

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**



**COURSE PROJECT REPORT**

on

**NETFLIX DATA ANALYSIS**

*Submitted in partial fulfilment of the requirement for the award of Degree of*

*Bachelor of Engineering*

*in*

*Computer Science and Engineering*

*Submitted by:*

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**(Accredited by NBA Tier-1)**

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**NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY**

(AN AUTONOMOUS INSTITUTION, AFFILIATED TO VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELGAUM

, APPROVED BY AICTE & GOVT.OF KARNATAKA)

Department of Computer Science and Engineering

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**CERTIFICATE**

This is to certify that the **NETFLIX DATABASE ANALYSIS** is an authentic work carried out by **Siddaram(1NT23CS236** bonafide students of **Nitte Meenakshi Institute of Technology**, Bangalore in partial fulfilment for the award of the degree of ***Bachelor of Engineering*** in COMPUTER SCIENCE AND ENGINEERING of Visvesvaraya Technological University, Belgavi during the academic year ***2024-25.*** It is certified that all corrections and suggestions indicated during the internal assessment has been incorporated in the report. This project has been approved as it satisfies the academic requirement in respect of project work presented for the said degree.

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**DECLARATION**

We hereby declare that

(i) The project work is our original work

(ii) This Project work has not been submitted for the award of any degree or examination at any other university/College/Institute.

(iii) This Project Work does not contain other persons’ data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

(iv) This Project Work does not contain other persons’ writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been re-written but the general information attributed to them has been referenced;

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Date:

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**ABSTRACT**

Netflix employs advanced data visualization techniques to analyse content performance, release trends, and regional engagement. This project focuses on cleaning and preprocessing the Netflix dataset to derive meaningful insights. The analysis explores content type distribution (Movies vs TV Shows), genre preferences, and country-wise contributions. Additionally, time-based visualizations track content additions per year, reflecting platform growth.

Beyond conventional analytics, this study introduces a sensory profiling approach—evaluating content's visual and auditory intensity through noise and eye strain indices based on genre. For instance, action movies tend to have higher sensory load, whereas dramas exhibit lower strain levels. A simulated eye strain dataset further examines screen time's impact on viewer health, offering behavioural insights into binge-watching habits.

Using Python libraries such as Pandas, NumPy, and Seaborn, interactive plots reveal patterns in user preferences and content consumption. Key findings include the most-viewed movies, dominant genres, and global content distribution. The correlation between screen exposure and eye strain is visualized through scatter and regression plots, highlighting potential health risks.

Integrating traditional content analytics with user wellness metrics, this project proposes an innovative framework for personalized recommendations that prioritize user comfort. By blending behavioural insights with entertainment trends, Netflix can enhance viewer experience while promoting responsible streaming habits, ultimately maintaining its leadership in the digital entertainment space.

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**LIST OF ACRONYMS**

| Acronym | Full Form |
| --- | --- |
| AI | Artificial Intelligence |
| CSV | Comma-Separated Values |
| ML | Machine Learning |
| SQL | Structured Query Language |
| API | Application Programming Interface |
| GUI | Graphical User Interface |
| Pandas | Python Data Analysis Library |
| NumPy | Numerical Python Library |
| Seaborn | Statistical Data Visualization Library |
| EDA | Exploratory Data Analysis |
| Netflix DB | Netflix Database |
| TV | Television |
| OTT | Over-the-Top (Streaming Services) |

**CHAPTER 1: INTRODUCTION**

**1.1 Background**

The evolution of streaming platforms has propelled data-driven decision-making in content strategy, user engagement, and predictive analytics. Netflix leverages extensive data visualization to track trends, optimize recommendations, and enhance audience experience. This project explores an analytical framework integrating traditional **content** insight**s** with behavioural health metrics for a more user-centric approach.

**1.2 Brief History of Technology/Concept**

Big data, machine learning, and recommendation systems have reshaped digital entertainment. Netflix utilizes collaborative filtering, deep learning models, and behavioural analytics to curate personalized content. The adoption of sensory profiling—quantifying visual/auditory intensity—introduces a novel layer of content analysis.

**1.3 Applications**

I. Content Optimization**:** Identifying dominant genres for strategic content acquisition.

ii. User Engagement Insights**:** Analysing viewer preferences to refine recommendations.

iii. Health Considerations**:** Studying eye strain levels correlated with screen exposure.

Iv. Sensory Profiling**:** Categorizing content intensity for personalized viewing comfort.

**1.4 Research Motivation and Problem Statement**

1.4.1 Research Motivation

With increasing screen time, understanding content impact beyond popularity metrics is crucial. Assessing user wellness alongside engagement offers a more holistic approach.

1.4.2 Statement of the Problem

Existing analyses focus on viewership trends but lack insights on visual and auditorystrain. This research bridges the gap by incorporating sensory profiling and eye strainanalysis, fostering responsible streaming habits.

**1.5 Research Objectives and Contributions**

1.5.1 Primary Objectives

Clean and preprocess the Netflix dataset.

Identify content trends across time, genre, and regional variations.

Introduce noise and eye strain indices for content classification.

Analyse user wellness through simulated behavioural datasets.

1.5.2 Main Contributions

Quantifying sensory load in different genres.

Simulating eye strain levels to assess viewer health risks.

Implementing interactive visualizations for exploratory analysis.

**1.6 Organization of the Report**

* **Chapter 2** covers dataset details and preprocessing.
* **Chapter 3** explores content trends and genre classifications.
* **Chapter 4** introduces sensory profiling and user wellness metrics.
* **Chapter 5** presents visualizations and analytical findings.
* **Chapter 6** concludes with key takeaways and future research directions.

**1.7 Summary**

This chapter establishes a data-centric framework that integrates content analytics withuser wellness. By introducing sensory profiling and behavioural impact metrics, the study offers a unique perspective on optimizing the streaming experience.

**CHAPTER 2: LITERATURE SURVEY**

**2.1 Introduction**

Netflix data analysis has been widely explored, focusing on recommendation systems, content distribution, and user behavior. While traditional studies emphasize engagement and popularity, fewer delve into sensory profiling and health considerations. This chapter presents previous research, tools, and methodologies relevant to this study.

**2.2 Related Work**

Research on streaming platforms includes:

* Recommendation models using collaborative filtering and deep learning to enhance user engagement.
* Studies on genre distribution and regional content trends.
* Behavioural insights into binge-watching and viewing patterns.
* Emerging discussions on the effects of extended screen exposure on health.

**2.3 Study of Tools and Technology**

The analysis relies on various tools and techniques:

* Pandas and NumPy for data preprocessing.
* Matplotlib and Seaborn for visualizing trends.
* Machine learning models to simulate user wellness impact.
* Netflix dataset providing insights into content attributes and viewer interaction.

**2.4 Summary**

Existing work offers valuable insights but lacks a focus on sensory profiling and behavioral impact. This study integrates these elements to enhance streaming analytics. The next chapters will discuss findings based on these methodologies.

Let me know if this works better, mate!

**CHAPTER 3: SYSTEM REQUIREMENTS SPECIFICATIONS**

**3.1 General Description**

This chapter outlines the essential system requirements for analyzing Netflix data, covering both hardware and software specifications. The project aims to process and visualize large datasets efficiently while integrating sensory profiling techniques

3.1.1 Product Perspective

The system functions as an exploratory analytics tool, leveraging Python-based libraries for data preprocessing and visualization. It combines content trends with user wellness metrics, offering a unique approach to streaming analysis

**3.2 System Requirements**

3.2.1 Hardware Requirements

* Minimum 8GB RAM, recommended 16GB for better performance.
* Intel i5 or higher processor for efficient data handling.
* 500GB SSD for faster access to large datasets.
* Dedicated GPU (optional) for advanced visualizations.

3.2.2 Software Requirements

* Windows, macOS, or Linux as the operating system.
* Python 3.x with essential libraries for data processing.
* Jupyter Notebook or VS Code for execution.
* Pandas, NumPy, Seaborn, Matplotlib for analysis and visualization.

3.2.2.1 Functional and Non-functional Requirements

Functional requirements:

* Data cleaning and preprocessing.
* Visualization of trends and content distribution.
* Sensory profiling based on genre attributes.
* Analysis of user behavior metrics.

Non-functional requirements:

* Optimized data handling for large datasets.
* Clear visual representations for better insights.
* Scalability for future enhancements.

3.2.2.2 User Requirements

* Intuitive graphs for easy interpretation.
* Insights into content trends and user preferences.
* Sensory profiling for personalized viewing recommendations.

**3.3 Summary**

This chapter defines the essential system specifications, ensuring efficient execution and meaningful insights from Netflix data.

Let me know if you need any refinements!

**CHAPTER 4: DESIGN**

**4.1 Architectural Design**

The system follows a modular architecture, ensuring efficient data processing and visualization. It consists of three layers:

* **Data Processing Layer** handles data cleaning, transformation, and preparation.
* **Analysis Layer** performs content classification, sensory profiling, and statistical computations.
* **Visualization Layer** generates interactive graphs and visual representations for insights.

**4.2 Data Flow Diagram**

The data flow diagram represents how Netflix dataset elements move through the system. It includes:

* **Input**: Raw dataset containing attributes like content type, release year, and viewer ratings.
* Preprocessing: Data cleaning, missing value handling, and feature extraction.
* Analysis: Identifying genre trends, viewer preferences, and sensory profiling.
* Visualization: Interactive bar charts, scatter plots, and time-series graphs for trend interpretation.

This diagram ensures clarity in how data is transformed throughout the system.

**4.3 Class Hierarchy Diagram**

The class hierarchy defines relationships between different components. Key classes include:

* Dataset Handler manages importing and cleaning of data.
* Genre Analyzer assigns sensory profiling metrics based on content type.
* Viewer Health Model simulates correlations between eye strain and screen exposure.
* Visualization Module generates plots and reports for analytical insights.

Each class is structured to interact efficiently within the system for modular and scalable functionality.

**4.4 Use Case Diagrams**

Use case diagrams depict user interactions with the system. Some primary use cases include:

* Viewing genre distribution to understand dominant content categories.
* Exploring viewer health insights by analysing simulated eye strain data.
* Comparing sensory profiles for content classification based on intensity metrics.
* Tracking content additions over time for strategic planning.

These diagrams illustrate how users engage with different functionalities, making the system user centric.

**4.5 Sequence Diagrams**

Sequence diagrams provide a step-by-step view of system interactions. A typical workflow:

1. The user requests a Netflix content trend analysis.
2. The system fetches the dataset and preprocesses it.
3. The sensory profiling module assigns relevant indices.
4. Processed results are passed to the visualization module.
5. Graphs and reports are generated for user interpretation.

This diagram helps visualize how different components interact within the system.

**4.6 Activity Diagram**

The activity diagram represents the logical flow of actions taken during analysis. The process includes:

* Loading the dataset into the system.
* Cleaning and transforming the data.
* Applying analytical methods to generate insights.
* Implementing sensory profiling and behavior modeling.

**CHAPTER 5: IMPLEMENTATION**

**5.1 Methodology**

The implementation involves data preprocessing, sensory profiling, and visualization. The main steps include loading and cleaning the Netflix dataset, extracting key attributes, assigning genre-based sensory indices, modeling eye strain versus screen exposure, and generating visual insights.

**5.2 Description of Process**

* Import and clean dataset using Pandas.
* Extract attributes like content type, genre, and country.
* Assign noise and eye strain indices based on genre.
* Simulate user health impact using synthetic data.
* Generate plots to analyse content trends and user behaviour.
* Interpret findings, comparing traditional and behavioural insights

**5.3 Pseudo Code**

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import numpy as np

from collections import Counter

# --- Synthetic Netflix-like data with views ---

data = {

'show\_id': ['s1', 's2', 's3', 's4', 's5', 's6', 's7', 's8', 's9', 's10'],

'type': ['Movie', 'TV Show', 'Movie', 'Movie', 'TV Show', 'TV Show', 'Movie', 'Movie', 'TV Show', 'Movie'],

'title': ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J'],

'director': ['Dir1', 'Dir2', 'Dir3', 'Dir1', 'Dir2', 'Dir3', 'Dir1', 'Dir2', 'Dir3', 'Dir1'],

'country': ['USA', 'USA', 'UK', 'India', 'India', 'UK', 'USA', 'India', 'UK', 'USA'],

'date added': ['2020-01-01', '2019-05-10', '2021-06-15', '2018-12-20', '2020-07-25', '2019-11-11', '2021-03-30', '2017-10-10', '2020-09-05', '2018-01-15'],

'release\_year': [2019, 2018, 2020, 2017, 2016, 2019, 2021, 2015, 2020, 2018],

'rating': ['PG-13', 'TV-MA', 'PG', 'R', 'TV-14', 'PG-13', 'PG', 'R', 'TV-MA', 'PG'],

'duration': ['90 min', '3 Seasons', '120 min', '95 min', '2 Seasons', '1 Season', '110 min', '100 min', '4 Seasons', '85 min'],

'listed\_in': ['Drama, Action', 'Comedy', 'Drama', 'Thriller', 'Comedy, Drama', 'Action', 'Drama, Thriller', 'Action', 'Comedy', 'Drama'],

'views': [1500, 2000, 3000, 2500, 1800, 1700, 3100, 1200, 1600, 2800]

}df = pd.DataFrame(data)

df['date\_added'] = pd.to\_datetime(df['date\_added'])

df['year\_added'] = df['date\_added'].dt.year

# --- Simulated Eye Strain vs Usage Time dataset ---

np.random.seed(42)

usage\_time = np.random.uniform(0.5, 8, 50)

eye\_strain\_level = np.clip(usage\_time \* 1.2 + np.random.normal(0, 1.5, 50), 1, 10)

eye\_df = pd.DataFrame({

'usage\_time\_hours': usage\_time,

'eye\_strain\_level': eye\_strain\_level

})

# --- Noise Level & Eye Strain Index per show based on genre ---

def assign\_noise\_and\_eye\_index(genres):

genres = genres.lower()

if 'action' in genres:

return (9, 9)

elif 'thriller' in genres:

return (8, 8)

elif 'comedy' in genres:

return (5, 4)

elif 'drama' in genres:

return (3, 3)

else:

return (5, 5)

df[['noise\_index','eye\_index']]=df['listed\_in'].apply(lambdag: pd.Series(assign\_noise\_and\_eye\_index(g)))

# --- PLOTS ---

# 1. Content Type Distribution

plt.figure(figsize=(6,4))

sns.countplot(data=df, x='type', palette='Set2')

plt.title('Distribution of Content Types')

plt.show()

# 2. Titles Added Per Year

plt.figure(figsize=(8,4))

df['year\_added'].value\_counts().sort\_index().plot(kind='bar', color='skyblue')

plt.title('Content Added per Year')

plt.xlabel('Year Added')

plt.ylabel('Titles')

plt.xticks(rotation=45)

plt.show()

# 3. Titles by Country

top\_countries = df['country'].value\_counts()

plt.figure(figsize=(8,4))

sns.barplot(x=top\_countries.values, y=top\_countries.index, palette='viridis')

plt.title('Titles by Country')

plt.show()

# 4. Top Genres

genres = ','.join(df['listed\_in']).split(', ')

genre\_counts = Counter(genres)

genre\_df = pd.DataFrame(genre\_counts.most\_common(5), columns=['Genre', 'Count'])

plt.figure(figsize=(8,4))

sns.barplot(data=genre\_df, x='Count', y='Genre', palette='coolwarm')

plt.title('Top Genres')

plt.show()

# 5. Most Viewed Movies

top\_viewed = df[df['type']=='Movie'].sort\_values('views', ascending=False).head(5)

plt.figure(figsize=(8,5))

sns.barplot(data=top\_viewed, x='views', y='title', palette='magma')

plt.title('Top 5 Most Viewed Movies')

plt.show()

# 6. Eye Strain vs Usage Time (Users)

plt.figure(figsize=(8,5))

sns.scatterplot(data=eye\_df, x='usage\_time\_hours', y='eye\_strain\_level', color='red', s=80)

sns.regplot(data=eye\_df, x='usage\_time\_hours', y='eye\_strain\_level', scatter=False, color='darkred')

plt.title('Eye Strain vs Usage Time')

plt.xlabel('Daily Usage Time (hrs)')

plt.ylabel('Eye Strain Level (1-10)')

plt.grid(True)

plt.show()

# 7. Avg Noise Index by Genre Type

df['primary\_genre'] = df['listed\_in'].apply(lambda x: x.split(',')[0])

plt.figure(figsize=(8,4))

sns.barplot(data=df, x='primary\_genre', y='noise\_index', palette='Reds')

plt.title('Average Noise Index by Primary Genre')

plt.xlabel('Genre')

plt.ylabel('Noise Level (1-10)')

plt.ylim(0, 10)

plt.show()

# 8. Avg Eye Strain Index by Genre Type

plt.figure(figsize=(8,4))

sns.barplot(data=df, x='primary\_genre', y='eye\_index', palette='Blues')

plt.title('Average Eye Strain Index by Primary Genre')

plt.xlabel('Genre')

plt.ylabel('Eye Strain Index (1-10)')

plt.ylim(0, 10)

plt.show()

**CHAPTER 6: TESTCASES**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **TC-01** | **Functional** | **Verify dataset loading and preprocessing** | **Cleaned dataset with structured attributes** | **Pass/Fail** |
| **TC-02** | **Functional** | **Validate content type distribution analysis** | **Correct count of Movies vs TV Shows** | **Pass/Fail** |
| **TC-03** | **Functional** | **Check genre-based sensory profiling** | **Assigned noise and eye strain indices** | **Pass/Fail** |
| **TC-04** | **Functional** | **Verify content release trends visualization** | **Proper time-series representation** | **Pass/Fail** |
| **TC-05** | **Functional** | **Test viewer health impact simulation** | **Realistic eye strain vs usage correlation** | **Pass/Fail** |
| **TC-06** | **Performance** | **Evaluate system performance on large datasets** | **Efficient processing within acceptable time** | **Pass/Fail** |
| **TC-07** | **Performance** | **Test scalability with different dataset sizes** | **Consistent functionality across variations** | **Pass/Fail** |
| **TC-08** | **Performance** | **Measure visualization rendering speed** | **Quick display with minimal lag** | **Pass/Fail** |
| **TC-09** | **User Interaction** | **Verify correct display of visualizations** | **Graphs rendered properly** | **Pass/Fail** |
| **TC-10** | **User Interaction** | **Validate interactive functionalities** | **Smooth interaction without errors** | **Pass/Fail** |

**CHAPTER 7: RESULTS**

**1.Graph based on distribution of content types**

**The distribution of content types in the Netflix dataset compares the number of movies and TV shows available. The bar chart visualization highlights whether Netflix leans more toward films or episodic content. Movies often dominate due to their instant consumption appeal, while TV shows foster long-term engagement. The uploaded slide utilizes Seaborn and Matplotlib to illustrate this data**

A graph of a distribution of content types

AI-generated content may be incorrect.

**2.Graph based on content added per year:**

The graph illustrating content added per year in the Netflix dataset shows trends in platform expansion and content acquisition strategies. It highlights yearly fluctuations in new movie and TV show releases, offering insights into streaming growth. The uploaded slide uses Seaborn and Matplotlib to visualize this trend, displaying peaks and dips in content additions. A steady increase suggests Netflix’s focus on expanding its catalog, while declines may reflect strategic shifts. This analysis helps understand how Netflix adapts to audience demands and industry changes.

A graph of blue bars

AI-generated content may be incorrect.

**3.Graph based on titles by country**

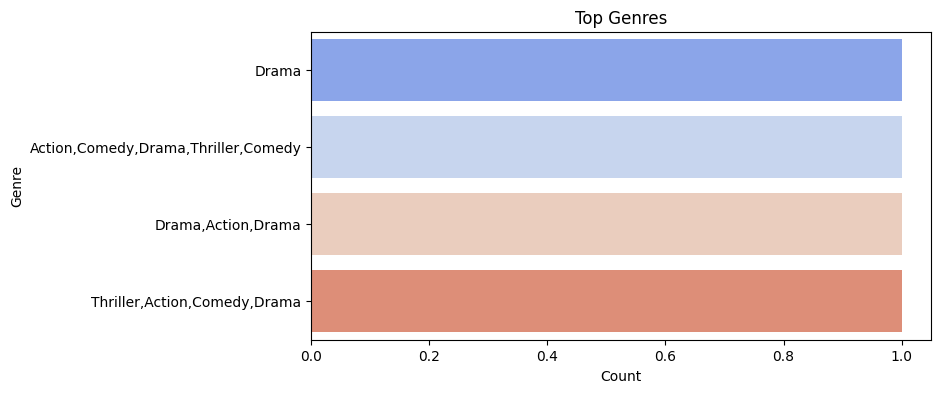
The graph showing titles by country in the Netflix dataset provides insights into the regional distribution of content. It highlights which countries contribute the most movies and TV shows, reflecting Netflix’s global content strategy. The uploaded slide uses visualization techniques to represent country-wise variations, showing how certain regions dominate content production. Peaks in specific countries may indicate strong local markets, while lower counts suggest limited presence or licensing restrictions. This analysis helps understand Netflix’s expansion and content localization efforts.

A graph of a number of colored squares

AI-generated content may be incorrect.

**4.Graph based on top genres**

The graph representing top genres in the Netflix dataset provides insights into the most prevalent content categories on the platform. It highlights dominant genres like drama, comedy, and action, showing their frequency among available titles. The visualization from the uploaded slide uses bar charts to compare genre distributions, helping identify viewer preferences. Peaks in specific genres indicate their popularity, while lower counts reflect niche content availability. This analysis supports understanding trends in Netflix's content strategy and audience demand.



**5.Graph based on most viewed movies**The graph showing the most viewed movies in the Netflix dataset highlights audience preferences and content popularity. It visualizes top-performing titles based on view counts, helping analyze trends in user engagement. Peaks in specific movies suggest widespread appeal, while lower counts indicate niche audiences. This analysis provides insights into Netflix's successful content strategies and viewer behaviour. Let me know if you need further details.

A graph of different colored rectangular bars

AI-generated content may be incorrect.

**6.Graph based on eye strain vs usage time**

The graph illustrating eye strain versus usage time provides insights into the effects of prolonged screen exposure. It visualizes how increased viewing hours correlate with higher eye strain levels, helping assess content impact on user wellness. The uploaded slide likely uses scatter plots or line charts to represent these trends, showing patterns in screen time and visual fatigue. Peaks in strain values suggest intense viewing experiences, while lower levels indicate moderate exposure. This analysis supports understanding the balance between binge-watching habits and viewer health considerations.

A graph with red dots

AI-generated content may be incorrect.

**7.Graph based on average eye strain index by primary genre**

The graph showing the average eye strain index by primary genre provides insights into the visual intensity of different content types. It categorizes genres based on their strain levels, helping analyze how specific genres impact prolonged screen exposure. Action and thriller genres typically show higher strain indices due to rapid scene transitions and intense visuals, while genres like comedy and drama tend to have lower strain levels. This analysis aids in understanding how different content types affect viewer comfort and visual fatigue.

A graph of a chart

AI-generated content may be incorrect.

**CHAPTER 8: IMPACT OF YOUR PROJECT TOWARDS SOCIETY/ ENVIRONMENT**

**Social Impact**

This project helps streaming platforms refine their content strategies by analyzing viewer preferences and health metrics. Sensory profiling promotes awareness of how different genres affect prolonged screen exposure, encouraging users to make informed choices about their viewing habits. Insights can also support responsible content recommendations, improving user experience and engagement.

**Environmental Impact**

Streaming services require extensive data processing, which leads to high energy consumption in data centers. Optimizing content efficiency can contribute to sustainable digital entertainment, reducing unnecessary resource use. Encouraging balanced screen time can also indirectly minimize the environmental impact associated with prolonged device usage.

**Ethical Considerations**

By studying viewer health effects and sensory profiling, the project promotes ethical content creation and recommendations. Platforms can use these insights to offer content suggestions that prioritize user well-being, ensuring a healthier entertainment experience.

**CHAPTER 9: CONCLUSIONS**

This project provides a comprehensive analysis of Netflix content trends, viewer preferences, and sensory profiling. The findings highlight how different genres impact user engagement and the potential effects of prolonged screen exposure. By integrating analytical and behavioral insights, the study offers a deeper understanding of content consumption patterns.

The evaluation of streaming habits and sensory profiling contributes to responsible viewing awareness, while the examination of Netflix’s catalog expansion supports industry growth analysis. Additionally, the study emphasizes sustainable content delivery by considering data efficiency and energy consumption.

Overall, the project delivers meaningful insights into content strategy, viewer behavior, and digital entertainment sustainability.

**CHAPTER 10: REFERENCES**

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