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A Comparative Study of OTT Market Demographic Grouping

Akshay Rai, Arayan Kataria, Vishnupriya

***Abstract:** This research paper aims to analyze the population and potential viewer count for different age groups, genders, and employment status in three distinct clusters of states in the United States. The clusters were formed based on demographic similarities using the K-means clustering for exploration and Hierarchical (Birch and Agglomerative) and Spectral clustering on a dataset that included information on the population, age, gender, employment status, and potential viewers for each state. The research then analyzed the clusters to determine the most significant factors contributing to the viewership in each segment and found that each cluster has unique demographic features, such as a high concentration of younger male viewers in one cluster and older female viewers in another. Additionally, the research identified the states and demographic groups with the highest potential viewership within each cluster. The results section will discuss the demographic features of each cluster, followed by an analysis of the states and demographic groups with the highest potential viewership within each cluster. Our analysis provides valuable insights into the audience's characteristics and preferences, which can be used to optimize marketing and content strategies for the streaming service. The paper will conclude by discussing the implications of these findings and possible future directions for research.*

***Index Terms:** Demographic Segmentation, Viewer Clustering, Hierarchical Clustering, Spectral Clustering, Elbow Method, Cross-Platform Segmentation, Targeted Marketing, Cluster Validation*

I. INTRODUCTION

The evolution of the Over-the-Top (OTT) industry has transformed the landscape of media consumption, demanding a nuanced understanding of viewer preferences. In response, this research embarks on a pioneering exploration, aiming to unravel the intricate demographics that shape the OTT market. Focused on granular information encompassing age, gender, and employment status, our study employs cutting-edge clustering techniques, including K-means, Hierarchical, and Spectral clustering. By leveraging two datasets—one rich in demographic details and the other providing market parameters—we seek to redefine the contours of market segmentation within the OTT sphere.

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The distinctive approach involves dimension selection and the application of the Elbow Method to ensure optimal clustering accuracy, addressing the challenges posed by multi-dimensional data. In contrast to conventional analyses, our study integrates various clustering methodologies, ensuring a comprehensive understanding of viewer clusters.

We introduce cross-platform segmentation, delving into how viewers engage across different OTT platforms and devices. The research extends beyond demographic categorization, incorporating linkage adjustment techniques to validate clustering results, thus ensuring the robustness and reliability of our segmentation. Mathematical calculations unravel the average viewership and population characteristics within each cluster, providing a detailed insight into the unique demographic profiles. Visualization techniques, such as scatter plots and pair plots, serve as intuitive tools to interpret and communicate the complex relationships and patterns discovered through cluster analysis. This study transcends the traditional boundaries of market analysis, contributing innovative insights that can inform targeted marketing and content creation strategies in the dynamic OTT industry [11][12][13]. As media consumption habits continue to evolve, our research endeavours to equip stakeholders with a sophisticated understanding of viewer behaviour, poised at the intersection of demographic intricacies and clustering methodologies.

II. PROBLEM STATEMENT

The rapidly evolving landscape of Over-the-Top (OTT) media consumption poses a significant challenge for content providers and marketers, as traditional market segmentation approaches struggle to capture the nuanced preferences of diverse viewer demographics. The existing methodologies often lack granularity, hindering the development of targeted marketing strategies and personalized content recommendations [14][15]. Additionally, the multi-dimensional nature of OTT datasets, encompassing variables such as age, gender, and employment status, demands innovative segmentation techniques to discern distinct viewer clusters effectively. Moreover, the absence of a unified and comprehensive methodology for demographic segmentation within the OTT market hinders the industry's ability to adapt and tailor content offerings to the evolving preferences of its audience. This research aims to address these challenges by introducing advanced clustering techniques and cross-platform insights, seeking to redefine the conventional understanding of viewer behaviour within the dynamic OTT landscape.

The lack of a precise and versatile segmentation approach limits the industry's potential for strategic adaptation, making it imperative to develop a methodological framework that aligns with the intricacies of contemporary media consumption patterns.

III. LITERATURE REVIEW

Various studies explore customer segmentation and engagement across diverse industries. Ashwani et al. [1] implement k-means clustering to segment mall customers based on specialized attributes, revealing age-related spending patterns and income-spending correlations. Durga et al. [2] emphasize the significance of data-driven segmentation for enhancing sales outcomes, while Reddy et al. [3] advocate for ongoing exploration of customer feedback to refine segmentation accuracy. Aouad et al. [4] introduce Market Segmentation Trees as an interpretable framework for personalized decision-making, enhancing response prediction accuracy. Patria et al. [5] analyze brand engagement and loyalty within the context of Spotify, while Yoshida et al. [6] validate a multidimensional scale of fan engagement behavior in sports. Castillo et al. [7] highlight the positive impact of social media-driven engagement on movie performance, while Abbasi et al. [8] investigate the effects of consumer engagement in esports on subsequent consumption behaviors. Teng [9] explores the role of film tourism experience and engagement in influencing tourist behavioral intentions. Umarani [10] evaluates KNN and Decision Tree models in predicting customer buying patterns in ecommerce.

IV. METHODOLOGY

A. Data Collection and Pre-Processing

The OTT Viewers information as well as the OTT Market information were collected as the first phase in this study. The OTT Viewer dataset includes granular information such as users' age, sex, and employment, whereas the OTT Market dataset includes constant variables a l s o i n c l u d i n g demographic, amount of marketplaces, and the total amount of media channels. Hence substantial pretreatment was required before the data from the OTT Viewer and OTT Market datasets were suitable for hierarchical clustering.

1. OTT Viewer	2. OTT Market
State	State
Gender	Market
Age group	Viewers
Status	TV Stations
Viewers	Media Channels
Population	
Potential_viewers	

Fig. 1. Features of the Two Datasets

This OTT Viewer dataset includes precise information such as consumers' age, sex, and employment, whereas the OTT Industry collection includes continuous parameters such as demographic, market size, and the total quantity of media outlets.

B. Dimension Selection

Whenever information comes to grouping, scale choice is quite crucial. All characteristics chosen for grouping are determined by the clustering aim, and many systems to identify and density reducing strategies come under the paradigm of model-based grouping. Another goal of model-based clustering is to optimize the probability of a set of univariate influence the perception from a K-component stochastic process. Hence, the fundamental idea behind model-based grouping is to represent the rows of X as separate univariate observations obtained from a probabilistic model with K components. Because unstructured approaches are dangerous, it is critical to choose characteristics with variability that make significant contributions to grouping. Thus model-based grouping exposes itself naturally to value choosing. This method for choosing features requires fewer hours than the original unattended learner. It also assists in determining which characteristics to employ as well as what clusters to generate.

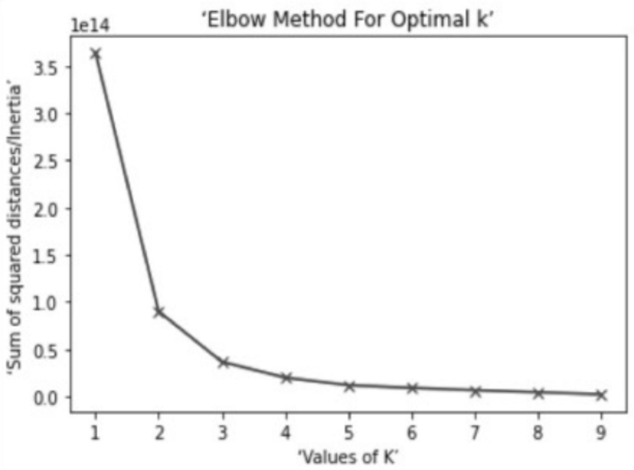

Fig. 2. Elbow Method Visual

In this study, we aimed to segment the OTT market based on demographic factors. To accomplish this, we started with the OTT market dataset, which included state, market, viewers, TV stations, and media channels as dimensions. We conducted a dimension selection process to determine the optimal combination of dimensions for our analysis.

We began by exploring different 2D clusters using three different analysis methods. First, we used the Elbow Method to determine the optimal number of clusters, which was found to be k=3. Elbow Method is a visual heuristic used to determine the optimal number of clusters in a dataset. The method involves plotting the explained variation as a function of the number of clusters, and selecting the number of clusters at the "elbow" point of the curve, where the explained variation starts to level off. The explained variation can be calculated using the within-cluster sum of squares (WSS) metric, which is the sum of the squared distances between each point and its assigned cluster centroid.

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The formula for WSS is

$$WSS = \Sigma i \Sigma j \ ||xi - cj||^2 \qquad (1)$$

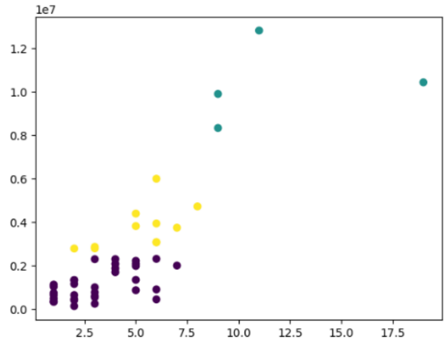
where xi is the ith data point, cj is the centroid of the jth cluster, and ||.|| denotes the Euclidean distance.

Then, we applied K-Means to explore which feature pairs gave good clusters. Our three analyses included Market and Viewers as features in Analysis 1, Viewers and TV Stations in Analysis 2, and Viewers and Media Channels in Analysis 3. K-means clustering is a popular unsupervised learning algorithm used for clustering data into k clusters. The algorithm aims to minimize the sum of squared distances between the data points and their assigned cluster centroids. The mathematical formula for k-means clustering can be expressed as:

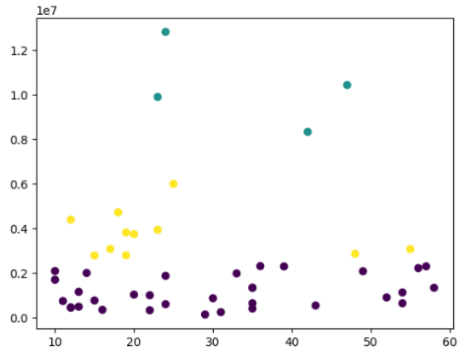
Given a set of n data points x1, x2, ..., xn, where each data point is a d-dimensional real vector, the partitioned data points into k (≤ n) clusters C1, C2, ..., Ck such that the sum of squares from points to the assigned cluster centroids is minimized. The objective function is given by:

$$J = \Sigma(xi - \mu j)^2 \qquad (2)$$

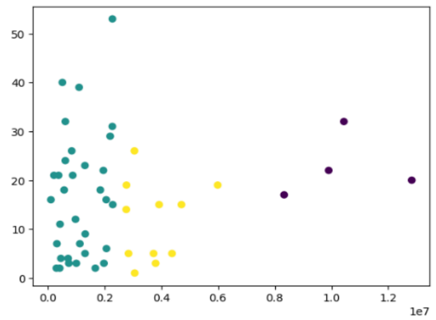
where xi is a data point, μj is the centroid of the jth cluster, and the summation is over all data points xi in cluster j.



Market and Viewers



Viewers and TV Station



Viewers and Media Channels

Fig. 3. Determining the Pairs of Dimension for Clustering

After conducting these analyses, we found that Analysis 3, which used Viewers and Media Channels as features, produced the best clusters. Therefore, we selected these dimensions for further analysis in our study. By selecting these dimensions, we aim to provide a more precise segmentation of the OTT market based on demographic factors.

C. Clustering

As a matter of fact Clustering is a powerful instrument for data evaluation because it allows you to properly comprehend the fundamental database schema. As a result, it is applied in a wide range of domains, from biology and medicine to advertising. This OTT Marketplace dataset was analyzed utilizing three separate classification method: Agglomerative, Birch Clustering techniques, and Spectral grouping. Agglomerative clustering was used to group similar markets based on the number of potential viewers and media channels. The agglomerative clustering algorithm used different linkage criteria to merge clusters based on the maximum distance between the farthest points in two different clusters. This approach helped to identify the markets that are more likely to have high potential viewership based on their media channel offerings. The distance between two clusters is defined by the average linkage method as:

$$d(Ci, Cj) = 1/(|Ci||Cj|) * \Sigma\Sigma \ dist(xi, xj) \qquad (3)$$

where Ci and Cj are two clusters, |Ci| and |Cj| are the number of data points in the two clusters, and dist(xi, xj) is the distance between two data points xi and xj.

Birch clustering was used to group the data points in a hierarchical structure. Birch clustering is a type of hierarchical clustering that uses a tree-like structure to organize the data. It works by constructing a Clustering Feature Tree (CFT) in which the data points are recursively merged into subclusters. The CFT allows for efficient clustering of large datasets and provides a compact representation of the data structure. In this project, Birch clustering was applied to the OTT market dataset to identify submarkets based on the number of viewers and TV stations. The resulting subclusters were used to assign labels to the OTT viewer dataset, allowing for analysis of the demographic information of viewers in each submarket. Spectral clustering was used in OTT market segmentation to identify groups of viewers based on their similarity in terms of media channel usage. The spectral clustering algorithm was applied to a similarity matrix calculated based on the viewers' media channel preferences. The resulting clusters were then used to gain insights into the market segmentation of OTT platforms. The final equation for spectral clustering is:

$$argmin\_S \ 1/2 \ \Sigma i,j \ Wij \ ||ui - uj||^2 \qquad (4)$$

where Wij is the affinity (similarity) between data points i and j, ui is the embedding of data point i in the k-dimensional space, S is the set of cluster assignments for the data points, subject to ||ui||^2 = 1, i=1,2,...,n

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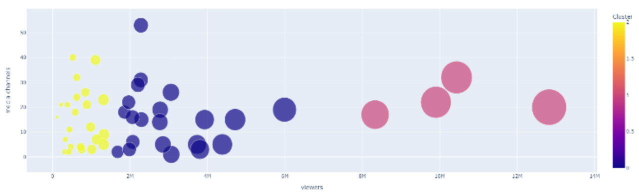

Fig. 4. Clusters after three Clustering Techniques Over Media Channels and Viewers

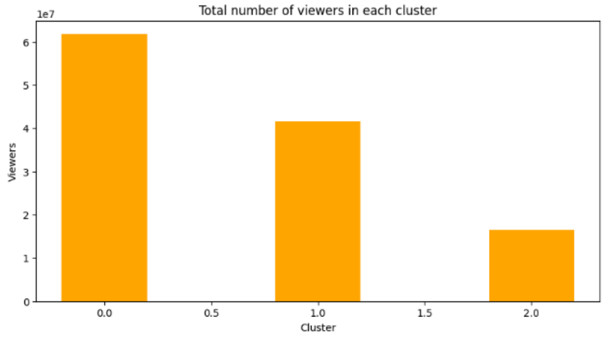

Fig. 5. Total Number of Viewers in Each Cluster

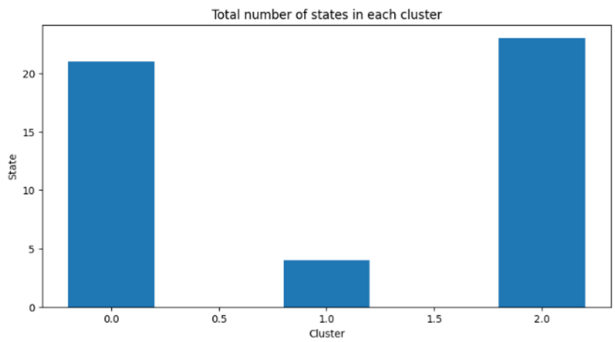

Fig. 6. Total Number of States in Each Cluster

D. Cluster Validation

Linkage adjustment is a technique used in cluster validation to assess the quality of a clustering algorithm. In this method, the linkage criteria are adjusted to evaluate the stability and consistency of the clusters obtained from the algorithm. Specifically, different linkage criteria such as complete, average, and single linkage are used to determine the optimal clustering result. The adjusted linkage criteria help to identify the optimal number of clusters that can effectively group the data points. This method was applied in the OTT market segmentation project to evaluate the stability and consistency of the clusters obtained from the agglomerative clustering algorithm. The results showed that adjusting the linkage criteria improved the quality of the clustering, leading to more accurate market segmentation. The mathematical formula for linkage adjustment can be expressed as:

$$\textbf{Adjusted Rand Index} = (\textbf{ARI} - \textbf{ARI\_null}) / (\max(\textbf{ARI\_oneside} - \textbf{ARI\_null}, 0)) \quad (5)$$

Where ARI is the regular Rand Index, ARI_null is the expected value of the Rand Index for a random partition, and ARI_oneside is the expected value of the Rand Index for a one-sided random partition.

Linkage Criteria	Average Total Adjustment
Ward	5.15
Complete	5.56
Average	5.88
Single	8.63

Fig. 7. Linkage Adjustment

E. Assigning Cluster Labels

Following the creation of the clusters, each item in the OTT Market database was allocated a group identifier. In accordance with the demographics wherein the viewers belongs, these tags were then utilized to provide cluster tags to each item in the OTT Viewer dataset. To reveal the fundamental trends and procedures, the data must be appropriately classified. Hence clusters were formed inside this OTT Marketplace collection, and that each entry was allocated a cluster label. The two hierarchical clustering algorithms - Agglomerative and Birch - produced similar clusters, and to obtain more reliable cluster labels, we assigned labels to the data points by taking the mean of the labels obtained from the two algorithms. This approach allowed us to take advantage of the strengths of both algorithms and assign more relevant cluster labels to the data points. The resulting labels were then used to further analyze the characteristics of each cluster and provide insights into the OTT market segmentation.

i. Merging Clusters into Main Dataframe

To merge the clusters formed into the main dataframe, we first assigned the cluster labels to each row in the original dataframe. This was done by using the index of the row to match it with the corresponding index in the cluster labels array. Once the labels were assigned, we created a new column in the dataframe to store these cluster labels. The merging was then done using the Pandas merge function, where we joined the original dataframe with the cluster label dataframe on the index. This resulted in a new dataframe with the same rows as the original dataframe but with an additional column for the cluster labels. This allowed us to analyze the characteristics of each cluster in the context of the original dataset.

S. No	State	Cluster
0	Alabama	0.0
1	Alaska	2.0
2	Arizona	0.0
3	Arkansas	2.0
4	California	1.0

Fig. 8. States Corresponding to the Particular Clusters

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ii.   Average Viewers and Population

We used the merged dataset to find the average viewers and average population in each cluster by calculating the mean of viewers and population for each cluster. This helped us to understand the characteristics of each cluster and identify the segments with high potential for growth. This information was used by us to design characterization to find the most valuable demographic cluster. Overall, the merging of clusters with the main dataset was an important step in our analysis as it helped us to derive actionable insights from the data.

Cluster	Avg_Viewers	Avg_Population
0.0	183825	476547
1.0	648392	1725362
2.0	44727	133845

Fig. 9. Average Viewers and Population Corresponding to Each Cluster

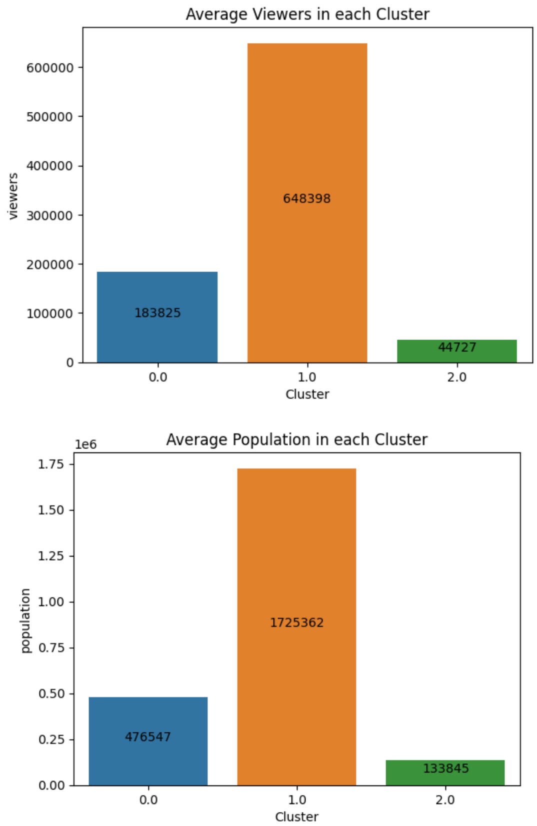

Fig. 10. Average Numbers of Viewers and Population in Each Cluster

We observe that Cluster 1 covers the most population as well as viewers. Looking at the bar graph, we see that there might be a good correlation between the count of Viewers and the Population in a cluster. Cluster 0 and Cluster 2 hold second and third position respectively in both, the viewers and the population count.

V. CHARACTERISTICS AND VISUALIZATION

A. Age-Group and State

In Cluster 1, people above the age of 50 years in the state of New York hold the majority of the viewers count. However, in Cluster 2, teenagers amongst the age bracket of 13-19 years belonging to the neighbouring state of Pennsylvania form the major viewers group. Similar to Cluster 1, people above the age of 50 years residing in the state of Oklahoma account for highest viewership in Cluster 2. Groups formed in Cluster 1 contributes maximum viewers count, followed by Cluster 0 which is nearly half of the prior one. Cluster 2 forms the smallest viewers count amongst the three.

Cluster	Age Group	State	Viewers
0.0	13-19	Pennsylvania	600190
1.0	50 above	New York	1220373
2.0	50 above	Oklahoma	158304

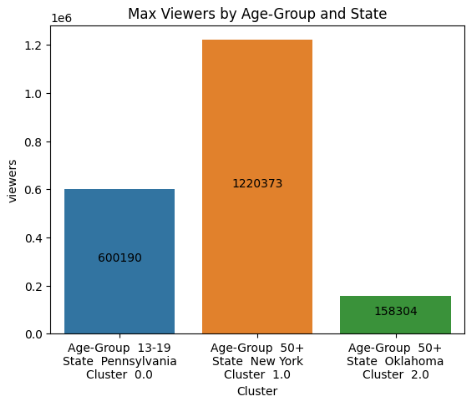

Fig. 11. Max Viewers by Age-Group and State in Each Cluster

Similarly, when we look at the maximum population from each of the clusters, we see that people in California from the age bracket of 20-29 years hold the maximum population count. Teenagers in the age group of 13-19 years living in Illinois show the largest population count in the Cluster 0. In Cluster 2, 20-29 year old people belonging to the state of Maryland account for the maximum population count.

Cluster	Age Group	State	Population
0.0	13-19	Illinois	1717899
1.0	20-29	California	3771377
2.0	20-29	Maryland	668324

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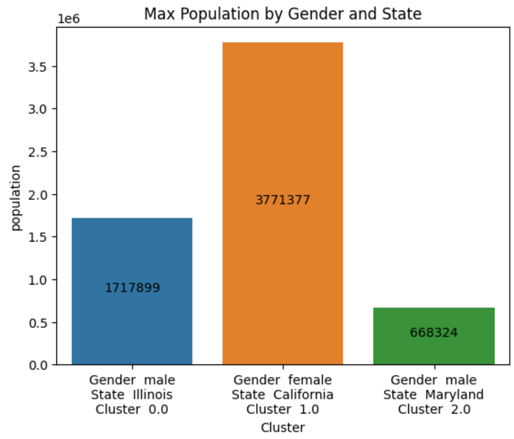

Fig. 12. Max Population by Age-Group and State in Each Cluster

B. Gender and State

When we group the viewers by Gender and States in each cluster, Female audience from New York hold the largest viewers count in Cluster 1. The largest viewers count in Cluster 0 is held by the Male individuals belonging to Pennsylvania. Females in Oklahoma account for the largest viewership in Cluster 2. Just like the Age and State, we observe that the groups formed in Cluster 1 contribute the highest to viewers count. Groups formed in Cluster 0 and Cluster 2 hold the second and third highest viewership, respectively.

Cluster	Gender	State	Viewers
0.0	Male	Pennsylvania	600190
1.0	Female	New York	1220373
2.0	Female	Oklahoma	158304

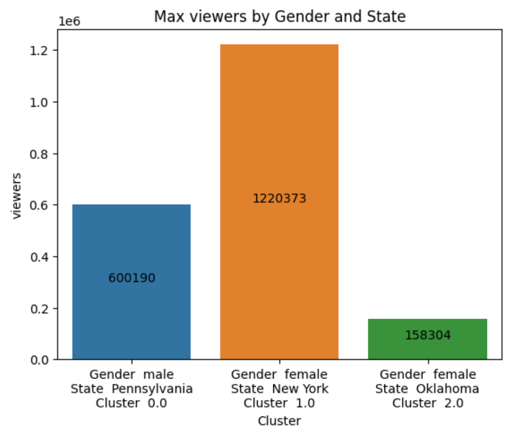

Fig. 13. Max Viewers by Gender and State in Each Cluster

Female individuals from the State of California contribute the maximum to the population of Cluster 1. In the Cluster 0, males belonging to the state Illinois hold the highest count of population. The largest population count in Cluster 2 is shown by male people based in the state of Maryland.

Cluster	Gender	State	Population
0.0	Male	Illinois	1717899
1.0	Female	California	3771377
2.0	Male	Maryland	668324

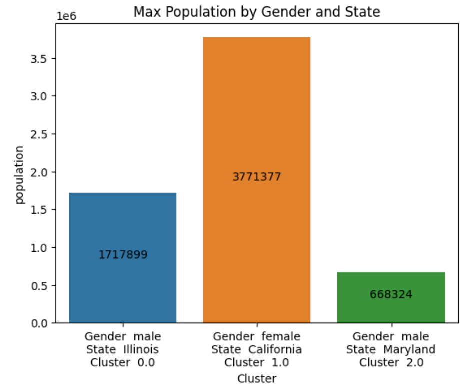

Fig. 13. Max Population by Gender and State in Each Cluster

C. Maximum Potential Viewers

Cluster	Age Group	Gender	Status	State	Potential Viewers
0	13-19	Male	Unemployed	Ohio	545453
1	13-19	Male	Unemployed	California	945841
2	20-29	Female	Employed	Nevada	114992

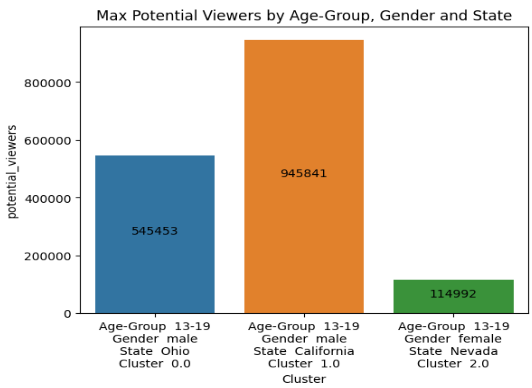

Fig. 13. Maximum Potential Viewers in Each Cluster

To find the maximum potential viewers in each cluster, we group the data frame by Age Group, State, Gender and Employment Status. While individual groupings may give certain insights, more accurate projections will be obtained if all the significant features are taken into consideration.

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It is found that Male Unemployed teenagers belonging to Age Group of 13-19 residing in California contribute maximum to the potential viewership for an OTT Platform amongst Cluster 1. Similar group residing in Ohio have the maximum potential viewership amongst Cluster 0. The potential viewership for an OTT platform amongst Cluster 2 is highest amongst Employed Female Individuals belonging to the age group of 20-29 and living in Nevada.

VI. CONCLUSION

In conclusion, this research has innovatively addressed the complexities of the Over-the-Top (OTT) market through advanced clustering techniques. By meticulously analysing granular demographic data, including age, gender, and employment status, distinct viewer clusters were identified. The utilization of the Elbow Method, dimension selection, and cross-platform segmentation added precision and relevance to the segmentation process. Robust cluster validation techniques ensured the reliability of findings. Mathematical analyses provided insightful average viewership and population characteristics within each cluster. Visualization techniques enhanced the interpretability of complex relationships. This study not only contributes a nuanced understanding of viewer behaviour in the OTT landscape but also offers actionable insights for targeted marketing and content strategies. The developed system architecture ensures an efficient workflow, setting the stage for future research and strategic adaptations in the dynamic OTT industry.

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DECLARATION STATEMENT

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Conflicts of Interest	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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