How to Track Eyes Online (Fast): Webcam-based heart rate measurement for detecting problematic social media content

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1 INTRODUCTION

The objective of this project is to explore the feasibility of utilizing skin color changes as an indicator of states of arousal while individuals engage with potentially controversial social media content. By employing feasible webcam data, and conventional image stream processing, we aim to unravel the intricate workings of the Autonomic Nervous System and its relationship with physiological responses.

To accomplish this, we employ video streams as a means to monitor and assess heart rate fluctuations in response to controlled content related to the COVID pandemic. The curated content includes Twitter posts and video data from both public and private personalities, ensuring a diverse range of stimuli for participants to interact with.

The central focus of our approach lies in the analysis of skin color changes that occur during the observation of social media content. Through the acquisition of video streams from participants' webcams and screens, we extract image data for subsequent processing. By employing sophisticated algorithms, we derive photoplethysmogram (PPG) estimates based on temporal variations in skin color. These estimations serve as indicators of fluctuations in heart rate, thereby enabling the identification of heightened physiological arousal.

By aligning the peaks in the photoplethysmogram with the corresponding content segments, we discern the specific elements that elicit pronounced bodily arousal in each participant. Furthermore, this methodology offers the potential to categorize and tag images, videos, and articles as potentially sensitive and provocative based on the observed physiological responses.

During the course of the study, participants engage with sequential content related to the pandemic, while also providing written opinions on their experiences. The comprehensive evaluation of the study incorporates the analysis of heart rate peaks, their correlation with specific content segments, and the participants' subjective viewpoints regarding pandemic discussions.

Our research endeavors to advance the understanding of human physiological responses to social media content by employing skin color changes as an objective measure of arousal. This investigation, situated within the realm of the Autonomic Nervous System, showcases the potential for more precise and personalized tagging of social media content, particularly within the context of the COVID pandemic. Using accessible technology to help people break out of negative social media habits serves as a first step towards a safer web-browsing experience in commercial, closed-source social media infrastructure.

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2 BACKGROUND

Heart rate monitoring is a crucial component in assessing an individual's physiological state and can provide valuable insights into their overall health and well-being. Traditionally, heart rate measurements have been obtained using contact-based methods such as electrocardiography (ECG) or photoplethysmography sensors. However, these methods often require direct skin contact, limiting their application in certain scenarios, especially when non-invasive and contactless monitoring is desired.

In recent years, the advancement of computer vision and machine learning techniques has paved the way for alternative approaches to heart rate monitoring. One such approach involves utilizing a webcam, a ubiquitous device found in most modern electronic devices, to capture facial videos and extract vital physiological information. This approach offers a non-invasive and contactless means of monitoring heart rate, enabling its application in various real-world scenarios.

Our implementation was supported by the work of Sani et al. [2015] to determine suitable heart rate data from PPG signals using a Fast Fourier Transformation. Building on top of the theory helped us make use of the current capabilities of computer graphics frameworks to further improve the signal of a noisy environment such as a webcam stream.

A notable study conducted by Monkaresi et al. [2014] explored the use of machine learning algorithms to improve contactless heart rate monitoring using a webcam. The researchers obtained heart rate data from a dedicated intrusive ECG device to conform with the measurements of the learning system's estimates of heart rate. Their findings imply that despite the promising results, the technology is still not suitable to provide accurate cardiac data.

Furthermore, Junianto and Rachman [2019] proposed the implementation of a text mining model for emotions detection on social media comments. By employing particle swarm optimization and a Naive Bayes classifier, the researchers aimed to extract emotional information from textual data posted in response to social media content. This work is relevant to our study as it highlights the influence of emotional stimuli, such as controversial social media feeds, on individuals' psychological and physiological responses. Integrating the insights gained from emotional analysis with webcam-based heart rate monitoring can provide a comprehensive understanding of the impact of social media content on individuals' emotional and physiological states.

In light of the above research, our study aims to build upon these findings and investigate the feasibility of establishing heart rate measurements using a webcam while participants engage with a controversial social media feed. By leveraging computer vision techniques, machine learning algorithms, and continuous wavelet filtering, we seek to remotely assess the instantaneous heart rate of participants in response to emotional stimuli encountered in the online environment. The COVID-19 pandemic, in particular, has highlighted the significant impact of social media on global health discourse. Platforms like TikTok have gained immense popularity and have been both praised and criticized for their role in facilitating the spread of information during the pandemic.

The study conducted by Basch et al. [2021] examined the presence of vaccine misinformation and disinformation on TikTok, revealing the alarming prevalence of misleading content related to COVID-19 vaccines. The authors emphasized the need to identify and address problematic content to mitigate its potential negative impact on public health. Misinformation and disinformation can lead to vaccine hesitancy, hindering vaccination efforts and endangering public health outcomes.

TikTok has also been explored as a platform for educational content during the pandemic. Putri [2021] conducted a case study on using TikTok as an online learning medium, specifically focusing on a dance creativity course. The study highlighted the potential of TikTok as an engaging and interactive platform for learning and fostering creativity during the pandemic. However, it is important to note that the platform's content diversity includes both positive and potentially problematic material.

As the COVID-19 pandemic unfolded, official accounts on TikTok played a significant role in communicating vital information to the public. Li et al. [2021] conducted a content analysis of TikTok videos from official accounts featured in the COVID-19 information hub. The study revealed the various types of content disseminated by these accounts, ranging from informational videos to entertaining content aimed at engaging users. It highlighted the potential of TikTok as a platform for health education and communication during times of crisis.

Given the widespread use and influence of social media platforms, it becomes crucial to assess the feasibility of identifying problematic content that may provoke negative physiological responses in consumers. The present study aims to explore the relationship between bodily arousal and social media consumption, particularly within the context of the COVID-19 pandemic. By leveraging advancements in technology, such as wearable devices and video analysis, we seek to analyze skin color changes as a potential indicator of states of arousal and evaluate the reliability of this approach in identifying potentially sensitive or provocative content.

Through this research, we strive to enhance our understanding of the potential implications of social media content consumption on individuals' physiological responses. Furthermore, by identifying problematic content, we aim to contribute to the development of effective strategies for content moderation and user protection on social media platforms, ultimately fostering a healthier and more responsible online environment.

3 METHODOLOGY

3.1 Participants

Our set of participants for the study was chosen among friends and family of different age and gender. Any tendency in the demographic is coincidental. To remain within the scope of our study, we chose a set of four participants. Our goal is to carefully analyze the data measured to not misrepresent their opinion and treat our deduction of bodily arousal sensitively. Table 1 represents the age group of our participants and their general content preference on the pandemic.

3.2 Materials

For the purpose of data collection and analysis, a questionnaire and a dedicated website were developed within the scope of this study. The objective was to create an experience that closely resembles common online content consumption and to develop software capable of efficiently processing raw data, thereby showcasing the potential of social media platforms in analyzing phone camera streams.

To establish participant profiles, a demographic questionnaire was administered, accompanied by inquiries regarding individual perspectives on personal experiences with COVID-19 and content consumption related to the topic. This information played a supportive role in the final analysis. Participants reporting negative experiences with the topic allowed for the identification of correct detection of bodily arousal when corresponding content elicited increased heart rate. All source code utilized throughout the study can be accessed on the GitLab repository of the Bauhaus-University of Weimar [Artur Solominik 2020].

3.2.1 PeekABoo: Content Feed. To emulate the conventional experience of a content feed encountered on social media platforms, a website was meticulously designed, both mechanically and aesthetically. The intention was to create a prototype that closely aligns with users' typical online content consumption. The platform's layout was inspired by the structure of TikTok, which emerged as a prominent social network across various age groups during the pandemic.

The website employed a one-page layout, enabling users to focus solely on navigating the feed. Limited interaction options and simplified feedback transformed the website into a streamlined media viewer with rating capabilities. The content feed consisted of three types of posts: "media" (comprising video or image posts from social platforms), "comment sections" (encouraging participant comments on the observed posts), and "preference deductions" (abstracting the content recommendation process by prompting users to indicate their interest in specific posts). Users were given the opportunity to select the design of the remaining content based on their personal preferences. All data is accessible in the GitLab repository.[Artur Solominik 2020]

P	age	social media activity	interesting content	uninteresting content
P1	30 to 39	Facebook, YouTube, Instagram	Perspectives from others, Status Information, Strategies for Dealing with the Pandemic	Post-Factual Reports, Reports on Small Events, Status Information on Specific Foreign Countries
P2	30 to 39	YouTube	Scientific Research	Conspiracy Theories
P3	18 to 29	YouTube	Scientific Research, Government Regulations	Conspiracy Theories, Post-Factual Reports
P4	30 to 39	Facebook, YouTube, Instagram	Status Information, Government Regulations, Campaign against Denialism	Post-Factual Reports

Table 1. Participant Demographic and Content Preference on the COVID-19 Pandemic

In addition to replicating a content consumption environment, the website served as the experimental setup for the study. User responses were tracked to facilitate the analysis of heart rate data in relation to content experiences. Results were exported in JSON format after each participant for further processing. The website was not publicly hosted and was only accessed locally to ensure privacy protection.

3.2.2 PaWeL: Heart Rate Analysis Tool. To analyze heart rate in the context of social media content consumption, a Python script named PaWeL (short for "Peak Analysis of Webcam and Screen Data for Heart Rate Estimation") was developed. Leveraging facial tracking technology within the OpenCV framework [1], the script determined participants' heart rates by processing video streams of their faces. The script identified peaks in the heart rate data and linked them to the corresponding content consumed during the study. The processing of the content feed occurred offline after the data recording phase to mitigate potential technical difficulties. A more detailed account of the script's implementation and its role in the research process and data analysis can be found in Section 4.

3.3 Design and Procedure

As a way of emulating the context of browsing a modern social media feed during the pandemic, participants were presented a user interface which is designed to show content to the viewer. Said content includes pictures, small article excerpts, headlines and videos on the topic of COVID-19. We made sure to get actual posts that were outside any individual social media bubble, and leaned in our collection process towards posts that seemed controversial and highly opinionated. Aside from that, we made sure to include posts that are mainly concerned with educating users and informing them. These two types of stimulation material will be consumed by the user via artificial social news feed.

In this context, the participants will consume less controversial content followed by opinionated and highly polarizing content. In total there will be *four sets* of *nine posts* (*3 informational*, *3 mild*, *3 opinionated*) within a time frame of approximately 20–25 minutes of consumption. The process is recorded on video through screen recording of the feed traversal, alongside a camera recording of the participant's face. To facilitate the analysis of physiological data, face recordings are conducted under similar light conditions and guided by the observing researcher.

[1]OpenCV: https://opencv.org/. Last Accessed: 21.06.2023

3.3.1 Establishing baseline measurements. Before the experiment can begin, participants are asked to stand still for 60 seconds while the webcam captures current lighting conditions, and baseline heart rate Each participant is informed of their task and how to behave while leaving at all times the opportunity to stop the experiment. After the first measurement, participants are asked to respond to the content they are provided with in different ways.

3.3.2 Questioning participant context. In order for us to know whether the user will be prone to content about the pandemic, we will ask the participants about their view on each of the topic. Aside from basic demographic data, we want to determine whether content that seemed problematic for us, will prevail to be problematic for them as well. This leads us to a questionnaire regarding their interest in different types of content, how the situation has affected them personally, and how much content they consume on a daily basis.

3.3.3 Creating varying content feeds. In order to give the impression that the experience is tailored according to the individual user, the website prompts different kinds of input fields that will determine whether one would look at mostly harmless informative posts or hateful comments. Firstly, the participants will look at a variety of content from different social media platforms surrounding the pandemic, as seen in Figure 1. A Likert scale from one to five is used to determine whether the post seemed interesting to the user or not. After every input, one can proceed with looking at the feed. After three to five posts, a text prompt appears asking about the user's opinion on prior content and how they feel similar to Figure 2. During the user's typing we are less interested in their text but rather in the physiological state they are in. After every comment, we ask the user to choose what type of content they would rather be interested in as in Figure 3 to get a better understanding of their content preferences.

3.3.4 Establishing Heart Rate. With the help of PaWeL, the system designed to capture the webcam stream during content exploration, we managed to estimate a heart rate measurement. The technical implementation is described in chapter 4. The resulting set of photoplethysmogram PPG values showcase color changes of the participant's skin, and serves as a first instance for assessing the

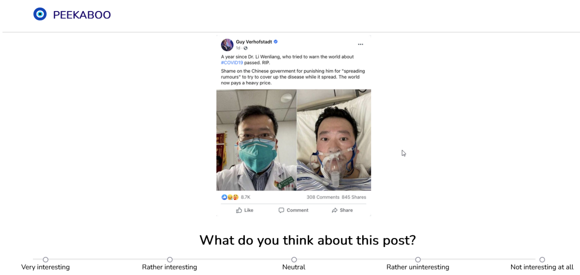

Fig. 1. Website view during content consumption

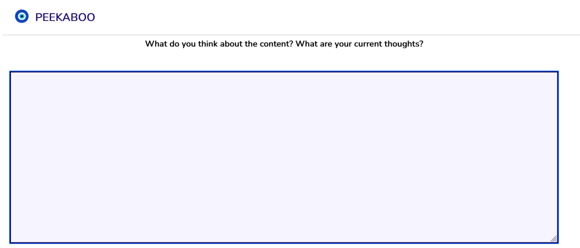

Fig. 2. Comment section for free writing

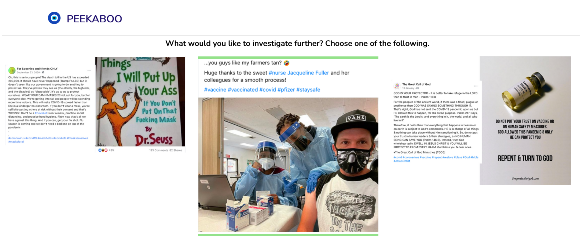

Fig. 3. Choice prompt for content exploration

mental load of every participant. Sampling the data, and establishing a PPG curve, presents in its maximum values the time periods of increased fluctuations of red value in the skin capture. These instances are the entry points for deducing mental load in regard to the content the participant observed.

3.4 Analysis

After the duration of the study, we obtained a dataset for every participant that included the tagged BPM, where time codes of heart rate peaks were assigned screenshots of the perceived content. Every dataset is screened for errors, and unusual measurements. The final analysis is motivated by finding the precision of the heart rate measurements and whether their peaks hit content the user might find more engaging than others. Our preliminary questionnaire serves as a support for estimating which content posts should provoke bodily arousal. After establishing where our estimation aligned with the tagged PPG, we can make further deductions on tagging content for every participant.

4 IMPLEMENTATION

For the realization of the study, we developed two tools that would support our effort of measuring heart rate while preserving a ground truth for our measurements without the need of external cardiac devices such as ECG. A Python script called PaWeL remains the focus of the project work as it processes the video stream to assess the PPG heart rate depending on constant color value fluctuations of the participant's skin. Our content feed, PeekABoo serves as the visualization of social media content as well as the questionnaire on the interest of the participant regarding the topic.

4.1 PaWeL

The fundamental process of finding a user's heart rate makes use of a computer's ability to perceive color changes where the human perception reaches its limits. Finding these constant fluctuations includes capturing a region of interest (ROI) that will not be affected by wrinkling, motion, hair or facial features, which left us with the forehead as a suitable ROI. With the help of OpenCV's Cascade Classifier[2], one can capture the forehead of each frame and extract green color values for further processing. To create a more stable tracking process, we try to minimize face detection efforts, which produce unsteady values when the face will be reestablished for every frame. Dismissing strong fluctuations of the ROI boundaries and further image filtering with Gaussian blur and thresholding enable more reliable data for estimating the PPG by calculating the Fast Fourier Transformation from the color value signals.

$$H_{\text{PPG}} = 60\left(\frac{1}{N}\sum_{k=0}^{N-1} X_k \cdot e^{i2\pi kn/N}\right), n \in Z$$

The final peaks of the recording are then tagged with the content the participants perceived or wrote about in their writing portions.

The computation of the BPM included the determination of the peaks within the PPG signal. While calculating the first derivative of the data, and highlighting its zero values seemed tempting at first, we further adjusted this approach through a sliding window algorithm which takes thresholds and a maximum amount of peaks into consideration.

4.2 PeekABoo: Content Feed Viewer

The content feed is implemented with a simple HTML file that is given a style of a minimal social media content feed, alongside trivial JavaScript logic that exports the Likert responses of the individual. With every post, a Gaussian blur reveals the content to avoid sudden color reflections of the skin that would obfuscate frequency measurements.

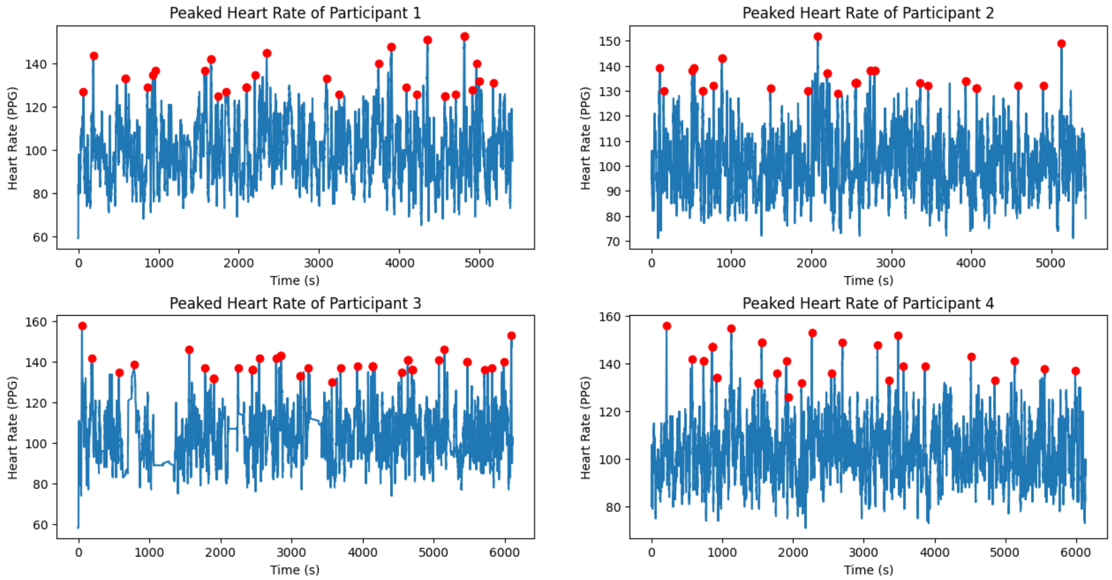

Fig. 4. Participant PPG Heart Rates during Content Observation

5 RESULTS

In the following, we present the resulting heart frequency measurements alongside the corresponding points in time when a post was being observed. All measurements can be seen in Figure 4. The peaks are filtered maxima, implying an increased red value in the color processing. While we can't be certain that the color changes are from a change of blood flow, its regular nature implies that the measurements produced the desired estimates.

With every peak, we obtained screen captures of the content observed at the time, as referenced in 5. All images in full resolution are hosted in our open repository.[Artur Solominik 2020] While participant 2 had the noticeable majority of PPG peaks, they are attributed to the longer videos, which were mostly embodiments of the conspiracy theories that the participant is largely uninterested in. All participants had frequent skin color changes during long videos, which implies that this technique is especially suitable for identifying controversial video stream content. Aside from that, periods of writing caused PPG peaks among all participants, which leaves to assume that acts of active engagement and discussion in the form of textual response are prone to PPG peaks as they are constant reflections on thoughts of arousal. As we can see in the Sankey Diagram of Figure 7, the most prominent peaks among all participants to an equal amount were the resources 1-2p, 2-2p, and 1-1m, while the content of the last cycle (4-*) remained not interesting to every individual. Aside from that, despite the low amount of peaks, images such as 1-0m, 1-2m, and 1-0m produced peaks that were shared among the group. This leaves to assume that those posts were more thought-provoking than others. To counter-balance these claims, it's crucial to confirm the responses with the ground-truth that the participants provided in the form of the Likert scale.

Individual Likert responses during content observations can be observed in Figure 8, 9, 10, 11. The figures showcase the interest of every participant, with -2 being very uninteresting, and 2 being very interesting. It's clear that most participants, especially P1, and P2 were largely uninterested in the content they observed which makes proving the established heart ratings difficult to interpret, rendering the variable of interest ineffective. P3, while mostly interested in some content consisted of the video posts, was intrigued by 2-1n, which also produced a PPG peak. P4 remained uninterested in the topic, with the more opinionated content leading to no interest at all. Unfortunately, barely any of the interest responses correlate to the measurements from the study; therefore, other methods of establishing ground-truth measurements are crucial for further investigation.

6 DISCUSSION

The results of our study suggest the potential for tracking a person's heart rate to determine their level of distress while consuming content. However, further investigation is warranted due to the subjective and complex nature of content impression, which is challenging to capture with a single measurement. In order to improve the reliability of our findings, we recommend the use of dedicated hardware for cardiac activity monitoring during webcam measurements.

[2] OpenCV Cascade Classifier: https://docs.opencv.org/3.4/db/d28/tutorial_cascade_classifier.html. Accessed: 21.06.2023

Fig. 5. Observed Content during Peaking PPG

The use of a webcam to calculate heart rate is a simple technique that has shown promise in providing rough measurements of bodily arousal. Although the accuracy of the results may be limited, advancements in video quality and image processing techniques could potentially enhance the outcomes. The applicability of these improvements should be tailored to the specific research context.

While our study primarily focused on identifying problematic content, selecting a suitable theme proved to be a challenge. Although Covid-19 is a topic that has impacted everyone, its subjective nature makes it difficult to define what constitutes common problematic content without resorting to extreme cases. While the chosen posts in our study varied in intensity and elicited corresponding responses, the number of consistent findings may decrease with a diverse participant pool. Each individual has their own unique experiences and perceptions of the pandemic, making it important to engage in conversations with participants to define problematic content more precisely. This will enable further analysis of the physiological measurements in a meaningful manner.

Our data revealed that each participant exhibited varied physiological responses during media consumption. The process of engaging with media involves numerous small reactions, emotional chains, and thought processes that are not easily captured solely through heart rate measurements. Although the overall measurements appeared consistent when the lighting conditions and project setup were controlled, we cannot definitively confirm that the observed physiological responses indicate distress. However, we were able to identify points in time when new content was consumed, as evidenced by heart rate fluctuations upon exposure to different types of posts. Additionally, sudden noises in the videos elicited minor increases in heart rate. These findings suggest room for improvement in utilizing webcam data to establish the presence of problematic content.

In conclusion, our study provides initial insights into the potential of webcam-based heart rate tracking to assess distress during content consumption. However, the complexity of content impression and the limitations of heart rate measurements highlight the need for further research and refinement of measurement techniques. By considering dedicated hardware, refining video quality and image processing, selecting appropriate research themes, and conducting in-depth discussions with participants, future investigations can yield more robust and meaningful findings.

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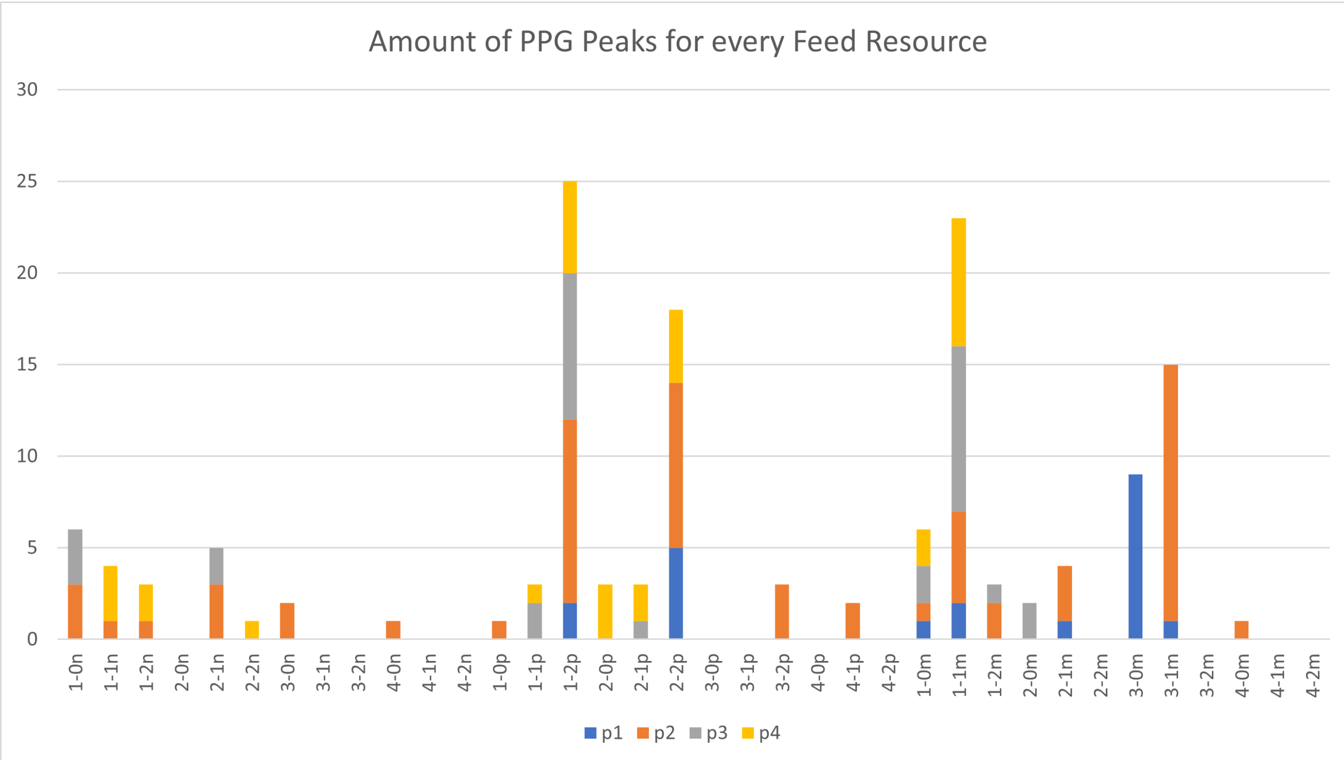

Fig. 6. Overall PPG Peaks of every Participant throughout the Feed

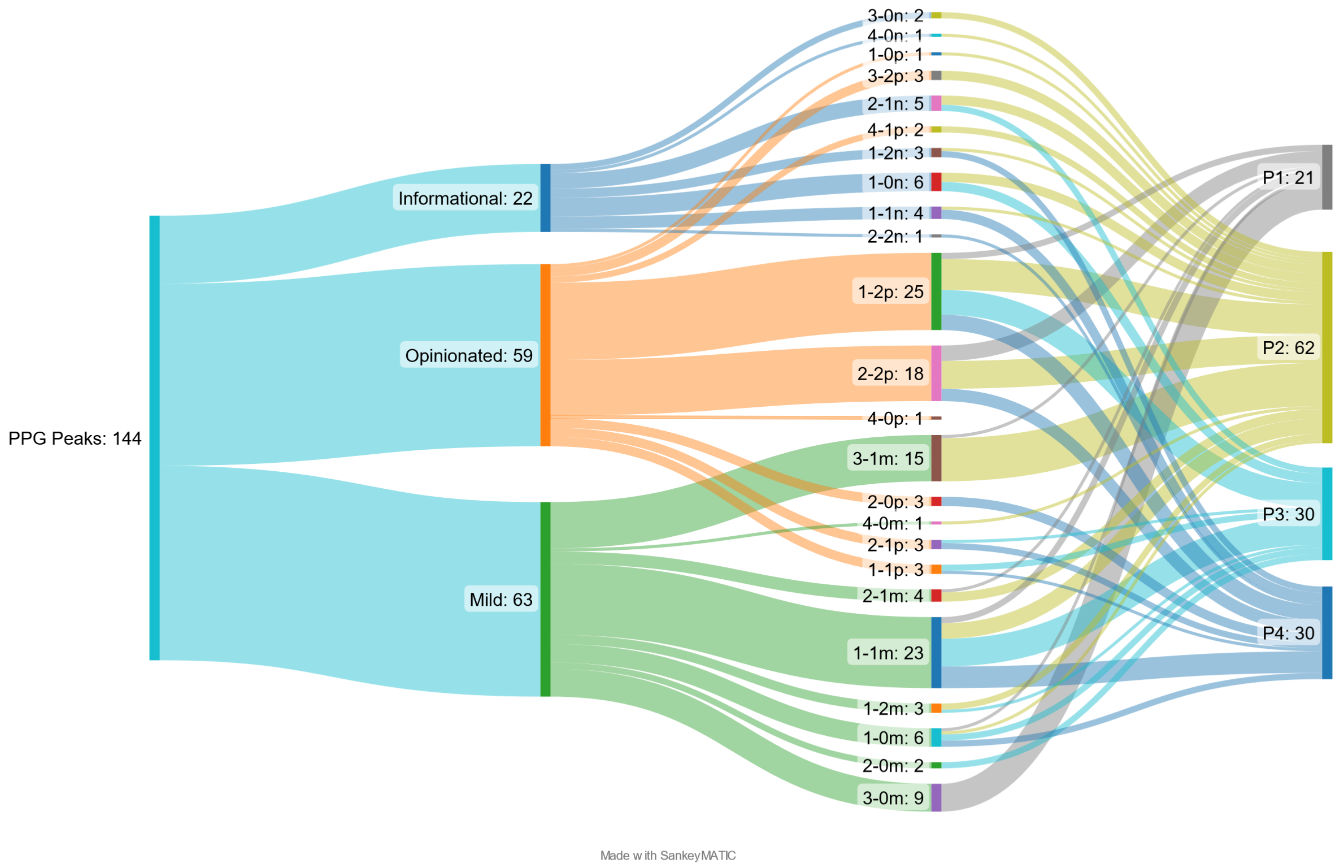

Fig. 7. Sankey Diagram of Peak Correspondence to Feed Content

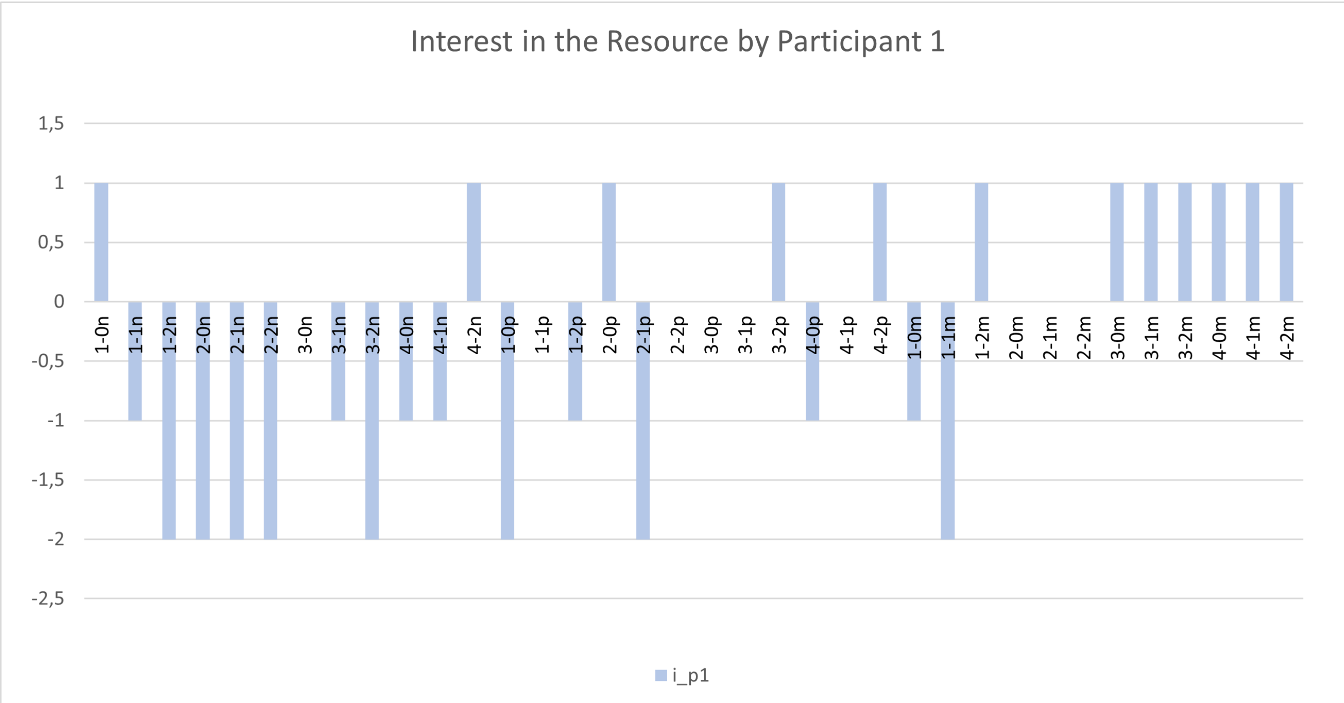

Fig. 8. Likert Response for Content by Participant 1

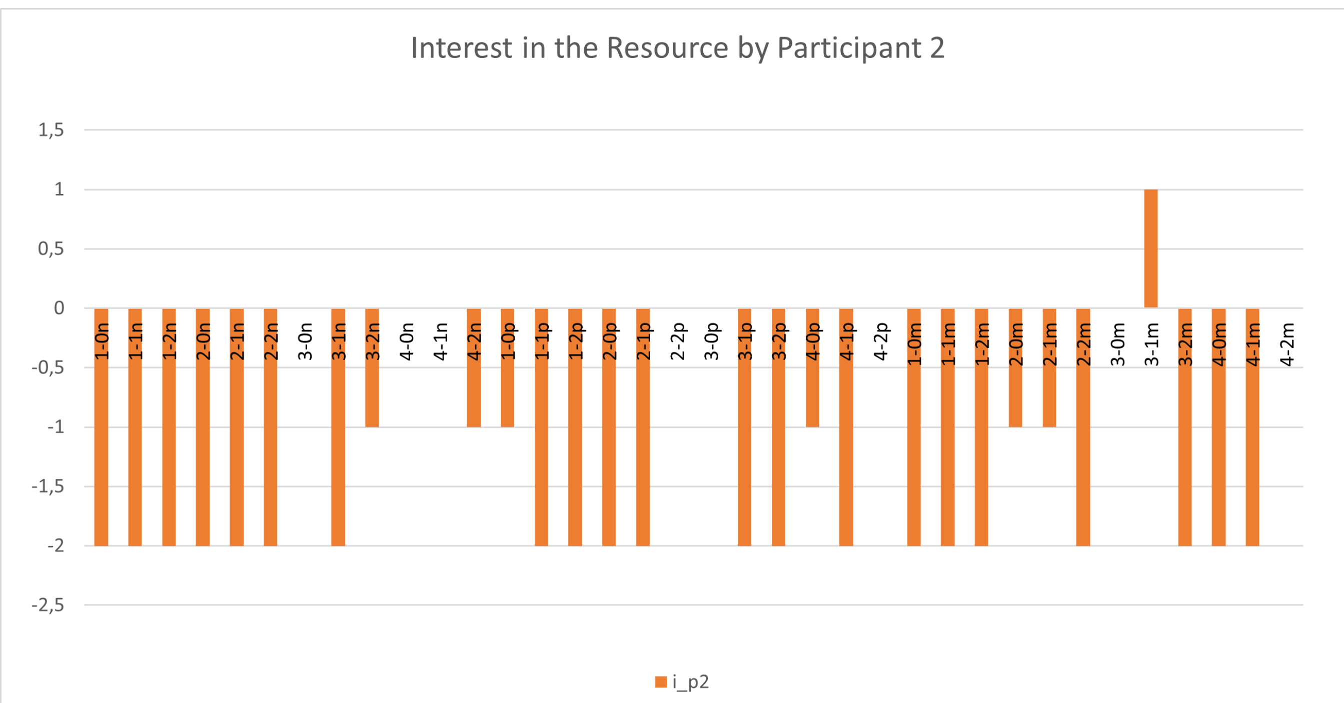

Fig. 9. Likert Response for Content by Participant 2

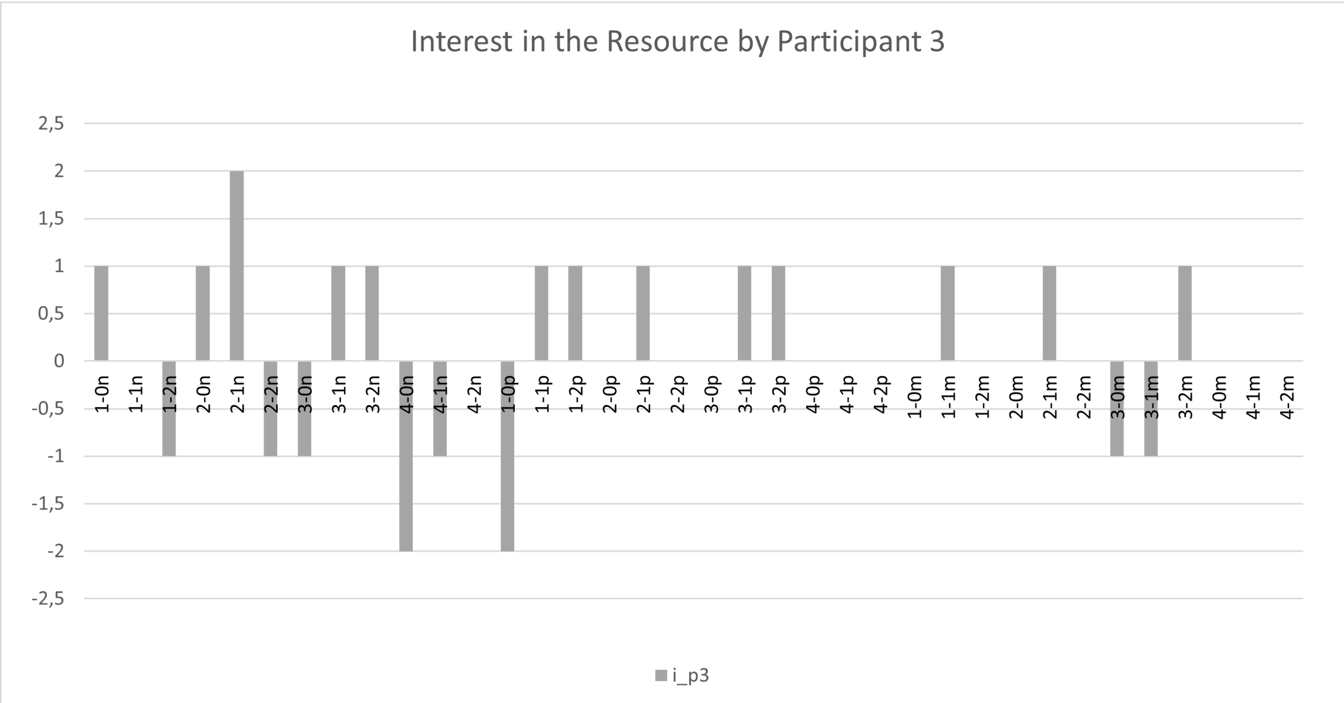

Fig. 10. Likert Response for Content by Participant 3

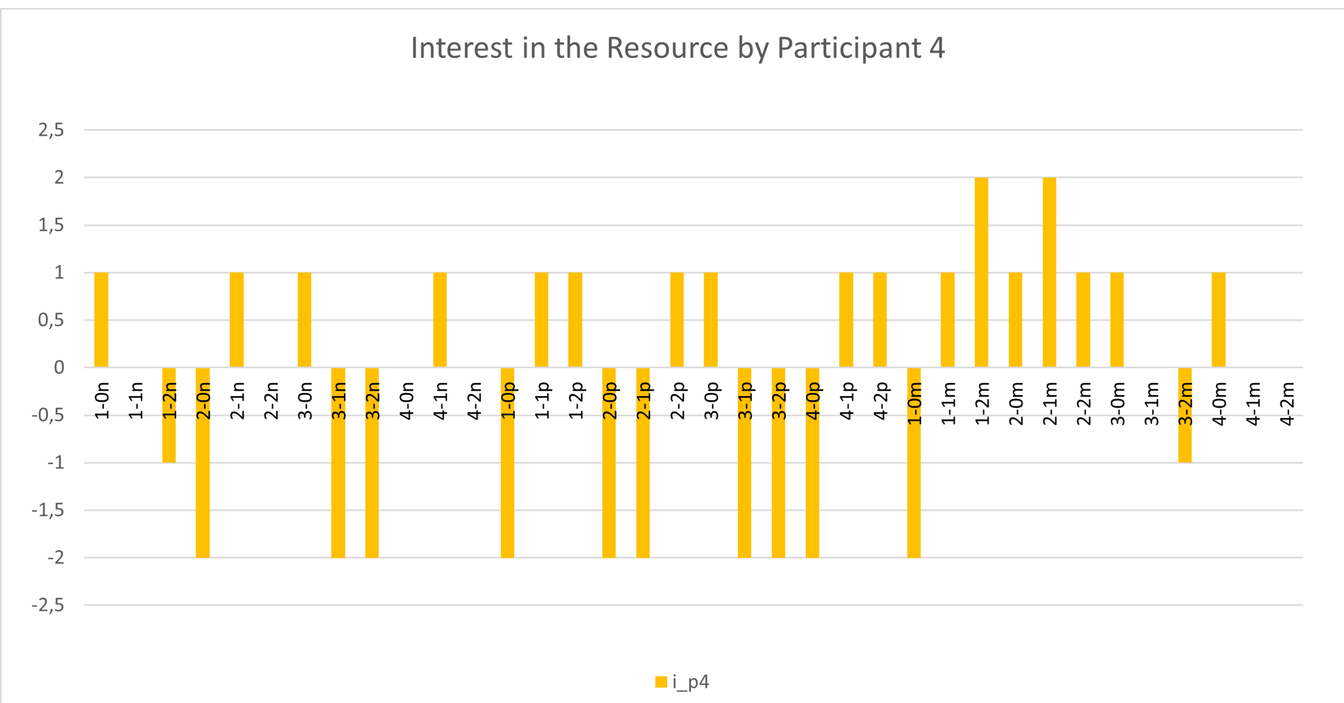

Fig. 11. Likert Response for Content by Participant 4