Socio-Economic and Demographic Patterns in Video Streaming: Unveiling City Dynamics in France

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***Abstract*—As part of the NetMob Data Challenge, this study aims to identify demographic and socio-economic similarities and differences between the city of Paris, Montpellier, and the various arrondissements within Paris. We achieve this by analyzing the usage data of different streaming platforms among residents of these cities. In our analysis, we employ two distinct techniques to uncover urban segregation trends: exploratory data analysis and a form of statistical analysis known as ANOVA. Our findings indicate that not only do the demographic and socio-economic characteristics of cities influence streaming service usage, but also global trends driven by popular TV shows and movies can lead to substantial spikes in platform usage. Interestingly, these trends may not necessarily correlate with significant variations in demographics and socio-economic levels.**

***Index Terms*—mobile data, demographic pattern, urban dynamics**

I. Introduction

This study is part of the challenge of The NetMob23[1], which focuses on cities in France and the internet usage data of different platforms and services.

We aim to understand whether the choice of streaming platforms in two cities in France reflects the socio-economic situation of the people or the demographics of specific communes. While looking at this, we will examine whether there is segregation in the urbanized areas of cities in France.

Schelling's segregation model sheds light on the field of urban segregation studies, revealing that people's housing preferences are influenced by their social, ethnic, and economic backgrounds [1]. This finding aligns with Tobler's first law of geography, which states that 'everything is related to everything else, but proximity has a stronger influence than distance' [2]. Thus, our primary focus in this study will be on examining maps, urbanization patterns, and various communes within the cities. This approach allows us to capture how the physical proximity and social connections shape the streaming platform preferences and, intriguingly, how similar neighborhoods can yield distinct outcomes.

In France the urban layout often takes on a spiral shape, spreading outwards instead of having a single city center. This results in the population being dispersed across larger regions of the urbanized centers and suburbs of France. The spread is influenced by strict building height limits and historical living habits that were shaped by rural immigration movements, particularly during World War II. This dispersal is even more pronounced in Southern France, where there are no specific city centers in these cities [3].

We have chosen Paris due to its status as the most populous and diverse city in France, and for comparison, we've selected Montpellier, a city in southern France [4]. However, our initial focus is on examining the population and development levels of these two cities. It is essential to clarify that we won't be working with the entire Paris arrondissements, which exceeded 10 million in population in 2019. Instead, we will specifically focus on the City of Paris, with a population of around two million residents distributed across 20 districts. Some of these regions houses approximately 500 thousand people, similar to the population of the City of Montpellier in the year of 2019. This similarity in population size allows us to make meaningful comparisons between the residents of the French Riviera and those of Paris.

[1]The NetMob 2023 Data Challenge is a competition aiming at deriving and exploiting insights from massive mobile service consumption information. Details can be found at https://netmob2023challenge.networks.imdea.org

II. Methodology

The objective of this study is to analyze the usage of different video content platforms, classified as paid and unpaid, in selected cities and the communes of those cities. Since the dataset [5] belongs to 2019, we have neglected YouTube Premium as it was not popular among people at that time. Instead, we have selected YouTube and Dailymotion as representative choices for unpaid video content platforms, including watching videos, TV series, and movies. These platforms will be mentioned as Unpaid Platforms and will be denoted as U if necessary. To represent paid streaming services, we have included Netflix, Apple Video, and Orange TV, similar to former services, we will be mentioning them as Paid Platforms and will be denoted as P. However, there are some differences between these three platforms; Netflix and Orange TV are subscription-based, while Apple Video offers rental and purchase options for movies and TV series. In order to simplify the analysis, we have excluded browser streaming or TOR, as these platforms provide both paid and unpaid pirate services.

In this study, downlink data for the mentioned platforms was collected at 15-minute intervals for each day between April 1, 2019, and April 30, 2019. The total daily usage values of these platforms were used to aggregate the points in the cities where each platform had the highest data usage. This was done for two different cities. $C_{Pxj}(t)$ and $C_{Mxj}(t)$ represent the amount of internet data used on day j at time t for platform x in Paris and Montpellier, respectively. The total internet usage in the cities over a span of 30 days is denoted as C_{Px} and C_{Mx}, as shown Equation 1.

$$C_{Px} = \sum_{j=1}^{30} \sum_{t=1}^{96} C_{Pxj}(t) \quad C_{Mx} = \sum_{j=1}^{30} \sum_{t=1}^{96} C_{Mxj}(t) \tag{1}$$

The quantities of platform usage for YouTube, DailyMotion, Apple Video, Orange TV, and Netflix in city i is denoted as y_i, d_i, a_i, o_i, and n_i, respectively. We represent the total internet usage on these platforms across all cities in our study as Y, D, A, O, and N. We categorize them into Paid Platforms and Unpaid Platforms, as defined in Equation 2 and Equation 3. We will use the category total usages and individual platform usage for different tests and analysis.

$$u_i = y_i + d_i; p_i = a_i + o_i + n_i \tag{2}$$

$$U = Y + D; P = A + O + N \tag{3}$$

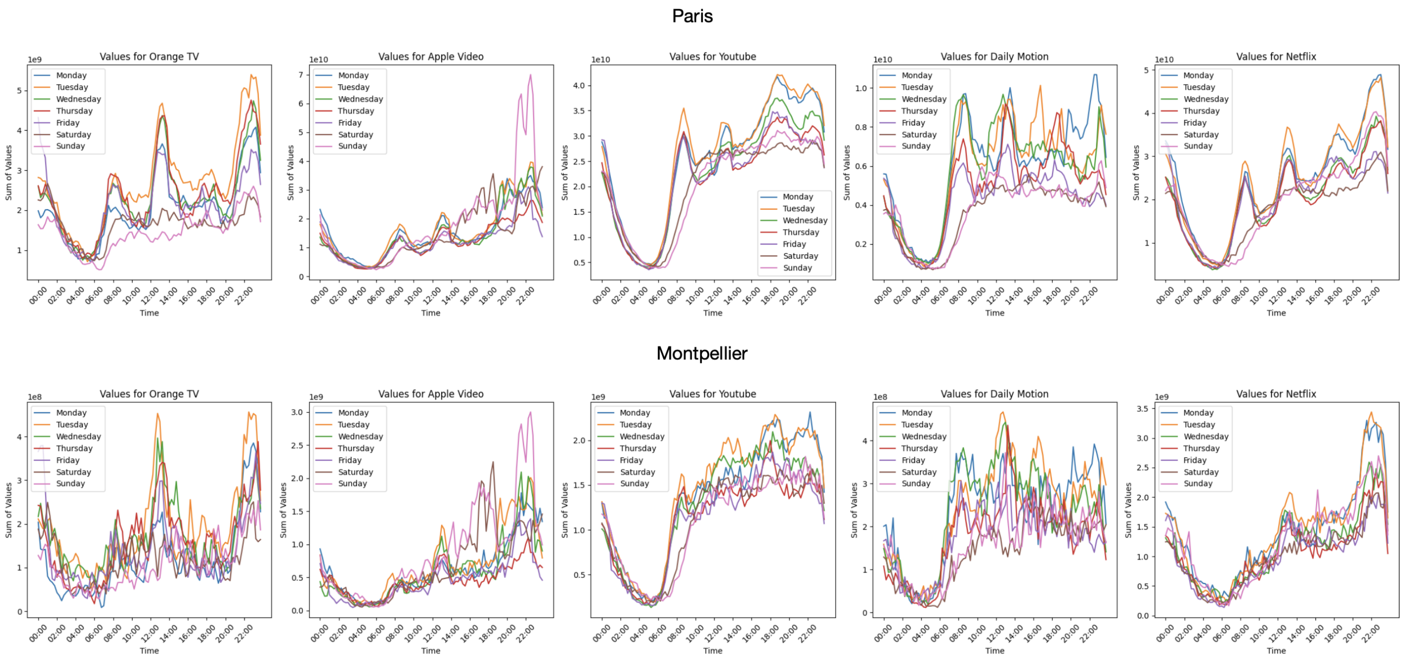

Fig. 1. Hour-Level Changes of Platform Usage for Paris and Montpellier.

We will begin by examining maps of these cities to visualize the dominant platform usage patterns and how these patterns change over the month of April, the time span we choose to analyze, for our exploratory data analysis. Following that, we will employ the statistical tool ANOVA [6] to gain insights into the differences between communes and cities, and subsequently, we will discuss the results of both analyses.

III. Exploratory Data Analysis

First and foremost, we are examining the times when people use these platforms throughout April. Aggregate daily usage of people living in cities of Paris and Montpellier is shown in Figure 1. In the figure, it is evident that people primarily use these platforms more during non-work hours such as lunch breaks and after work hours. This indicates that these platforms are popular leisure-time activities for people. On the other hand, it is observed that internet usage on these platforms is generally less on weekends than on weekdays. These findings align with the Acumen Daily Report on Youth Video Diet, which surveyed a sample of individuals aged 13-24 years. The results of the survey reveal that these individuals typically watch videos when bored or to fill their free time, with a preference for doing so after work or school and during lunchtime. Therefore, our findings underscore that this activity is indeed a leisure-time pursuit, with people choosing to engage in it primarily on weekdays after school or work hours.

It is important to note that our analysis represents only a small aspect of these individuals' lives. Through our analysis, we aim to gain insights into the demographics of areas within cities and the socio-economic conditions of neighborhoods, all based on a limited snapshot of people's leisure-time activities.

To investigate the similarity between the cities regarding platform usage, we employ the dissimilarity index in our study. The dissimilarity index was originally introduced by Duncan and Duncan in 1955 to assess ethnic and population disparities [7]. This index's values range between zero and one, where zero signifies complete integration, and one indicates complete segregation between paid and unpaid platform usage.

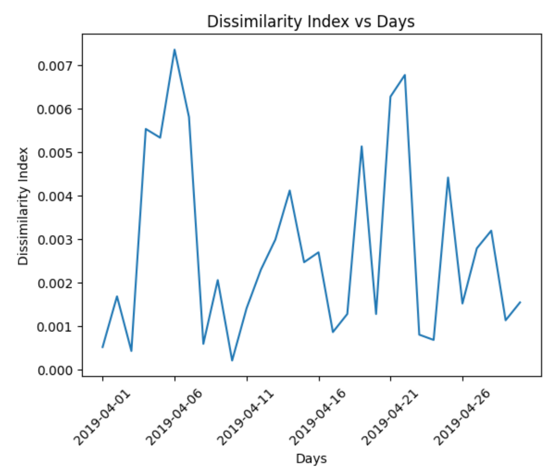

Fig. 2. Day-Level Change in Dissimilarity Index

The dissimilarity index is calculated to determine how much the two cities differ from each other in terms of daily platform usage, as shown in Equation 4. We conduct a thorough analysis by individually scrutinizing the fluctuations in the dissimilarity index values for each day. This examination allows us to pinpoint any potential outlier days within this dataset. Throughout the 30-day period presented in Figure 2, these values range between 0.001 and 0.007. These small values indicate that the cities are very similar in terms of their platform usage.

$$D = 1/2 * \sum_{i=1}^{2}(|\frac{u_i}{U} - \frac{p_i}{P}|) \tag{4}$$

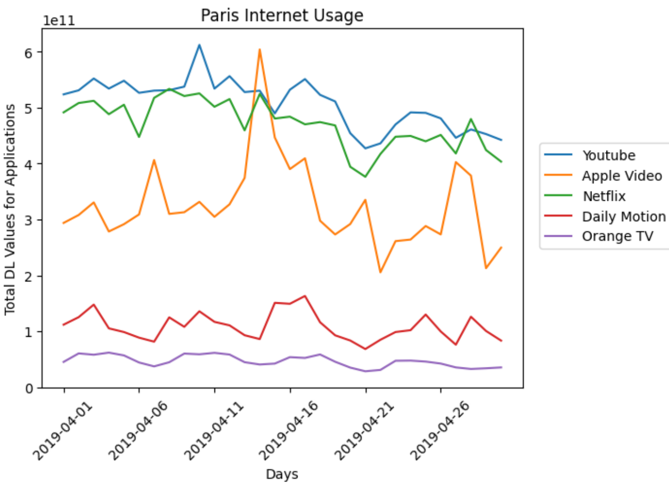

Fig. 3. Day-Level Change in Paris Internet Usage

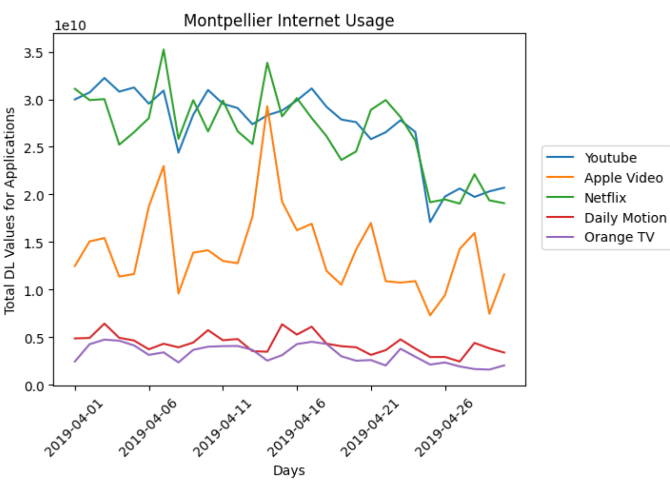

Fig. 4. Day-Level Change in Montpellier Internet Usage

To understand the proportion of how these platforms are used in relation to each other, we examine the usage of all platforms in the cities of Paris and Montpellier in Figures 3 and 4. Our goal is to discern whether certain days differ from others, providing insights into people's reactions to daily life and their preferences for streaming platforms. For example, we observe a significant increase in the usage of Apple Video on April 14, 2019. When we investigate the cause of this spike, we find that it coincided with the final season premiere of HBO's TV series Game of Thrones in Apple Video [8]. This finding demonstrates how the hype surrounding a TV series can lead to an extraordinary surge in platform usage and highlights the susceptibility of people's online video-watching habits to trends and hype. Following the premiere episode, we observe an increase in usage every Monday, but none of these subsequent increases match the magnitude of the first episode's spike. If our data extended to the series finale, we could also comment on people's behavior when it comes to watching both the first and last episodes. It's worth noting that we did not encounter another similarly dramatic instance like this on any of the other platforms.

As Figures 3 and 4 show, both cities primarily use YouTube and Netflix as their most popular platforms. Due to the dominance of these platforms, it is unlikely to observe a clear distinction between paid and unpaid platforms, as previously mentioned in the dissimilarity index analysis. The same can be said for Apple Video, DailyMotion and Orange TV. Apple Video ranks in the middle in terms of usage in both cities; DailyMotion and Orange TV are the least used platforms. While we cannot discern a distinct difference in the usage trends of these platforms, the y-axis of Figures 4 and 3 reveals a dramatic contrast in the scales of platform usage. This discrepancy aligns with the population and size differences between the two cities.

In Figure 5, we present the usage distributions of various platforms for both Grand Paris and Montpellier. We initially examine Grand Paris to identify any areas within the city with higher internet usage and reconsider to exclude them from our analysis. Upon analysis, we find that the density of video-watching is notably high in the city of Paris. In contrast, for Montpellier, we consider the city as a whole rather than focusing solely on the city center, as our aim is to compare Paris and Montpellier, not just the central commune of Montpellier.

However, regardless of the city, we observe that the most dominant usage of all platforms tends to be concentrated in the city centers. In Paris, despite the greater prevalence of Apple Video and Netflix in the city center, Orange TV emerges as the most widespread platform across the entire Grand Paris. This aligns with our earlier findings explaining the lower usage of Orange TV in the city of Paris. In Montpellier, we don't observe a widespread distribution of any single platform across the city; instead, Apple Video and Orange TV are more prevalent in various areas compared to other platforms.

From a socio-economic perspective, we notice that in economically developed arrondissements of Paris, such as Champs-Élysées, all platforms experience more extensive usage. Conversely, in areas further from the city center, such as La Courneuve, where socio-economic challenges are more pronounced, platform usage is significantly lower. Figures 6 and 7 visually depict the spread of dominant applications across arrondissements in the City of Paris and Montpellier.

When we examine each region of City of Paris in Figure 6, we observe that only three platforms are the most used. YouTube and Netflix stand out as dominant platforms, while Apple Video is scattered specific parts of the central and western of the city. YouTube dominates the in the central and western parts of the City of Paris, while Netflix is the most used platform. The regions where Apple Video is most used are the northwest and central areas. DailyMotion or Orange TV, on the other hand, are not the most used platforms in any region of the city.

Similar to Paris, the number of most used platforms is also three in Montpellier, with YouTube and Netflix exhibiting a dominant spread in Figure 7. However, domination of Apple Video is observed in a much smaller number of regions compared to Paris. While YouTube is more heavily used in the center and south, Netflix is used much more in the northern part of Montpellier. Also, it is observed that the regions where Netflix is dominant are more in Montpellier compared to the City of Paris. DailyMotion and Orange TV, like in Paris, are not the most used platforms in any region of Montpellier.

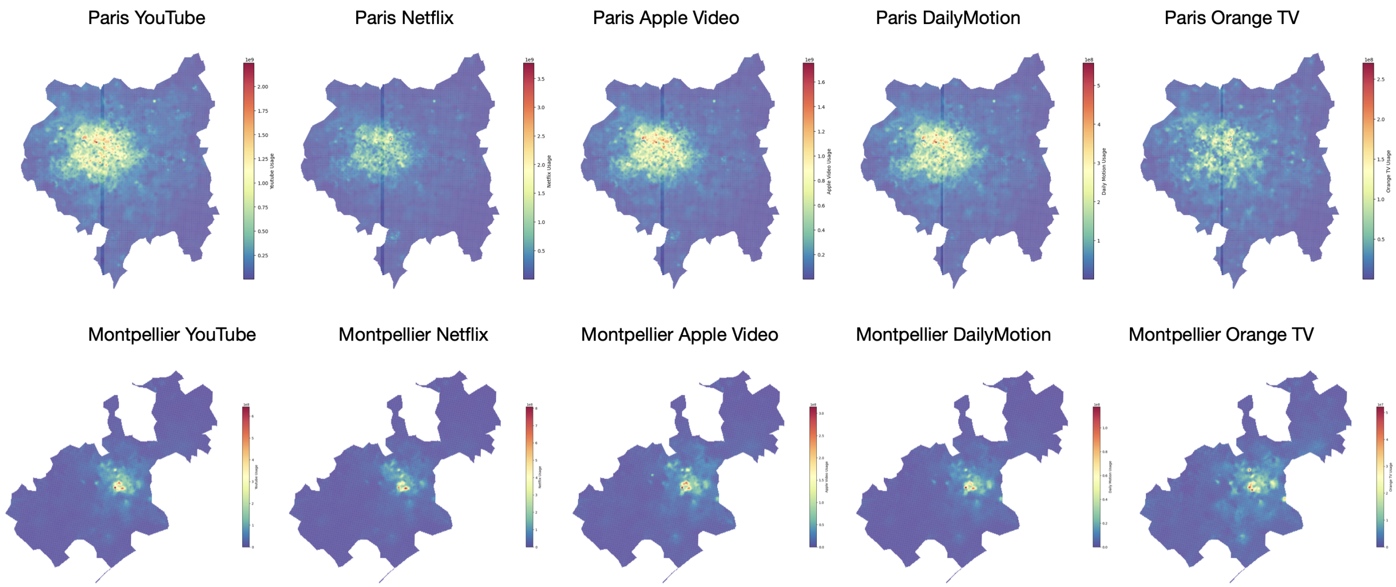

Fig. 5. Usage Spread of Platforms in Grand Paris and Montpellier

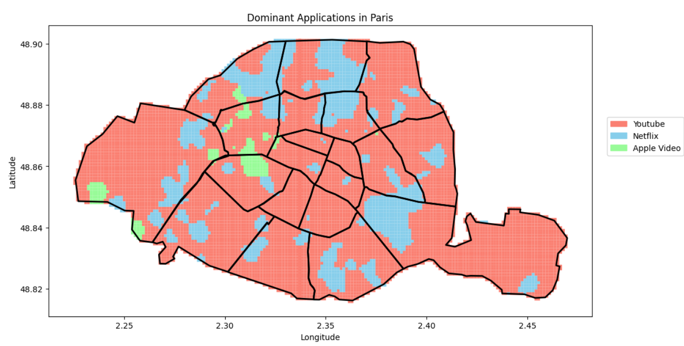

Fig. 6. Dominantly Used Platforms in Paris

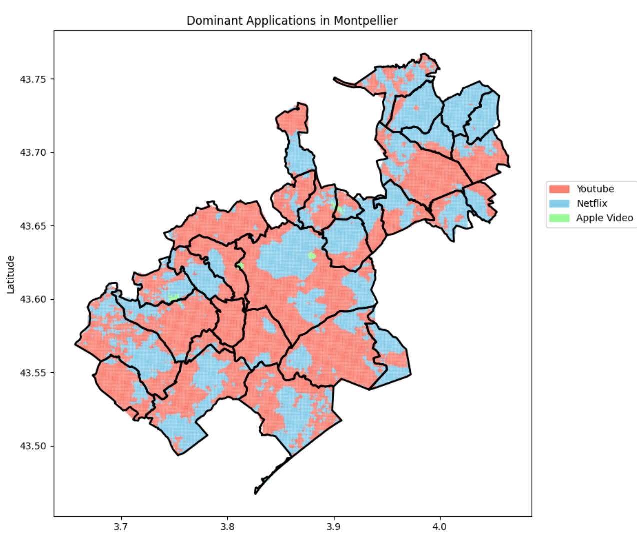

Fig. 7. Dominantly Used Platforms in Montpellier

IV. ANOVA ANALYSIS

As evident from the map in the preceding section, there is a significant disparity in population between the cities. Therefore, we'll be working with average data for each unit, which is normalized by its respective population. We plan to use ANOVA to detect any differences in the average usage data between the Paris commune with 20 arrondissements and Montpellier. This approach will help us gain insights into the demographics and socio-economic conditions of both similar and distinct regions within the cities.

In the context of an ANOVA (Analysis of Variance) analysis, equations 5, 6, and 7 pertain to examining whether the means of variables across more than two groups are statistically significantly different. These steps are formulated through equations. Within-group and between-group variances form the foundation of the analysis. In this context, SS_{within} represents the sum of squares within groups, while $SS_{between}$ signifies the sum of squares between groups. n_i denotes the number of observations in the ith group, X_{ij} represents the value of the jth observation in the ith group, $\bar{X}_i$ stands for the mean of group i, and $\bar{X}$ represents the overall mean.

$$SS_{\text{within}} = \sum_{i=1}^{k} \sum_{j=1}^{n_i} (X_{ij} - \bar{X}_i)^2 \quad SS_{\text{between}} = \sum_{i=1}^{k} n_i (\bar{X}_i - \bar{X})^2 \tag{5}$$

$df_{between}$ symbolizes the degrees of freedom between groups, while df_{within} represents the degrees of freedom within groups. $MS_{between}$ and MS_{within} represent the mean squares between groups and within groups, respectively. N represents the total number of observations in the study, and k represents the total number of groups.

$$MS_{\text{between}} = \frac{SS_{\text{between}}}{df_{\text{between}}} \quad MS_{\text{within}} = \frac{SS_{\text{within}}}{df_{\text{within}}} \tag{6}$$

$$df_{\text{within}} = N - k \quad df_{\text{between}} = k - 1 \quad F = \frac{MS_{\text{between}}}{MS_{\text{within}}} \tag{7}$$

In this study, an ANOVA analysis was conducted on 20 arrondissements of the city of Paris and the city of Montpellier, focusing on streaming platforms' usage categorized as paid or unpaid. A total of 21 different groups were analyzed, initially based on the regions' usage of paid applications. The analysis revealed a statistically significant difference among the groups. The F-value for the analysis was 357887.347, and the p-value was 0.000, indicating strong statistical significance.

As a statistically significant difference was observed among the groups, it became necessary to determine which specific groups exhibited this difference and whether it held statistical importance. To investigate this, a post-hoc test, namely Tukey's Honestly Significant Difference (HSD) test [9], was employed. This test allowed for the examination of differences between all pairs of groups. It is noteworthy that nearly all differences between groups were found to be statistically significant, as evidenced by p-values below 0.001. The outcome of the Tukey's HSD test illustrated the variations between groups and is depicted in the visual representation in Appendix.

According to Tukey's HSD test, there is a statistical difference in the use of paid streaming applications between Arrondissement 7, one of the regions where Netflix and Apple Video, both paid applications, are commonly used, and Arrondissement 12, where Netflix has a relatively larger share of usage in terms of location. Although Arrondissement 12 has a population approximately three times that of Arrondissement 7, their age distributions exhibit relatively similar percentage proportions. For instance, the population aged 15-29 in both regions is slightly less than 25%. In contrast, the percentage proportion of the population aged 30-44 is around 1/6 for Arrondissement 7 and slightly less than 25% for Arrondissement 12. Additionally, when comparing the level of education, Arrondissement 7 has a significantly higher proportion of individuals with university and postgraduate education compared to its population size when compared to Arrondissement 12.

Statistically, there is nearly no difference in the use of paid platforms between two neighboring regions, Arrondissement 19 and Arrondissement 20. Upon examining their population distributions, there are significant similarities both in terms of total population and age distribution. In these two regions, despite Arrondissement 19 having slightly more young population, Arrondissement 20 has a higher proportion of middle-aged individuals. The percentage of elderly population is approximately the same in both regions. Moreover, when considering higher education levels, Arrondissement 19 has a significantly higher percentage of individuals with undergraduate and postgraduate degrees, despite having only slightly more population [4]. Economically, Arrondissement 20 has a slightly higher number of employed individuals aged 15 and above, but proportionally, the regions are nearly identical. Taking age distribution, education, and economic conditions into account, it can be inferred that these two similar regions exhibit similar viewership tendencies regarding paid streaming platforms.

In order to assess potential disparities in the utilization of unpaid streaming platforms across various regions, a subsequent ANOVA analysis was carried out. The outcomes of this analysis indicated the presence of statistically significant differences among the regions concerning their usage of unpaid platforms (p-value = 0.000, F-value = 265025.66). To pinpoint which specific regions exhibit divergent usage patterns and ascertain the statistical significance of these distinctions, HSD test was subsequently employed. The inter-regional p-values and difference values are comprehensively documented in the Appendix for reference and further scrutiny.

When examining two regions, Arrondissement 14 and Arrondissement 17, which do not exhibit statistical differences in the usage of unpaid platforms, it is noteworthy that they display significantly different demographic and viewing patterns. Despite having a smaller population, Arrondissement 14 hosts a considerably higher number of undergraduate and postgraduate students. This is attributed to Arrondissement 14 being home to some of France's top institutions such as the Paris School of Economics and the University of Paris. In contrast, Arrondissement 17 has approximately 15,000 more employees in total. Although the usage of applications like YouTube and Daily Motion is quite similar in these two regions, there are radical differences in specific areas mentioned earlier.

One of the regions that statistically resembles Montpellier the most, with significant differences in the usage of both unpaid and paid applications, is Arrondissement 12. Both YouTube and Netflix are widely prevalent in both regions, and when examining these areas, it becomes evident that both regions have a young population with a percentage exceeding fifty percent. In Montpellier, the number of undergraduate and postgraduate students is approximately 1/7 of the population, whereas in Arrondissement 12, this proportion is approximately around 10%. When analyzing the number of individuals aged 15 and above who are employed, Montpellier shows a workforce participation rate of approximately 1/3 of the population, while in Arrondissement 12, this rate is approximately 45% [4].

V. Conclusion

In this study, we exclusively concentrate on data related to people's usage of specific streaming platforms to uncover the livelier, younger, and wealthier areas within the cities of Paris and Montpellier. This research illuminates mobile data usage patterns in connection to people's leisure activities, with the goal of identifying unique areas of mobile data usage.

It becomes apparent that the choice of streaming platforms not only reflects the socio-economic conditions and demographics of neighborhoods but is also influenced by global trends and hype. Thus, the mid-level timespan of our study offers only limited insights into the broader aspects of these neighborhoods. To gain a deeper understanding, we could analyze year-level data and weekly reports from these streaming services, particularly focusing on the TV series they offer. Such an approach would provide us with insights into how these cities align with global trends. By examining their alignment with these trends, we can infer the age and education levels of these cities' populations.

Additionally, when we investigate these services individually, we discover that Orange TV streams football matches. Considering the presence of French football teams like PSG, Lille, and Lyon in the Champions League in 2019, and recognizing the importance of watching football as a leisure activity in less advantaged neighborhoods, we can draw connections between the availability of Orange TV and the socio-economic situations of the people in those areas. However, this would require smaller-scale, more focused studies to provide meaningful insights.

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Appendices

	Paris Arrondissement 1	Paris Arrondissement 2	Paris Arrondissement 3	Paris Arrondissement 4	Paris Arrondissement 5	Paris Arrondissement 6	Paris Arrondissement 7	Paris Arrondissement 8	Paris Arrondissement 9	Paris Arrondissement 10	Paris Arrondissement 11	Paris Arrondissement 12	Paris Arrondissement 13	Paris Arrondissement 14	Paris Arrondissement 15	Paris Arrondissement 16	Paris Arrondissement 17	Paris Arrondissement 18	Paris Arrondissement 19	Paris Arrondissement 20	Montpellier
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Paris Arrondissement 6	0.000	0.000	0.000	0.000	0.000																
Paris Arrondissement 7	0.000	0.000	0.000	0.000	0.000	0.000															
Paris Arrondissement 8	0.000	0.000	0.000	0.994	0.000	0.000	0.000														
Paris Arrondissement 9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000													
Paris Arrondissement 10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000												
Paris Arrondissement 11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000											
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Paris Arrondissement 14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000								
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Paris Arrondissement 16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.017	0.000	0.000						
Paris Arrondissement 17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
Paris Arrondissement 18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Paris Arrondissement 19	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.000			
Paris Arrondissement 20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.154		
Montpellier	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Fig. 8. Tukey's HSD Significance Differences for Paid Streaming Platforms

	Paris Arrondissement 1	Paris Arrondissement 2	Paris Arrondissement 3	Paris Arrondissement 4	Paris Arrondissement 5	Paris Arrondissement 6	Paris Arrondissement 7	Paris Arrondissement 8	Paris Arrondissement 9	Paris Arrondissement 10	Paris Arrondissement 11	Paris Arrondissement 12	Paris Arrondissement 13	Paris Arrondissement 14	Paris Arrondissement 15	Paris Arrondissement 16	Paris Arrondissement 17	Paris Arrondissement 18	Paris Arrondissement 19	Paris Arrondissement 20	Montpellier
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Paris Arrondissement 14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000								
Paris Arrondissement 15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000							
Paris Arrondissement 16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000						
Paris Arrondissement 17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000					
Paris Arrondissement 18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000				
Paris Arrondissement 19	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.000			
Paris Arrondissement 20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002		
Montpellier	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

Fig. 9. Tukey's HSD Significance Differences for Unpaid Streaming Platforms

	Paris Arrondissement 1	Paris Arrondissement 2	Paris Arrondissement 3	Paris Arrondissement 4	Paris Arrondissement 5	Paris Arrondissement 6	Paris Arrondissement 7	Paris Arrondissement 8	Paris Arrondissement 9	Paris Arrondissement 10	Paris Arrondissement 11	Paris Arrondissement 12	Paris Arrondissement 13	Paris Arrondissement 14	Paris Arrondissement 15	Paris Arrondissement 16	Paris Arrondissement 17	Paris Arrondissement 18	Paris Arrondissement 19	Paris Arrondissement 20	Montpellier
Paris Arrondissement 1																					
Paris Arrondissement 2	96,864																				
Paris Arrondissement 3	441,536	344,673																			
Paris Arrondissement 4	526,962	430,098	85,426																		
Paris Arrondissement 5	831,864	735,000	390,327	304,902																	
Paris Arrondissement 6	617,472	520,608	175,936	90,510	-214,392																
Paris Arrondissement 7	743,125	646,262	301,589	216,164	-88,738	125,653															
Paris Arrondissement 8	525,590	428,726	84,053	-1,372	-306,274	-91,882	-217,536														
Paris Arrondissement 9	671,646	574,782	230,110	144,684	-160,218	54,174	-71,479	146,056													
Paris Arrondissement 10	816,201	719,337	374,665	289,239	-15,663	198,729	73,076	290,611	144,555												
Paris Arrondissement 11	946,450	849,586	504,914	419,488	114,586	328,978	203,325	420,860	274,804	130,249											
Paris Arrondissement 12	1.012,094	915,231	570,558	485,133	180,231	394,622	268,969	486,505	340,449	195,893	65,644										
Paris Arrondissement 13	1.002,579	905,716	561,043	475,618	170,716	385,108	259,454	476,990	330,934	186,378	56,130	-9,515									
Paris Arrondissement 14	973,156	876,292	531,620	446,194	141,292	355,684	230,031	447,566	301,510	156,955	26,706	-38,939	-29,424								
Paris Arrondissement 15	999,651	902,788	558,115	472,689	167,788	382,179	256,526	474,062	328,005	183,450	53,201	-12,443	-2,928	26,495							
Paris Arrondissement 16	1.004,307	907,443	562,770	477,345	172,443	386,835	261,181	478,717	332,661	188,106	57,857	-7,788	1,727	31,151	4,655						
Paris Arrondissement 17	960,395	863,532	518,859	433,434	128,532	342,924	217,270	434,806	288,750	144,194	13,946	-51,699	-42,184	-12,760	-39,256	-43,911					
Paris Arrondissement 18	992,363	895,500	550,827	465,402	160,500	374,891	249,238	466,774	320,717	176,162	45,913	-19,731	-10,216	19,207	-7,288	-11,943	31,968				
Paris Arrondissement 19	1.014,036	917,172	572,499	487,074	182,172	396,564	270,910	488,446	342,390	197,835	67,586	1,941	11,456	40,880	14,384	9,729	53,640	21,672			
Paris Arrondissement 20	1.012,227	915,363	570,690	485,265	180,363	394,755	269,101	486,637	340,581	196,025	65,777	0,000	9,647	39,071	12,575	7,920	51,831	19,863	-1,809		
Montpellier	1.059,128	962,264	617,592	532,166	227,264	441,656	316,003	533,538	387,482	242,927	112,678	47,033	56,548	85,972	59,477	54,821	98,732	66,765	45,092	46,901	

Fig. 10. Tukey's HSD Differences for Paid Streaming Platforms

	Paris Arrondissement 1	Paris Arrondissement 2	Paris Arrondissement 3	Paris Arrondissement 4	Paris Arrondissement 5	Paris Arrondissement 6	Paris Arrondissement 7	Paris Arrondissement 8	Paris Arrondissement 9	Paris Arrondissement 10	Paris Arrondissement 11	Paris Arrondissement 12	Paris Arrondissement 13	Paris Arrondissement 14	Paris Arrondissement 15	Paris Arrondissement 16	Paris Arrondissement 17	Paris Arrondissement 18	Paris Arrondissement 19	Paris Arrondissement 20	Montpellier
Paris Arrondissement 1																					
Paris Arrondissement 2	100,787																				
Paris Arrondissement 3	485,621	384,834																			
Paris Arrondissement 4	562,325	461,539	76,705																		
Paris Arrondissement 5	861,931	761,145	376,311	299,606																	
Paris Arrondissement 6	620,518	519,732	134,898	58,193	-241,413																
Paris Arrondissement 7	817,074	716,287	331,453	254,748	-44,858	196,555															
Paris Arrondissement 8	585,112	484,325	99,491	22,787	-276,819	-35,407	-231,962														
Paris Arrondissement 9	743,369	642,582	257,748	181,043	-118,563	122,85	-73,705	158,257													
Paris Arrondissement 10	907,703	806,916	422,082	345,378	45,772	287,185	90,629	322,591	164,334												
Paris Arrondissement 11	1015,986	915,199	530,365	453,66	154,054	395,467	198,912	430,874	272,617	108,283											
Paris Arrondissement 12	1089,266	988,479	603,645	526,94	227,334	468,747	272,192	504,154	345,897	181,563	73,28										
Paris Arrondissement 13	1075,022	974,235	589,401	512,696	213,09	454,503	257,948	489,91	331,653	167,319	59,036	-14,244									
Paris Arrondissement 14	1038,053	937,267	552,433	475,728	176,122	417,535	220,98	452,941	294,685	130,35	22,068	-51,212	-36,968								
Paris Arrondissement 15	1072,204	971,418	586,584	509,879	210,273	451,686	255,131	487,092	328,835	164,501	56,219	-17,061	-2,817	34,151							
Paris Arrondissement 16	1079,941	979,155	594,321	517,616	218,01	459,423	262,867	494,829	336,572	172,238	63,956	-9,324	4,919	41,888	7,737						
Paris Arrondissement 17	1038,437	937,65	552,816	476,111	176,505	417,918	221,363	453,325	295,068	130,734	22,451	-50,829	-36,585	0,000383	-33,768	-41,504					
Paris Arrondissement 18	1068,96	968,174	583,34	506,635	207,029	448,442	251,887	483,848	325,592	161,257	52,975	-20,305	-6,061	30,907	-3,244	-10,981	30,524				
Paris Arrondissement 19	1086,538	985,752	600,918	524,213	224,607	466,02	269,464	501,426	343,169	178,835	70,553	-2,727	11,516	48,485	14,334	6,597	48,101	17,578			
Paris Arrondissement 20	1083,458	982,671	597,837	521,133	221,527	462,94	266,384	498,346	340,089	175,755	67,472	-5,808	8,436	45,405	11,254	3,517	45,021	14,498	-3,08		
Montpellier	1137,372	1036,586	651,752	575,047	275,441	516,854	320,299	552,26	394,004	229,669	121,387	48,107	62,351	99,319	65,168	57,431	98,936	68,412	50,834	53,914	

Fig. 11. Tukey's HSD Differences for Unpaid Streaming Platforms