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Analysis of Human Focus Patterns Using Uniform Manifold Approximation and Projection

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ABSTRACT: Defining “focus” scientifically has been challenging due to the reliance on subjective self-reports with no objective measurement methods. The advent of AI for data analysis presents new opportunities to discover correlations in human behavior using techniques such as unsupervised clustering and dimensionality reduction. Our study analyzed an online dataset from 51 participants who reported their focus levels while completing tasks under four audio conditions: silence, Endel, Apple Music, and Spotify. The Uniform Manifold Approximation and Projection (UMAP) technique, utilizing gradient descent for dimensionality reduction, revealed two distinct clusters in the data. Brainwave indicated focus levels demonstrate a strong correlation with the revealed clusters, but other variables in the dataset, including participant gender, age, audio type, and their self-reported focus levels, do not correlate well with the clusters. The findings suggest that self-reports may not accurately reflect focus, highlighting the need to reconsider how focus is measured in research.
KEYWORDS: Behavioral and Social Sciences, Neuroscience, Human Focus, Unsupervised Clustering, Visualization.

Introduction

As a qualitative trait, focus has been hard to scientifically define, as there is no proven method established to identify it without the use of EEG devices. Because “focus”– and similarly, “hyperfocus”– levels are usually self-reported in studies, they are undefined as an observation with no scientific proof.[1] Historically, the measurement of focus has relied heavily on self-reported data due to the lack of established, objective methods. Surveys and subjective ratings have been the primary tools, with participants providing their perceived focus levels during various tasks.[2,3] While practical and straightforward, this approach is inherently limited by biases and individual differences in perception, making results unreliable and inconsistent.[4] In more recent studies, physiological data, such as eye tracking [5], heart rate variability,[6] and EEG recordings,[7] have been explored as potential objective measures to complement or replace self-reports.

The advent of artificial intelligence in data analysis offers a new way to explore correlations of multiple variables with human focus levels and find patterns in multidimensional data. Unsupervised clustering and dimension reduction are key techniques in data analysis and machine learning, particularly useful for understanding complex datasets without labeled outcomes. Unsupervised clustering is a technique that groups data points based on their inherent similarities, with the goal of identifying distinct clusters within the data that share common characteristics.[8] Dimension reduction is the process of reducing the number of variables under consideration while preserving as much information as possible.[9] The Uniform Manifold Approximation and Projection (UMAP) offers several significant benefits for dimension reduction and data visualization. First, it effectively preserves both local and global structures in the data, making it particularly useful for exploring complex datasets. UMAP is also scalable, allowing it to handle large datasets efficiently, which is essential for big data applications. Additionally, UMAP generally operates faster than other dimensionality reduction techniques, such as t-SNE, enabling quicker analysis. Furthermore, UMAP produces results in visually distinct clusters, enhancing the interpretability of complex data.[10]

This study aims to use UMAP to analyze the patterns and ambiguity of “focus” through a publicly available research dataset,[11] including their demographic information, self-reported focus level, and EEG data, when performing tasks under four different audio stimuli. We hypothesize that brainwave data demonstrates a stronger correlation with distinct clusters that emerged from UMAP than the self-reported focus data and participant demographic information.

While previous studies have explored measures of human focus, they largely relied on traditional methods that oversimplify complex focus dynamics. Our research fills this gap by introducing state-of-the-art machine learning models capable of capturing multidimensional associations with more insights.

Methods

Data Collection:

We utilized an online JSON public research dataset,[11] which recruited 51 participants from an opt-in screening panel–they were all ensured that their native language was English, they were all distributed evenly along the five major regions of the continental United States, and they all had normal hearing, normal vision or corrected normal vision. The participants included 34 males and 17 females. The age range of participants was between 18 and 53 years, with an average age of 36

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years and a standard deviation of 8.04 years. Brainwave data was recorded using Neuros, a headband that collects electroencephalogram (EEG) sensor data non-invasively, and then decoded using Neuros SDK decoding algorithms. Focus was measured using two methods in this dataset: brainwave data from EEG headbands (ranging from 0.0 to 1.0, with a neutral or baseline focus level at 0.5) and a cursor-based app (also ranging from 0.0 to 1.0). Deviations from 0.5, either above or below, indicated an increase or decrease in focus, respectively. Both focus levels were recorded for each of the four different audio stimuli in the dataset for every participant: silence, Endel, Apple Music, and Spotify. Among the various UMAP hyperparameter combinations tested, the 2D visualization using 15 neighbors and a minimum distance of 0.1 resulted in the most distinct and interpretable clustering, with clear correlation to brainwave-based focus levels. This configuration also provided the best visual separation for interpretability.

Data Analysis:

Brainwave data was trimmed to the minimum length present in the dataset (9297 timesteps). All timesteps past this length were removed for each participant. Figure 1 illustrates the brainwaves of one example participant in the dataset.

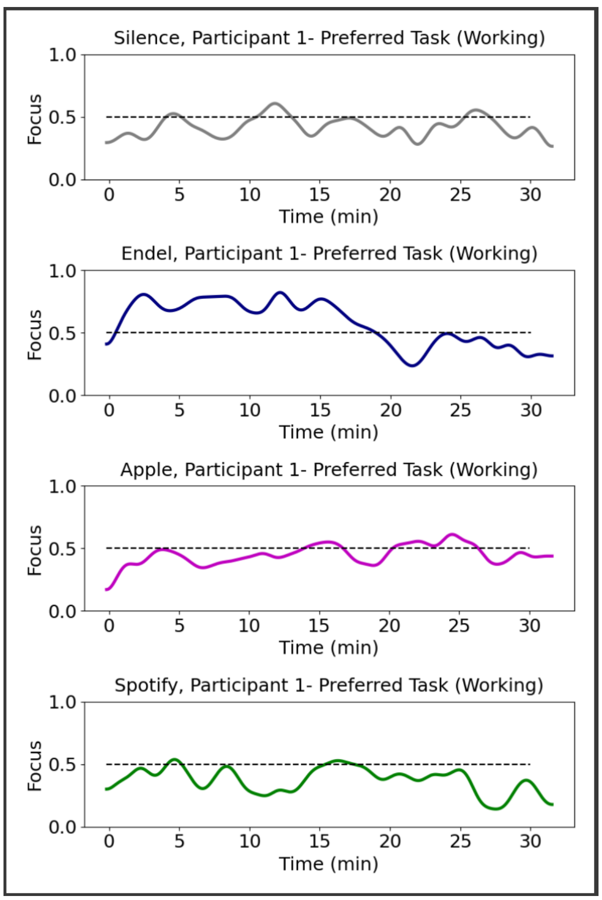

Figure 1: Brainwaves of one example participant. This was graphed utilizing the focus level data from EEG devices, which was then normalized to be centered around 0.5.

To categorize the brainwave data, the average of the 9297 timesteps was taken and binned into focus improved (>0.5) or focus did not improve (<=0.5). For self-reported focus levels, we took the difference between the self-reported focus (collected via a slider in the Neuros app, ranging between 0 and 1) after the study and the self-reported focus at the start of the study. If there was an increase, we labeled it "improved," and the latter "did not improve."

Various UMAP hyperparameters and settings were tested, including the number of neighbors (5, 10, 15, 20, 30, 40, and 50) and the number of reduced dimensions (3D, 4D, 5D, and 6D). We then ran a gradient descent, and the process was stopped after 200 iterations to check for convergence. The following variables were explored to determine which most correlated with the UMAP clusters: i) participant gender (M/F), ii) binned participants age (categorized into four groups: under 25, 25-30, 31-35, and over 35), iii) audio stimulus type: Apple (pure focus playlist), Spotify (focus flow playlist), Endel (personalized soundscape including a mixture of noise and musical properties engineered by the Endel app), and silence (no audible sound), iv) self-report focus improvement (improved/did not improve), and v) brainwave focus improvement (improved/did not improve).

Result and Discussion

The quick conversion of cross-entropy (CE) of 2D-UMAP, as shown in Figure 2, suggests the analysis results in reliable visual clusters and clear patterns. The 2D-UMAP visualization, shown in Figure 3, illustrates two distinct clusters that emerged from the analysis. Figures 4 through 8 show Figure 2 colored with respect to the different variables in the dataset. Figure 8 shows a clear correlation between the cluster and coloring.

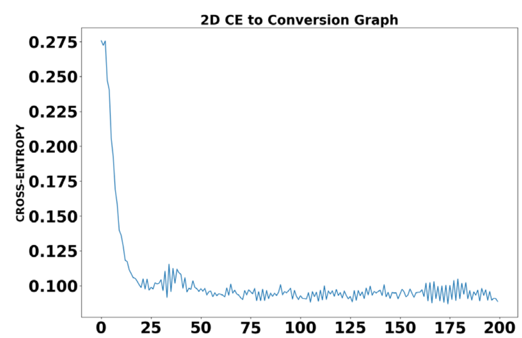

Figure 2: Conversion of the cross-entropy of 2D UMAP. Figure 2 shows the loss function of the algorithm converging successfully.

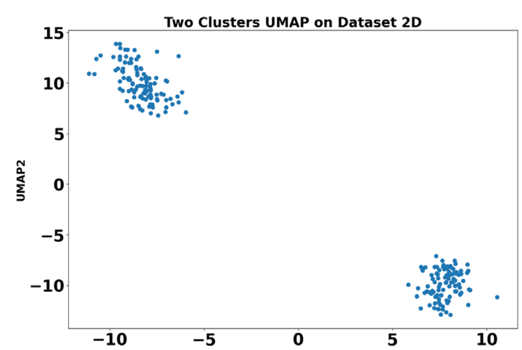

Figure 3: Visualization of 2D clustering using UMAP. Figure 3 shows that the data has been grouped into two distinct groups.

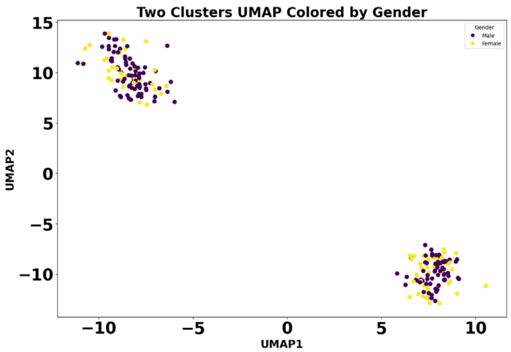

Figure 4: 2D UMAP visualization colored by gender. Figure 4 shows the 2D UMAP visualization, colored by gender, where purple and yellow dots represent male and female participants, respectively.

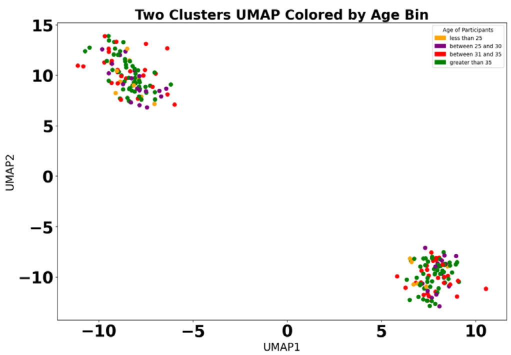

Figure 5: 2D UMAP visualization colored by age groups. Figure 5 shows the 2D UMAP visualization, colored by age groups, where orange, purple, red, and green dots correspond to the age groups of less than 25, between 25 and 30, between 31 and 35, and greater than 35, respectively.

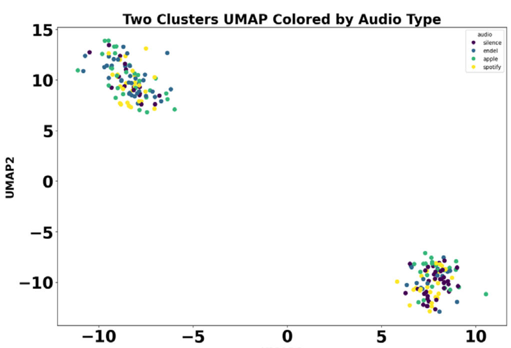

Figure 6: 2D UMAP visualization colored by audio type. Figure 6 shows the 2D UMAP visualization, colored by audio type, where purple, blue, green, and yellow dots correspond to the four audio types used in the dataset: silence, Endel, Apple, and Spotify, respectively.

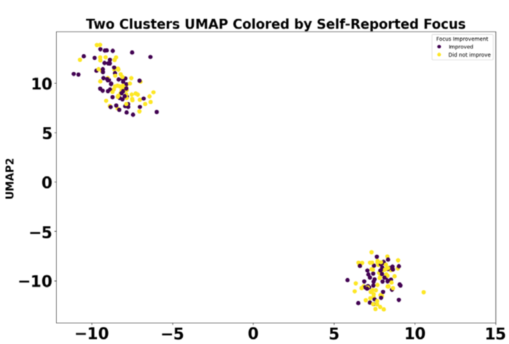

Figure 7: 2D UMAP visualization colored by self-reported focus. Figure 7 shows the 2D UMAP visualization, colored by self-reported focus levels, where purple and yellow dots correspond to participants' self-reported focus levels, improved and not improved, respectively.

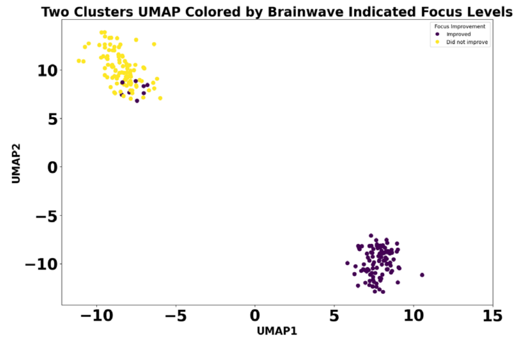

Figure 8: 2D UMAP visualization colored by brainwave indicated focus. Figure 8 shows the 2D UMAP visualization, colored by brainwave-indicated focus levels, where purple and yellow dots correspond to participants' self-reported focus levels, improved and not improved, respectively.

Comparing the distributions of data points in the 2D-UMAP figures, Figures 4-8, we can see that the brainwave data show the strongest correlation with the emerged clusters, which supports our hypothesis. Self-reported focus levels, however, do not correlate well with the clusters discovered through UMAP, suggesting that self-reported data may not accurately reflect patterns in the underlying data. These findings reveal the limitations of self-reported focus and suggest that objective data, such as brainwave analysis, can provide more reliable insights.

Conclusion

Focus is a critical trait in human performance, yet it lacks a clear scientific definition or objective measurement method, relying heavily on subjective self-reports. Using unsupervised clustering and dimensionality reduction, we analyzed data from 51 participants performing tasks under four audio stimuli (silence, Endel, Apple Music, Spotify). In particular, UMAP was used for dimensionality reduction and clustering patterns, with gradient descent applied to optimize cross-entropy convergence. Significant patterns emerged in 2D UMAP clusters, aligning with participants' decoded brainwave data. However, no associations were found between clusters and other variables, including age, gender, audio type, or self-reported focus levels. These findings suggest that self-reported focus may not accurately reflect objective patterns, raising questions about its validity in scientific research. This study highlights the need for more reliable, data-driven approaches to measuring focus in human studies. One limitation of this study is the relatively small and homogeneous participant pool (n = 51), which may affect the generalizability of the findings. Additionally, although EEG data provides an objective measurement, it may still contain noise or be influenced by environmental factors during data collection. Another limitation is the potential variability in individuals' reactions to audio stimuli, which was not controlled beyond categorizing stimulus types.

For future work, different audio genres and physical monitoring[5] as control variables should be used to explore the genres' unique effects on focus. Furthermore, future research should examine how the magnitude of focus levels varies with participants' individual preferences, such as the inclination to listen to streamlined music during work.[12] Lastly, self-reported

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variables can be explored alongside positive illusion studies,[13] leading to more reliable measures.

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References

1. Ashinoff, B. K.; Abu-Akel, A. Hyperfocus: The Forgotten Frontier of Attention. *Psychological Research*, 2019, 85, 1–19.
2. Strachan, D. L. *The Space between the Notes: The Effects of Background Music on Student Focus*. Master of Arts in Education Research. (2015). https://cdm17519.contentdm.oclc.org/digital/collection/maed/id/167/rec/1 (accessed 2024-09-30).
3. Kiss, L.; Linnell, K. J. The Effect of Preferred Background Music on Task-Focus in Sustained Attention. *Psychological Research* 2021, 85, 2313-2325.
4. *The Science of Self-Report: Implications for Research and Practice*.; Stone, A. A.; Turkkan, J. S.; Bachrach, C. A.; Jobe, J.B.; Kurtzman, H.S.; Cain, V. S. Eds.; Mahwah, NJ: Lawrence Erlbaum Associates, 2000.
5. Unsworth, N.; Robison, M. K. Pupillary Correlates of Lapses of Sustained Attention. *Cogn Affect Behav Neurosci* 2016, 16, 601–615.
6. Loudon, G.; Zampelis, D.; Deininger, G. Using Real-Time Biofeedback of Heart Rate Variability Measures to Track and Help Improve Levels of Attention and Relaxation. In *Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition (C&C'17 '17)*, Association for Computing Machinery, New York, NY, USA, pp.348–355.
7. Sethi, C.; Dabas, H.; Dua, C.; Dalawat, M.; Sethia, D. EEG-Based Attention Feedback to Improve Focus in E-Learning. In *Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence (CSAI'18)*. Association for Computing Machinery, New York, NY, USA, 2018, pp.321–326.
8. Saxena, A.; M. Prasad, A. Gupta, N. Bharill, O.P. Patel, A. Tiwari, M. J. Er, W. Ding, C-T Lin, A Review of Clustering Techniques and Developments, *Neurocomputing* 2017, 267, 664-681.
9. Jindal, P.; Kumar. D. A Review on Dimensionality Reduction Techniques. *Int. J. Comput. Appl* 2017, 173.42-46.
10. McInnes, L.; Healy, J.; Saul, N.; Großberger, L. UMAP: Uniform Manifold Approximation and Projection. arXiv 2018. *arXiv preprint arXiv*:1802.03426, 10.
11. Haruvi, A.; Kopito, R.; Brande-Eilat, N.; Kalev, S.; Kay, E.; Furman, D. Measuring and Modeling the Effect of Audio on Human Focus in Everyday Environments Using Brain-Computer Interface Technology. *Frontiers in Computational Neuroscience* 2022, 15.
12. Makridakis, S.; Moleskis, A. The Costs and Benefits of Positive Illusions. *Front Psychol* 2015. 6, 859.
13. Mossbridge, J. The Influence of Streamlined Music on Cognition and Mood, arXiv 2016. *arXiv preprint arXiv*:1610.04255.

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