Clustering Analysis of Screen Time and Wellness

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***Abstract*—We explore the impact of device usage on personal wellness by leveraging a dataset that records device hours and technology habits alongside wellness metrics. Our approach segments users based on shared digital behaviors and wellness indicators to recommend personalized strategies for improving well-being.**

***Index Terms*—wellness, clustering, technology usage, mental health, unsupervised learning**

I. Introduction

Increased use of technology has been associated with negative effects on mental health and general well-being. This work aims to analyze technology use patterns—across devices such as phones, laptops, tablets, and TVs, and purposes such as social media, work, entertainment, and gaming —and relate them to wellness metrics like sleep quality, mood, stress, mental health scores, and other lifestyle indicators.

II. Dataset

The dataset contains 5,000 rows and is publicly available from Kaggle. It describes device usage hours (phone, laptop, tablet, TV), usage types (social media, work, entertainment, gaming), and an array of wellness metrics (sleep quality, mood, stress levels, mental health score, healthy eating, caffeine intake, weekly anxiety, weekly depression, and mindfulness). I will be able to use this dataset for

III. Related Work

Using the results from existing research on clustering algorithms on market segmentation,

J. M. John, O. Shobayo, and B. Ogunleye [1] A study on UK's retail market compares different state of the art clustering algorithms such as K-means, Gaussian mixture model (GMM), density-based spatial clustering of applications with noise (DBSCAN), agglomerative clustering and balanced iterative reducing and clustering using hierarchies (BIRCH). The research paper concludes that GMM outperformed the other algorithms mentioned by having a Silhouette Score of 0.80.

Looking at research on the relationship between well-being and technology use

IV. Methods

We propose a classification and clustering approach to technology user profiling. Gaussian Mixture Models (GMMs), which support soft clustering, will be used to identify overlapping user clusters, in contrast to hard clusterers like K-Means—deemed inappropriate here since individuals may exhibit several overlapping behaviors. Following the footsteps of J. M. John, O. Shobayo, and B. Ogunleye [1] of reducing the dimensions of

For our toolset, I will primarily use Python due to its rich ecosystem of libraries. For data manipulation and exploratory analysis, Polars will serve as the main dataframe library. Data analysis and modeling will be handled using sklearn, which provides robust functions for machine learning tasks. Altair will be utilized for clear and effective data visualization.

For interactive prototyping and notebook functionality, I'll use Marimo as an alternative to Jupyter, enabling easy prototyping and convenient export to multiple file formats. Once the model demonstrates satisfactory performance, I'll develop a prototype frontend using Streamlit to showcase results and facilitate interaction.

All dependencies and packages will be managed with uv, a modern, Rust-based alternative to pip to promote a reproducible setup.

V. Expected Outcomes

We expect to identify meaningful user clusters that reflect different profiles of technology use and wellness. Our framework will suggest targeted ways for individuals to improve their overall well-being without requiring them to abandon technology, but rather use it more mindfully. The methodology and findings can inform personalized treatment or advice tools for digital wellness.

References

[1] J. M. John, O. Shobayo, and B. Ogunleye, "An Exploration of Clustering Algorithms for Customer Segmentation in the UK Retail Market," *Analytics*, vol. 2, no. 4, pp. 809–823, 2023, doi: 10.3390/analytics2040042.