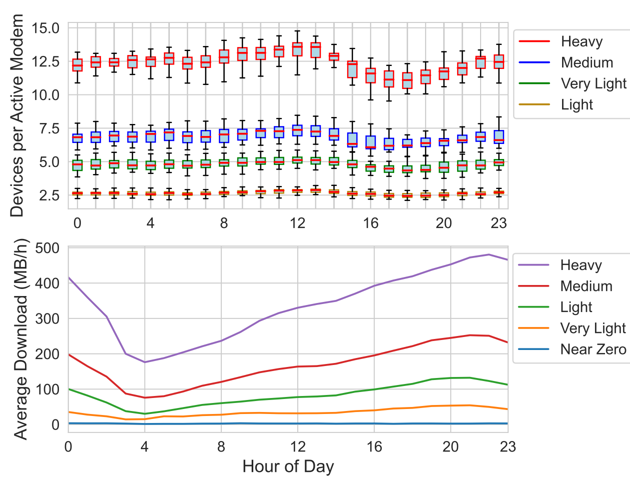

Figure 7: The relation between the number of connected user devices at each hour and the average hourly download for the private LTE network.

like the private LTE network, we did not see significant differences in the connection quality of different user groups.

Takeaway: Improving signal quality leads to better connection quality in some situations. However, this improvement is limited. Beyond a certain point, further enhancements in signal quality yield minimal gains, as other factors become the primary bottlenecks affecting the user's connection quality.

4.8 Service Reliability / Uptime

We utilize modem reboots and operational information to estimate and validate service uptime. The provider scheduled a daily reboot for both modem vendors. Additionally, we observed that during network outages, the Sierra Wireless modems experience multiple reboots. During the data-gathering period, we noticed that we had not received any data points for the Sierra wireless devices for a period lasting 10 hours. By examining outage detectors, we identified an outage that occurred during the same period. Furthermore, in the same period, we did not observe any spike in modem reboots. Therefore, this outage affected only the instrumentation system and did not impact users' service availability.

The mean uptime is 86.8% with a median of 93.9%. We noticed that some devices with very low availability had very weak signal reception strength, which explains the difference between the mean and median. In total, we detected one complete network outage that lasted for 6 hours, which, according to the non-profit organization, was due to maintenance. Furthermore, we noticed three partial outages.

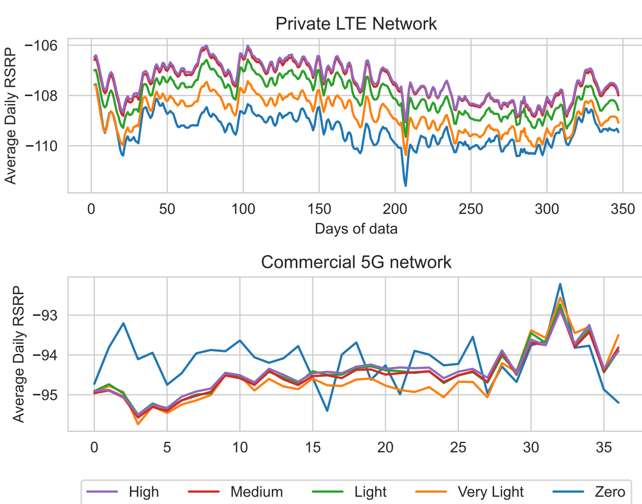

Figure 8: RSRP changes over time for both networks. In the private LTE network, we experienced signal degradation until day 300. Around that day, the organization performed maintenance on the cellular towers, and we can see an improvement in RSRP after that point.

For the commercial 5G network, the modems did not have scheduled daily reboots. Due to the daily reporting frequency, we were unable to measure any hourly outages directly, and we did not notice any daily outages. We expect these commercial networks to have high reliability in urban areas.

Takeaway: Although providing three nines of uptime is challenging for small-scale networks due to cost constraints, we observed that it is still possible to deliver a reliable service using a private LTE network. Furthermore, we identified that not all outages necessarily disrupt user service, and it may only affect the provider. Therefore, technology diversity can make these systems more resilient.

5 DISCUSSION

Infrastructure Maintenance: Periodic physical and electronic (configuration and optimization) maintenance of network infrastructure adds operating cost to the operators but is critical to maintaining a QoS to the users. We experienced one round of radio infrastructure maintenance during the deployment period.

Private vs Commercial/large Operators: Although commercial/large operators provided better QoS, the private network may have certain advantages in certain geographics or user segments as long as they provide adequate QoS to the users. The Private LTE networks sometimes have advantages over commercial networks in specific scenarios.

Router Instrumentation: In digital inclusion programs, most users lack the deep technical knowledge to solve connectivity problems or follow tech support team's complicated instructions. Modems need good instrumentation and remote access capabilities. The remote access capabilities can range from SSH to the modem to performing speed tests and remote setting uploads. Having these will allow tech support to be more effective while helping households with low digital literacy. These capabilities are still not universally available in all off-the-shelf modems.

Usage Patterns: Low data volume usage by users can be caused by different reasons. These reasons range from infrastructure problems to a lack of knowledge about Internet use cases. Therefore, it is necessary to isolate the source of the problem using technical support and modem instrumentation to improve the program's effectiveness.

User Devices: The rising trend of various types of Internet-connected devices (e.g., smart gadgets), even among low-income households, as shown in our study, creates an opportunity to update and expand digital inclusion initiatives that traditionally focus on phone and laptop connectivity and using laptops and desktops for school work and personal productivity only.

Network Instrumentation or Surveys: Network instrumentation can continuously observe user habits and changes without interfering with the user. Furthermore, surveys can introduce human errors, have limited outreach, and raise privacy concerns but on the positive side, capture information about user intent and struggles, we cannot capture on the network. Digital-inclusion organizations are advised to consider using both methods to analyze the effectiveness of their programs.

6 CONCLUSION

To our knowledge, this study represents the first digital inclusion connectivity program assessment using in-network instrumentation data. Our private LTE network provided Internet access to more than 3580 low-income households. Furthermore, we provided modems for 935 low-income households with commercial 5G networks. We compared these two network types as an infrastructure for free connectivity programs. We found out that although a commercial 5G network can provide better coverage in urban areas and higher speeds, the private LTE network can also be a good alternative for areas without commercial Internet coverage since most of the application's nature does not change with higher Internet speeds. We categorized the users based on absolute volume and relative ranking to analyze the usage patterns. We also discovered that usage habits rarely change significantly over a year, and lack of usage is not necessarily due to poor service. Despite lower digital literacy, low-income households showed the same usage patterns as the general population. Also, by studying user devices, we discovered that not only entertainment and IoT devices are becoming more popular in low-income households, but there is also a relation between the mix of devices used by households and their traffic volume. These insights will help decide what type of networks may be appropriate for future Internet subsidy programs and the need to incorporate IoT and other devices in digital empowerment programs.

A ETHICS AND DATA AVAILABILITY

This research has been reviewed and approved by the IRB at the University of Houston. This research does not collect or analyze data about online website or app usage by the users to safeguard user privacy. Under the current data agreement, the research team is unable to share the data used and analyzed in this paper with the broader research community.

REFERENCES

[1] H Atasoy, LEE DAVENPORT, and JIGYASA SHARMA. 2023. Lessons from the Social Impact Evaluation of Project OVERCOME.

[2] Speedtest by Ookla Global Fixed and Mobile Network Performance Maps. 2024. Switched Off: Why Are One in Five U.S. Households Not Online? https://registry.opendata.aws/speedtest-global-performance. Accessed: 2024-11-15.

[3] Namkee G Choi and Diana M DiNitto. 2013. The digital divide among low-income homebound older adults: Internet use patterns, eHealth literacy, and attitudes toward computer/Internet use. *Journal of medical Internet research* 15, 5 (2013), e93.

[4] Anja Feldmann, Oliver Gasser, Franziska Lichtblau, Enric Pujol, Ingmar Poese, Christoph Dietzel, Daniel Wagner, Matthias Wichtlhuber, Juan Tapiador, Narseo Vallina-Rodriguez, et al. 2020. The lockdown effect: Implications of the COVID-19 pandemic on internet traffic. In *Proceedings of the ACM internet measurement conference*. 1–18.

[5] José Luis García-Dorado, Alessandro Finamore, Marco Mellia, Michela Meo, and Maurizio Munafo. 2012. Characterization of isp traffic: Trends, user habits, and access technology impact. *IEEE Transactions on Network and Service Management* 9, 2 (2012), 142–155.

[6] Simon Heine, Florian Völk, Robert T Schwarz, and Andreas Knopp. 2022. Concept and evaluation of 5G backhauling via starlink. In *39th International Communications Satellite Systems Conference (ICSSC 2022)*, Vol. 2022. IET, 69–75.

[7] Tristan Henderson, David Kotz, and Ilya Abyzov. 2004. The changing usage of a mature campus-wide wireless network. In *Proceedings of the 10th Annual International Conference on Mobile Computing and Networking* (Philadelphia, PA, USA) *(MobiCom '04)*. Association for Computing Machinery, New York, NY, USA, 187–201.

[8] Md Imran Hossain, Md Shahinur Rahman, and Kim Hyung Jun. 2024. Determinants of internet of things (IoT) smart home technology (SHT) adoption behavior of consumers: Empirical evidence from a least developed country (LDC). *Information Development* (2024), 02666669241254054.

[9] F Jejdling. 2023. Ericsson mobility report. *Nov* (2023).

[10] Haarika Manda, Varshika Srinivasavaradhan, Laasya Koduru, Kevin Zhang, Xuanhe Zhou, Udit Paul, Elizabeth Belding, Arpit Gupta, and Tejas N Narechania. 2024. The efficacy of the connect America fund in addressing US internet access inequities. In *Proceedings of the ACM SIGCOMM 2024 Conference*. 484–505.

[11] Michael Martin et al. 2021. Computer and Internet use in the United States: 2021. *American Community Survey Reports* (2021).

[12] Tanya Notley, Gokcen Karanfil, and Abdul Aziz. 2024. The smart TV in low-income migrant households: Enabling digital inclusion through social and cultural media participation. *Media, Culture & Society* 46, 8 (2024), 1638–1656.

[13] Ryan Oliveira, Ilan Correa, Leonardo Ramalho, and Aldebaro Klautau. [n. d.]. Digital Inclusion in Amazon with Starlink Backhauling and Mobile Telephony. ([n. d.]).

[14] National Telecommunications and Information Administration (NTIA). 2022. Switched Off: Why Are One in Five U.S. Households Not Online? https://www.ntia.gov/blog/2022/switched-why-are-one-five-us-households-not-online Accessed: 2024-11-15.

[15] Alisha Ukani, Ariana Mirian, and Alex C Snoeren. 2021. Locked-in during lock-down: undergraduate life on the internet in a pandemic. In *Proceedings of the 21st ACM Internet Measurement Conference*. 480–486.

[16] Javier Valentín-Sívico, Casey Canfield, Sarah A Low, and Christel Gollnick. 2023. Evaluating the impact of broadband access and internet use in a small underserved rural community. *Telecommunications Policy* 47, 4 (2023), 102499.

[17] Jie Yang, Yuanyuan Qiao, Xinyu Zhang, Haiyang He, Fang Liu, and Gang Cheng. 2014. Characterizing user behavior in mobile internet. *IEEE transactions on emerging topics in computing* 3, 1 (2014), 95–106.