Research Article

Analyzing Audience Engagement in Static Versus Dynamic Media Content Using Eye-Tracking and Instagram Metrics Through the Lens of TPB and CLT

Kareem Mohamed Abdelhafeez Mahfouz Hussein[1], Bahire Efe Ozad[2]

1. Independent researcher; 2. Radio, TV and Cinema Department (Chair), Eastern Mediterranean University, Cyprus

Understanding audience engagement in media content is essential, as neuroscientific techniques provide insights into psychological and cognitive responses. This study conducts a quantitative comparative analysis of audience engagement with static designs and dynamic audiovisual content using Realeye.io, a webcam-based eye-tracking tool. Fifteen participants (60% female, 40% male) were analyzed, revealing that dynamic content outperforms static designs. The number of fixations was higher for dynamic media (M = 155.2, SD = 18.00) than for static (M = 27.33, SD = 3.79), with longer fixation duration (M = 43.85s, SD = 5.72) compared to static (M = 25.4s, SD = 2.69), confirmed by the Wilcoxon signed-rank test (Z = -3.297, P < 0.001). The study also examines Instagram engagement metrics for 30 movie posters and trailers. Results show that trailers receive more likes (M = 124,945, SD = 187,019) than posters (M = 71,597, SD = 174,257), except for Mission Impossible, where the poster (900k likes) outperformed the trailer (250k). Findings were interpreted using the Theory of Planned Behavior and Cognitive Load Theory (CLT), emphasizing behavioral and cognitive mechanisms. Limitations include a small sample size, reliance on a single eye-tracking tool, and Instagram as the sole data source. Ethical approval was obtained from Eastern Mediterranean University, and all procedures involving human participants complied with relevant ethical standards

Correspondence: papers@team.qeios.com — Qeios will forward to the authors

1. Introduction

The rapid evolution of digital media has significantly altered audience engagement patterns, necessitating an in-depth exploration of cognitive and behavioral responses to different content formats. With the growing reliance on visually driven platforms such as Instagram, Facebook, and TikTok, media professionals and scholars are increasingly seeking to understand how static and dynamic content influence user interaction. While dynamic audiovisual formats are widely perceived as more engaging due to their motion and temporal sequencing, static media remains a fundamental component of visual communication, particularly in advertising, journalism, and branding. However, limited empirical research has systematically compared these formats using both eye-tracking technology and social media engagement metrics, leaving a crucial gap in the understanding of audience perception and interaction. Existing literature has extensively examined user engagement with digital content, yet much of this research remains descriptive, failing to provide a robust theoretical grounding. Studies often focus on basic engagement indicators, such as likes, shares, and comments, without integrating cognitive and psychological frameworks to explain underlying audience behaviors. This study addresses this limitation by adopting the Theory of Planned Behavior (TPB) and Cognitive Load Theory (CLT) to investigate how user attitudes, cognitive load, and media design influence engagement with static and dynamic content. By doing so, this research contributes to a deeper theoretical and empirical understanding of the mechanisms that drive audience interaction in contemporary digital environments. The Theory of Planned Behavior (TPB) offers a well-established framework for predicting audience engagement based on attitudes, subjective norms, and perceived behavioral control. In the context of digital media, TPB suggests that audience interaction is shaped by their perceptions of content effectiveness, peer influence, and ease of consumption. Meanwhile, Cognitive Load Theory (CLT) provides a complementary perspective by examining how different media formats impose varying cognitive demands on users. Dynamic audiovisual content is generally thought to reduce extraneous cognitive load, facilitating sustained attention and deeper engagement, whereas static designs may require greater interpretative effort due to their lack of motion cues. The integration of these two theories enables a more comprehensive analysis of how cognitive and behavioral factors influence audience engagement with digital media. To empirically test these theoretical assumptions, this study employs a comparative experimental design involving eye-tracking analysis and social media engagement metrics. Eye-tracking technology provides precise measurements of audience attention, including fixation count, duration, and saccades, offering insights into cognitive processing. Simultaneously, Instagram engagement data from 30 movie posters and their

doi.org/10.32388/F16VXK

corresponding trailers serve as real-world indicators of user interaction and preference. By combining these methods, the study aims to establish a direct relationship between cognitive load, planned behavior, and media engagement, thereby advancing both theoretical and applied knowledge in media psychology.

Understanding the audience's engagement through their perceptions, attention, and emotions has become crucial for analyzing media companies, systems, organizations, and professionals for more effective, personalized, and engaging strategies and campaigns to develop media content. Integrating audience perception metrics as patterns and reactions preserves valuable and beneficial insights into how they react, respond, and perceive different media contents, influencing the message's effectiveness, credibility, persuasiveness, and retention, as discussed by[1]. In the rapidly evolving technological advancements through techniques, tools, and software impacting communication and media landscapes, the race for developing successful engaging media content and campaigns guides and routes systems and businesses to analyze and measure audience perception metrics accurately and critically. The comparative analysis of audience reactions towards static designs and dynamic audiovisual media content allows researchers and scholars to analyze and understand the detailed differences between audience attention and emotions through different formats. Dynamic audiovisual merges temporal visual elements that substantially impact audience engagement. On the opposite side, static formats depend on contiguous symmetrical visual arrangement and hierarchy through design principles and gestalt elements.

1.1. Aim of the study

The aim and objective of the research is to compare audience attention and emotional responses to three static designs and one dynamic audiovisual using realeye.io as a webcam eye-tracking tool, revealing different numbers of fixations, total duration of fixation, attention, and emotions for audience engagement. Furthermore, the research aims to compare 30 movies through their posters and trailers on Instagram, analyzing the number of likes on each. Integrating eye-tracking and Instagram metrics will provide valuable insights for content creators, media professionals such as editors and developers, and scholars aiming to optimise audience perception and engagement in the rapidly rising technological media landscape.

1.2. Theoretical framework

The theoretical foundation of this study integrates TPB and CLT to explain both the *behavioral intention* (why users engage) and *cognitive processing* (how users engage) involved in media consumption. The theory of planned behavior posits that engagement behaviors are influenced by attitudes, subjective norms, and perceived behavioral control[2]. Within the context of media, this implies that user interaction, such as liking or sharing a post, is shaped by their evaluation of content quality (attitudes), peer influence (norms), and ease of understanding (control). For example, Truong[3] found that ease of access and perceived value were stronger predictors of digital engagement than social norms. Fielden[4] extended TPB by showing that influencers can shape audience attitudes and trust, making TPB particularly relevant in a social media context.

Cognitive Load Theory explains how content design affects mental processing by distinguishing among intrinsic, extraneous, and germane cognitive load[5][6]. Dynamic media may reduce extraneous load by guiding attention through motion and pacing, thereby promoting germane load that facilitates learning or narrative comprehension. In contrast, static designs may increase extraneous load due to their interpretative demands. Research suggests that motion cues help maintain attention, and eye-tracking metrics such as fixations and saccades can reflect these differences in cognitive load[7][8].

[9] addresses the significant integration of several key psychological theories in understanding audience perception through their emotional and cognitive engagement with media content. Utilizing the theory of planned behavior can provide an invaluable framework to understand and analyze the implications of audience engagement in different media formats through their attitudes, subjective norms, and perceived behavioral control as defined by[2], which is a critical theoretical lens to shape audience's perception within various different media contents dynamically or statically through pre-existing attitudes, organizational norms, and perceived abilities. [3] addresses the importance of utilizing psychological factors for understanding audience engagement in digital media by evaluating the theory of planned behavior (TPB) to examine the viewer's perception of TV programs and online audiovisual content, emphasizing that perceived behavioral control is the crucial consideration showcasing their user-friendliness and accessibility rather than the moderate effects of attitude and subjective norms as a consequence of privacy and difficulty of the actual consumption patterns. [4] utilizes the theory of planned behavior as a framework to evaluate the impact of influencers on social media on audience perception, trust, and preferences, revealing significant implications for their attitude and the crucial need to leverage famous content creators and bloggers in campaign communication for better engagement. Complementing the psychological and behavioral perspective, Cognitive Load Theory (CLT), [6] provides a valuable analysis of how different media contents can place different cognitive and mental challenges on viewers' attention and emotions, distinguishing between intrinsic, germane cognitive

loads, and extraneous, revealing the differences in audience patterns and emphasizing the role of emotional factors in understanding, learning, and education through four ways of impacting motivation, memory processes, storage, retrieval, encoding, and decoding. [5] believes that understanding human cognitive psychological measures through three types of loads such as intrinsic, extraneous, and germane by utilizing Cognitive Load Theory (CLT) as a framework for optimizing learning and education through enhanced instructional structure through evidence-based strategies as audiovisual contents effectively impact memory capacity, grasp attention through information and knowledge within the expertise, and reduce the cognitive load, which significantly affects the outcomes of the instruction.

1.3. Research Questions

- **RQ1**: To what extent do eye-tracking metrics (fixation count, fixation duration) differ between static and dynamic media content?

H1: Audience engagement with dynamic audiovisual content will be higher than with static designs due to positive attitudes toward visually rich and immersive formats, as predicted by TPB.

- **RQ2:** How do social media engagement metrics (e.g., likes, shares) relate to media format type?

H2: Perceived behavioral control will moderate engagement levels, with lower cognitive effort enhancing interaction with dynamic content (TPB).

- **RQ3**: In what ways do TPB constructs (attitudes, subjective norms, perceived behavioral control) influence audience engagement with static and dynamic content?

H3: Eye-tracking metrics (fixation count and fixation duration) will be significantly higher for dynamic audiovisual content than for static images due to enhanced cognitive processing (CLT).

- **RQ4:** How does cognitive load (CLT) explain differences in visual attention and engagement across media formats?

H4: Instagram engagement metrics (likes, shares) will reflect cognitive load differences, with higher interaction rates for dynamic content due to reduced processing effort and increased germane cognitive load (CLT).

2. Literature Review

2.1. Attention Capture in Dynamic vs. Static Media

Dynamic audiovisual formats tend to capture and sustain audience attention more effectively than static visuals due to the presence of motion, sequencing, and audio cues. These elements align with the human visual system's evolutionary predisposition to detect movement and sound[10]. Research confirms that motion not only attracts initial attention but also maintains it through dynamic changes and narrative flow[11][12]. This supports **RQ1 and H1**, which hypothesize that dynamic content yields higher fixation metrics and sustained attention. In contrast, static visuals rely on design features such as visual hierarchy, symmetry, and Gestalt principles to direct attention[1]. Although these can be effective, they often require more cognitive resources to process, thereby increasing intrinsic cognitive load; a point directly linked to **RQ4** and **H4**. The comparative difference in attentional mechanisms suggests that dynamic content has a natural advantage in audience engagement.

2.2. Measuring Cognitive Processing Through Eye-Tracking

Eye-tracking technology has become a prominent method for analyzing media engagement by providing objective insights into users' visual attention. Key metrics such as fixation duration, saccades, and gaze paths are used to evaluate cognitive processing depth and attentional focus[7][13]. These metrics support the operationalization of **RQ1 and RQ4**, particularly in testing **H1 and H4,** by offering quantifiable data on attention and cognitive load. Platforms like RealEye.io, a webcam-based eye-tracking tool, have demonstrated validity in remote experimental contexts including media, education, and advertising[8][14]. Rahal[15] integrates eye-tracking with social psychology to record real-time cognitive behaviors, using infrared detection of eye reflections and pupil centers. Similarly, Beesley[16] emphasizes eye-tracking as a critical method in psychology and media research for understanding attentional dynamics and emotional response to visual content. Federico[10] utilized RealEye.io in a study involving 3D object engagement, revealing that semantic and mechanical cues influence user attention and motor reasoning, even under distraction. These findings support the methodological reliability of eye-tracking tools and justify their use in the present study to investigate media format preferences, reinforcing the empirical basis of **RQ1 and H4.**

2.3. Emotional Engagement and Psychological Measures

Emotional engagement significantly impacts how audiences interact with media. Studies employing facial coding, sentiment analysis, and physiological sensors show that emotionally resonant content enhances viewer satisfaction and promotes sharing behavior[17]. Entertainment-oriented media, in particular, can reduce stress and evoke positive emotions, contributing to favorable attitudes and increased behavioral intention[18][19]. These findings support TPB predictions related to **RQ3 and H3**, highlighting the affective drivers of engagement. Dias[20] conducted a systematic literature review emphasizing that memory, identity, and experience shape emotional responses to media. The study also identified a shift toward active audience roles in content interaction, which necessitates integrating psychological and social dimensions into engagement studies. Córdoba-Tlaxcalteco[21] expands on this by evaluating how smart media tools and eye-tracking data enhance learning and emotional feedback in interactive content environments. These studies demonstrate the importance of emotional resonance in media design, further supporting the theoretical grounding of **RQ3 and H3.**

2.4. Cognitive Load and Media Format Design

Cognitive Load Theory (CLT) provides a valuable lens for evaluating how media formats affect mental processing. Dynamic audiovisual content often reduces extraneous load by guiding viewers through visual sequences, making comprehension more intuitive[5][6]. In contrast, static visuals may increase cognitive load, particularly when design elements are ambiguous or lack directional cues—adding strain to the viewer's working memory. Research shows that media with lower cognitive demands typically result in higher user satisfaction and behavioral engagement[22][23]. These findings validate RQ4 and H4, and also support H2, which posits a connection between cognitive efficiency and behavioral interaction. By minimizing unnecessary processing, dynamic content can enhance comprehension and emotional immersion, leading to stronger engagement outcomes.

2.5. behavioral Engagement on Social Media Platforms

Engagement metrics on social media; likes, shares, comments—serve as behavioral proxies for user intention and content effectiveness. While often dismissed as superficial, these actions reflect deeper cognitive and emotional responses when analyzed through the Theory of Planned behavior[2][24]. This line of inquiry informs R**Q2 and H2,** emphasizing how behavioral intention manifests through measurable social media activity. Pozharliev[25] highlights how social media metrics can inform media psychology by evaluating how visual and emotional elements influence attention and decision-making. Pittman[22] connects engagement levels to cognitive load, revealing that users rely on heuristics; such as comment count or likes; to evaluate content credibility and form intentions. Habibi[23] confirms that dynamic media formats, particularly videos, consistently outperform static content in eliciting interaction across social platforms. Dai[26] adds that credibility and accessibility increase perceived behavioral control, making users more likely to engage. Influencer endorsements and high view counts also serve as heuristic cues that reinforce normative pressures, supporting **RQ3 and H3**. These insights strengthen the need for a theory-informed, dual-method approach; merging cognitive processing via eye-tracking with behavioral metrics from digital platforms; to fully understand engagement in media contexts.

3. Methodology

The research study utilized a quantitative methodological approach by employing eye tracking to compare different audience perceptions between static designs and dynamic media content through a comparative experimental design and integrating Instagram engagement metrics through 30 movies, comparing the number of likes on static posters and dynamic trailers. SPSS was applied and implemented through normality tests and paired t-tests for statistical analysis. In comparison, it incorporates critical theoretical frameworks such as the theory of planned behavior and the cognitive load theory to clarify and examine the findings in communication, media studies, and the evolving digital media landscape.

3.1. Research Design

The study applies a quantitative comparative experimental design to analyze the audience's experience through their number of fixations, total time of fixations, emotional engagement as happy and surprised, and the attention between static designs and dynamic audiovisual media contents under controlled conditions in the experimental setup. Furthermore, a comparative analysis of IG engagement metrics has been utilized to analyze viewers' engagement through their number of likes on 30 different movies on their static posters and dynamic trailers, providing real-world insights into nuanced behavior measures suited for media professionals, businesses, scholars, and studies.

3.2. Sampling

The study employs a purposive sampling method for the eye-tracking experimental case study through realeye.io to engage and select 15 participants (60% female, 40% male) from the researcher's affiliated

doi.org/10.32388/F16VXK

organization, sharing common knowledge, experience, and background, demographic variability, and providing measurements and insights related and accurate to specific segments. Additionally, for the Instagram engagement metrics, 30 movies were chosen as a representative sample of popular movies, according to a diverse range of genres and preferences, through their posters and trailers to collect a broader spectrum of engagement, emotional, and behavioral patterns.

3.3. Data Collection

The data collection for the research has 2 phases. Firstly, the eye-tracking case study, which was conducted through realeye.io, an online webcam software recording participants' interaction in 60 seconds in real-time directly after the end of perceiving each media content, abiding by the NMSBA code of ethics, which provides an analytical dashboard to analyze the audience's emotions, attention, and the ability to extract an Excel sheet with detailed measurements of the number of fixations, saccades, gaze points, and the total time of fixations. For the 2nd phase, the number of likes of 30 different movies through each static poster and dynamic trailer was collected through their official pages and accounts on Instagram.

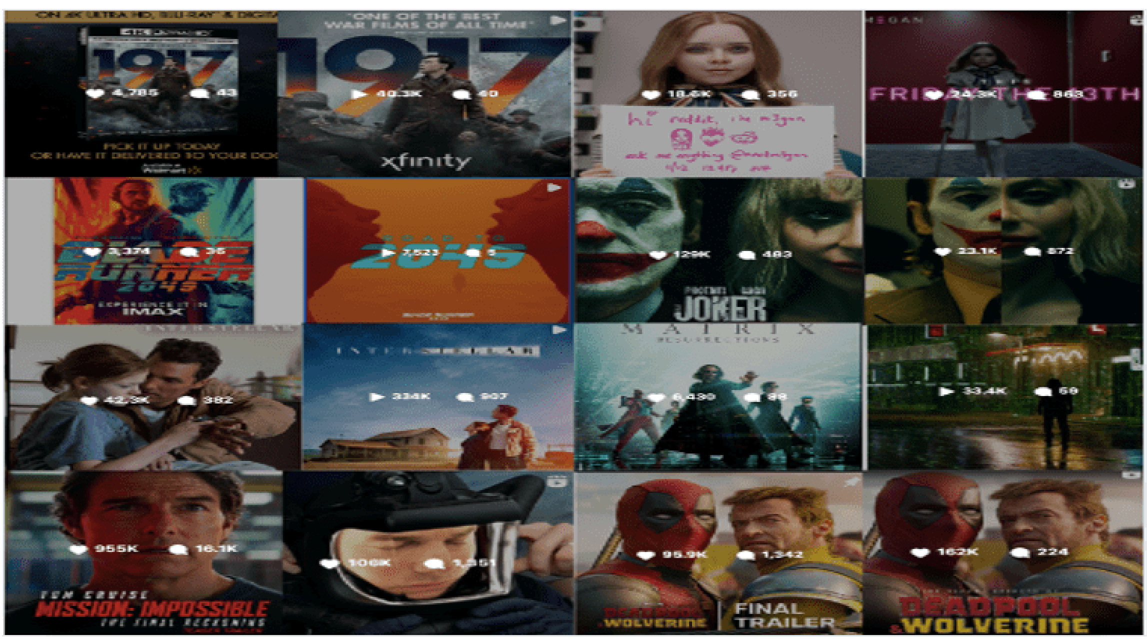

Figure 1. Collection of movie posters and trailers on Instagram.

doi.org/10.32388/F16VXK

3.4. Data Analysis

The study's data analysis was conducted through four phases. Firstly, the realeye.io analytical dashboard visually represents the audience's emotional and attentional measurements, exporting a detailed Excel sheet for the fixations, saccades, total time, and gaze points. Secondly, SPSS statistics software was employed through a normality test to confirm, check, and prove the normal distribution. A Wilcoxon signed rank test was employed to reveal if there was a significant difference in audience perception between static and dynamic media contents for the experimental eye-tracking study. Thirdly, the IG engagement metrics were analyzed quantitatively in a visual graph representing the number of likes for each static poster and dynamic trailer for the selected 30 movies. Finally, theoretical frameworks such as the theory of planned behavior and the cognitive load theory were utilized to distinguish the audience's attitude, subjective norms, perceived behavioral control, intrinsic, germane cognitive loads, and extraneous.

3.5. Ethical Considerations

This research received formal approval from the Social, Humanities and Administrative Sciences Ethics Subcommittee at Eastern Mediterranean University (Ref No: ETK00-2024-0197), dated 27 November 2024. All participants were adult volunteers who gave informed consent prior to participating in the webcam-based eye-tracking experiments. Participation was entirely voluntary, and steps were taken to ensure data anonymity and confidentiality. The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and followed the NMSBA Code of Ethics for behavioral and neuromarketing research involving human participants.

4. Results and Discussion

A. Realeye.io Results for Fixations & Gazepoints on Both Audiovisual and Designs

Parameters of Realeye.io	Details
Sampling Rate	Up to 60 Hz
Accuracy	Average 124 pixels on desktops/laptops, 60 pixels on mobile devices
Precision	Average 76 pixels
Freedom of Head Movement	Limited; participants are asked to return to the original position if they move too much
Latency	Real-time, dependent on hardware and internet connection
Recommended Screen Size	Minimum resolution of 1024x968 pixels
Data Sample Output	CSV files including raw gaze data, fixations, duration, AOI data, attention, and emotional levels
Calibration Quality	Varies by calibration scheme; 13-point calibration offers higher accuracy
Environmental Conditions	Good lighting conditions recommended; light source should illuminate face evenly
Heatmap Resolution and Fixation Filter Settings	Customizable; can zoom in/out and adjust point size, Adjustable parameters like minimum fixation duration and gaze velocity threshold, Detailed statistics for specific areas within stimuli.

Table 1. Key Parameters of Realeye.io webcam-based eye-tracking

The parameters of RealEye.io as a webcam-based eye-tracking online software can be summarized as follows: It offers a frequency sampling rate of up to 60 Hz, an average accuracy of 124 pixels on desktops and laptops, and 60 pixels for mobile phones within an average precision level of 76 pixels. The freedom of head movement is limited, where participants are expected to avoid excessive motions to maintain data reliability and accuracy within the recommended screen resolution of at least 1024×968 pixels, due to the latency dependency on the utilized hardware, internet connection, and proper lighting conditions. The analytical dashboard of the software offers real-time data such as the number of fixations, gaze counts, average duration of fixation, filter settings, heatmap resolution, attention, and emotional engagement, with the option to export the findings in CSV format.

Participants	fixations	Frequency	Total time of fixations	Average fixation duration
1	146	28 Hz	43.8 sec	0.3
2	120	24 Hz	36 sec	0.3
3	153	28 Hz	46 sec	0.35
4	145	28 Hz	43.5 sec	0.3
5	143	28 Hz	42.9 sec	0.3
6	148	31 Hz	44.4 sec	0.3
7	186	31 Hz	55.8 sec	0.4
8	162	30 Hz	48.6 sec	0.35
9	156	30 Hz	46.8 sec	0.35
10	147	31 Hz	44.1 sec	0.3
11	189	28 Hz	37.8 sec	0.4
12	149	28 Hz	44.7 sec	0.3
13	136	30 Hz	40.8 sec	0.3
14	167	31 Hz	50.1 sec	0.35
15	181	31 Hz	32.4 sec	0.4

Table 2. Realeye.io Results for Dynamic Audiovisual Media Content

The eye-tracking results for the audiovisual stimuli showed varying numbers of fixations among the participants, between 186 and 120 fixations, with a mean of 155.2 (SD = 18.99); the frequency of eye movements also varied, with the lowest being 24 Hertz and the highest being 31 Hertz. The total time of fixations ranged from 32.4 seconds to 55.8 seconds, with a mean of 43.85 seconds (SD = 5.72). The average fixation duration was reasonably consistent among participants, ranging from 0.3 to 0.4 seconds.

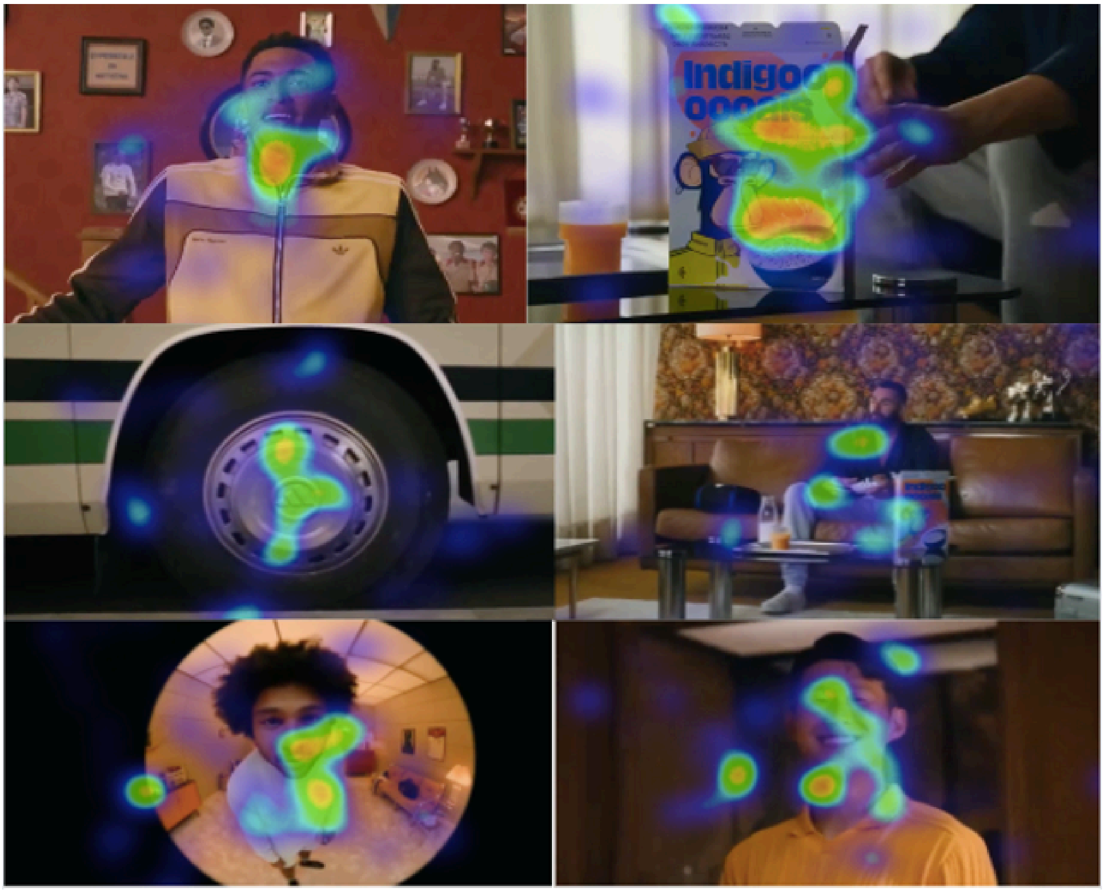

Figure 2. Gazes on the audiovisual clip.

Participants	fixations	Frequency	Total time of fixations	Average fixation duration
1	31	28 Hz	29 sec	0.35
2	18	24 Hz	19 sec	0.29
3	27	28 Hz	25 sec	0.35
4	28	28 Hz	25.3 sec	0.3
5	28	28 Hz	25.3 sec	0.3
6	29	31 Hz	26.2 sec	0.3
7	24	31 Hz	23 sec	0.4
8	27	30 Hz	25 sec	0.35
9	28	30 Hz	25.3 sec	0.35
10	29	31 Hz	27 sec	0.3
11	25	28 Hz	23.9 sec	0.4
12	27	28 Hz	26.7 sec	0.3
13	27	30 Hz	27.2 sec	0.3
14	26	31 Hz	24.3 sec	0.35
15	36	31 Hz	29.9 sec	0.4

Table 3. Realeye.io Results for Three Static Designs

The eye-tracking results for the three static designs showed varying fixations, between 36 and 18 fixations among the participants, with a mean of 27.33 fixations (SD = 3.79). The frequency of eye movements also varied, with the lowest being 24Hz and the highest being 31Hz. The total time of fixations ranged from 19 seconds to 29.9 seconds, with a mean of 25.4 seconds (SD = 2.59). The average fixation duration was reasonably consistent among participants, ranging from 0.28 to 0.4 seconds.

doi.org/10.32388/F16VXK

Figure 3. Gazes on the three static designs.

We derived K, calculated for each participant, as the mean difference between standardised values (z-scores) of each saccade amplitude (ai+1) and its preceding fixation duration (di):

$$K_i = \frac{d_i - \mu_d}{\sigma_d} - \frac{a_{i+1-\mu_a}}{\sigma_a} \quad (1)$$

 doi.org/10.32388/F16VXK

Where μd and μa are the mean fixation duration and saccade amplitude, respectively, and σd and σa are the fixation duration and saccade amplitude standard deviations, computed over all n fixations and, hence, n Ki coefficients (i.e., over the entire duration of stimuli presentation).

We can now define that if, at a given moment:

- K > 0 indicates relatively long fixations, followed by short saccade amplitudes, indicating focal processing.
- K < 0 indicates relatively short fixations, followed by relatively long saccades, indicating ambient processing. K = 0 indicates a rare situation in which a person exhibits long saccades preceded by long fixations or short fixations followed by short saccades.

$$k = \frac{1}{n} \sum_{n} k_i \qquad (2)$$

doi.org/10.32388/F16VXK

B. Attention Measurement of Realeye.io through emotional levels and K-Coefficient means for Audiovisual and designs

Figure 4. Realeye.io Analytical Dashboard for Emotional Responses.

The Realeye.io dashboard visualization helps in collecting emotional response data such as happiness and surprising levels, attention, attention normalized, and attention raw measurements, with options for heatmap display and analyzing different areas of interest (AOIs), allowing for detailed analysis of visual attention patterns, user behavior, and comprehensive visual attention data gathering.

doi.org/10.32388/F16VXK

Part.	Happy	Surprise	Att. Raw	Att. Normalized	Att. Mean Raw
1	0.23 to 1	0.05 to 0.59	-1 to 0.45	- 4.59 to 2.23	0.07
2	0.22 to 0.67	0.39 to 0.93	-1 to 0.71	-3.4 to 2.05	0.02
3	0.28 to 0.55	0.05 to 0.95	-0.96 to 0.51	-4.19 to 2.26	0.23
4	0	0.39 to 0.54	-0.98 to 0.41	-4.14 to 1.67	0.25
5	0	0	-1 to 2.16	-4.8 to 2.16	0.18
6	0.21 to 0.29	0.38 to 0.95	-1 to 0.35	-4.84 to 1.68	0.27
7	0.23 to 0.74	0.05 to 0.99	-0.99 to 0.94	-3.23 to 3.06	0.34
8	0.2 to 0.42	0.19 to 0.67	-1 to 0.75	-2.92 to 2.19	0.37
9	0.21 to 0.33	0.38 to 0.87	-1 to 0.4	-4.48 to 1.77	0.29
10	0.28 to 0.83	0.38 to 0.55	-0.9 to 0.33	-4.45 to 1.55	0.28
11	0 to 0.2	0.39 to 0.9	-0.99 to 0.83	-3.95 to 3.29	0.39
12	0.21 to 0.39	0.39 to 0.95	-1 to 0.37	-4.19 to 1.55	0.20
13	0.2 to 0.34	0.39 to 0.52	-1 to 0.46	-4.78 to 2.2	0.38
14	0.2 to 0.6	0.04 to 0.64	-0.99 to 0.44	-3.52 to 1.56	0.38
15	0.2 to 1	0.04 to 0.43	-1 to 0.55	-4.58 to 2.54	0.23

Table 4. Results of Emotional levels & Attention for the Audiovisual media content

The table explores the audience's emotional and attentional engagement patterns with the dynamic audiovisual media content across the 15 selected participants. Happiness levels varied from 0 to 0.83; surprise levels ranged between 0.05 to 0.99, suggesting a moderately balanced degree.

doi.org/10.32388/F16VXK

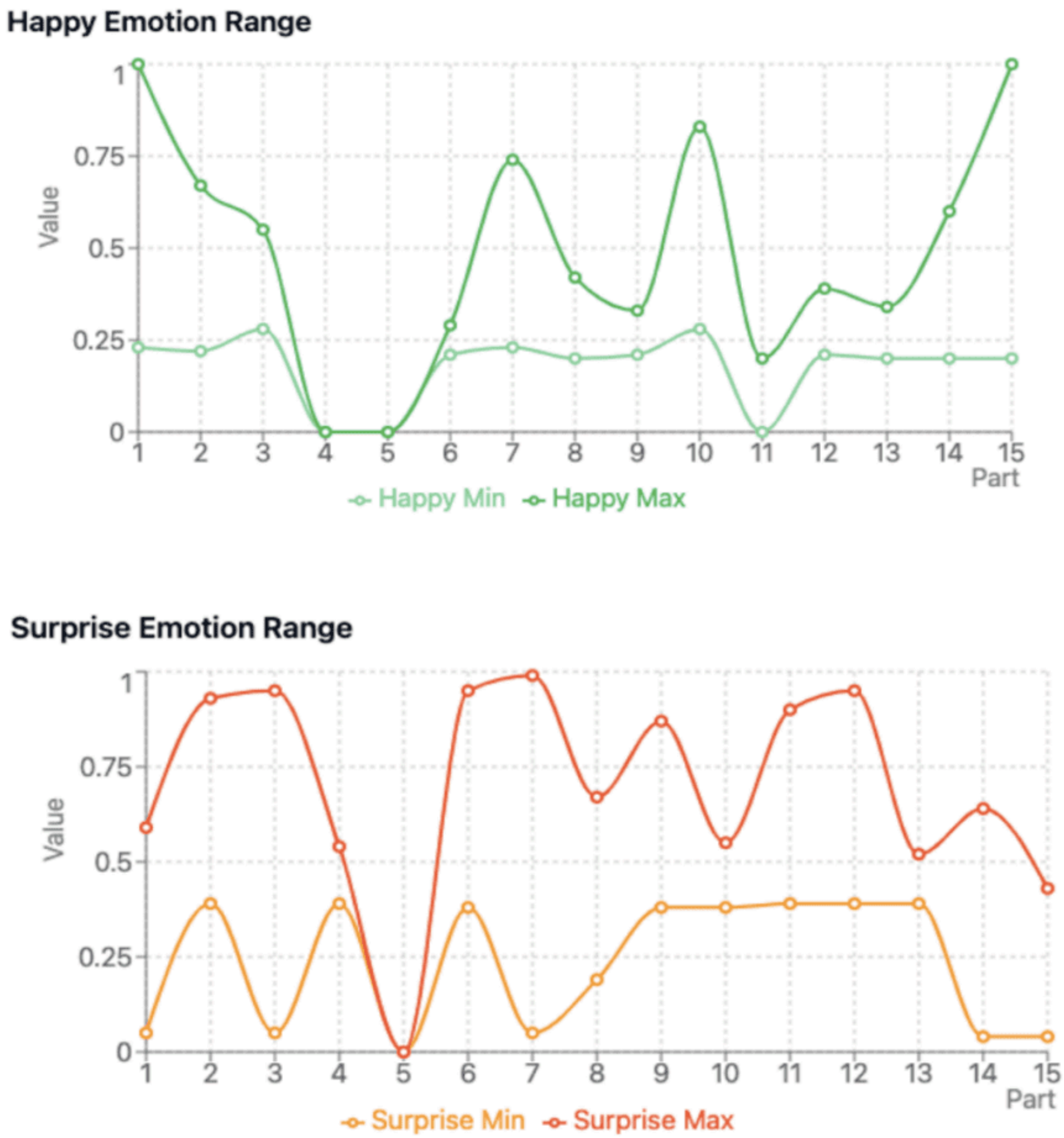

Figure 5. The range of happiness and surprise levels in dynamic media

Additionally, the attention metrics showed exciting variations where the mean raw attention varied between 0.02 and 0.39, with participants having high attention levels of 0.34, 0.37, and 0.39. Meanwhile, the attention raw and normalized varied between (-1 and 0.75) to (-4.59 and 3.06), respectively, indicating valuable differences in how viewers responded and interacted with the exposed format.

doi.org/10.32388/F16VXK

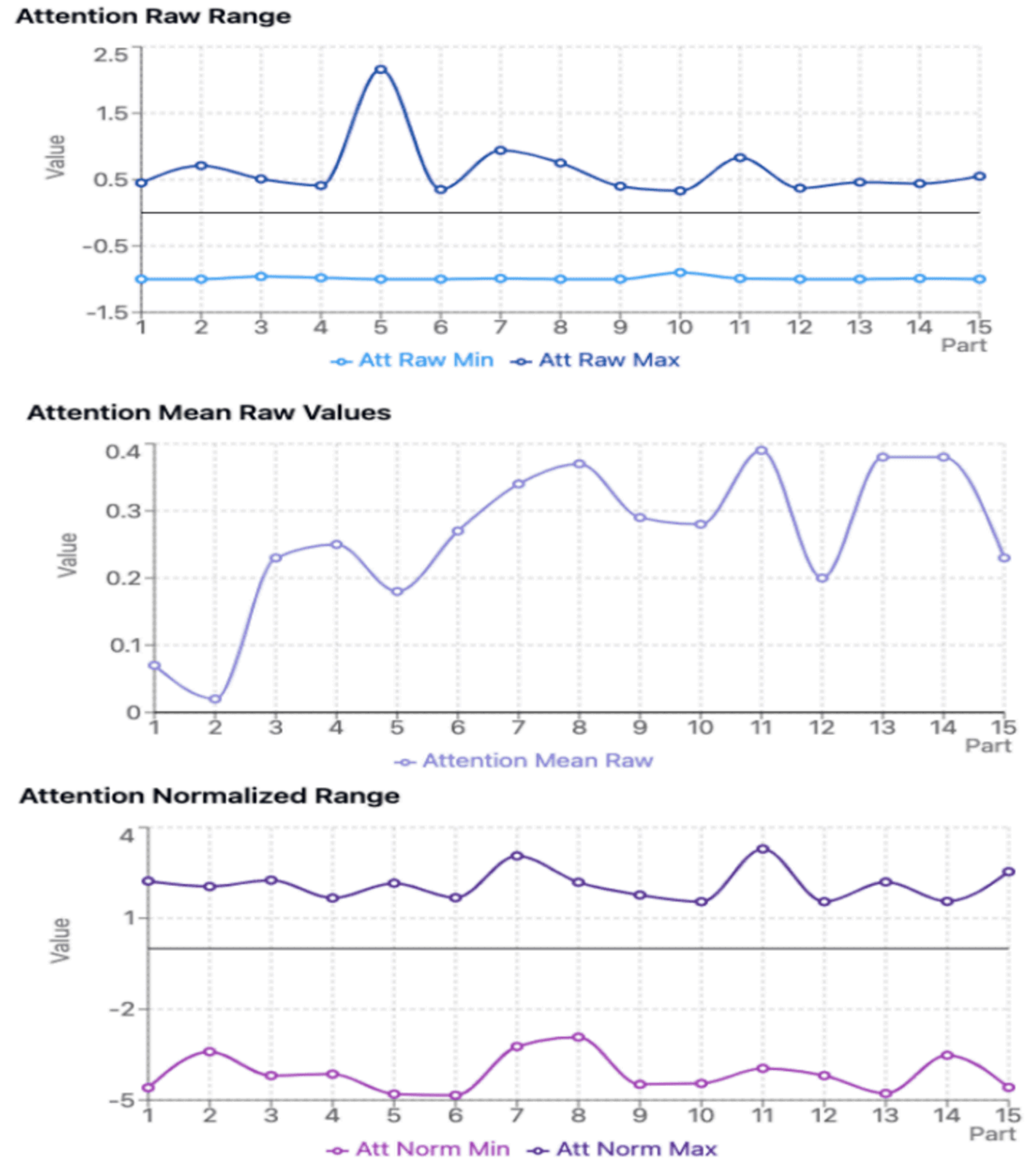

Figure 6. The range of attention levels in dynamic media

Part.	Happy	Surprise	Att. Raw	Att. Normalized	Attention Mean Raw
1	0.22 to 0.6	0.39 to 0.59	-1 to 0.7	-3.52 to 2.48	0.47
2	0.22 to 0.67	0.38 to 0.95	-0.66 to 1	-2.17 to 3.29	0.61
3	0.23 to 0.64	0.05 to 0.88	-1 to 0.73	-2.94 to 2.15	0.38
4	0.21 to 0.84	0.05 to 0.94	-0.98 to 0.5	-3.73 to 1.91	0.30
5	0.20 to 0.49	0.06 to 0.51	-1 to 0.67	-4.15 to 2.8	0.17
6	0.21 to 0.43	0.19 to 0.61	-1 to 0.7	-3.16 to 2.54	0.29
7	0	0.05 to 0.51	-0.93 to 1	-2.84 to 3.04	0.46
8	0	0	-1 to 0.55	-3.9 to 2.14	0.28
9	0	0.2 to 0.41	-1 to 0.63	-3.28 to 2.06	0.49
10	0.21 to 0.25	0.38 to 0.57	-1 to 0.86	-3.49 to 3	0.43
11	0	0.38 to 0.95	-0.82 to 0.95	-2.86 to 3.3	0.17
12	0.27 to 0.79	0.38 to 1	-1 to 0.76	-3.43 to 2.59	0.32
13	0.22 to 0.27	0	-1 to 0.8	-2.73 to 2.18	0.26
14	0.21 to 0.25	0.38 to 0.99	0.1 to 0.44	-5.69 to 2.48	0.09
15	0.20 to 1	0.39 to 0.95	-1 to 0.88	-2.73 to 2.39	0.29

Table 5. Results of Emotional Levels and Attention for the Three Designs

The table showed the audience's perception through 3 static designs exposed consecutively to participants in 60 seconds, 20 seconds for each, revealing more varied and muted emotional measures in contrast to the dynamic audiovisual where more viewers had lower happiness and surprise levels, even up to 0, suggesting less consistent stimulation and engagement emotionally.

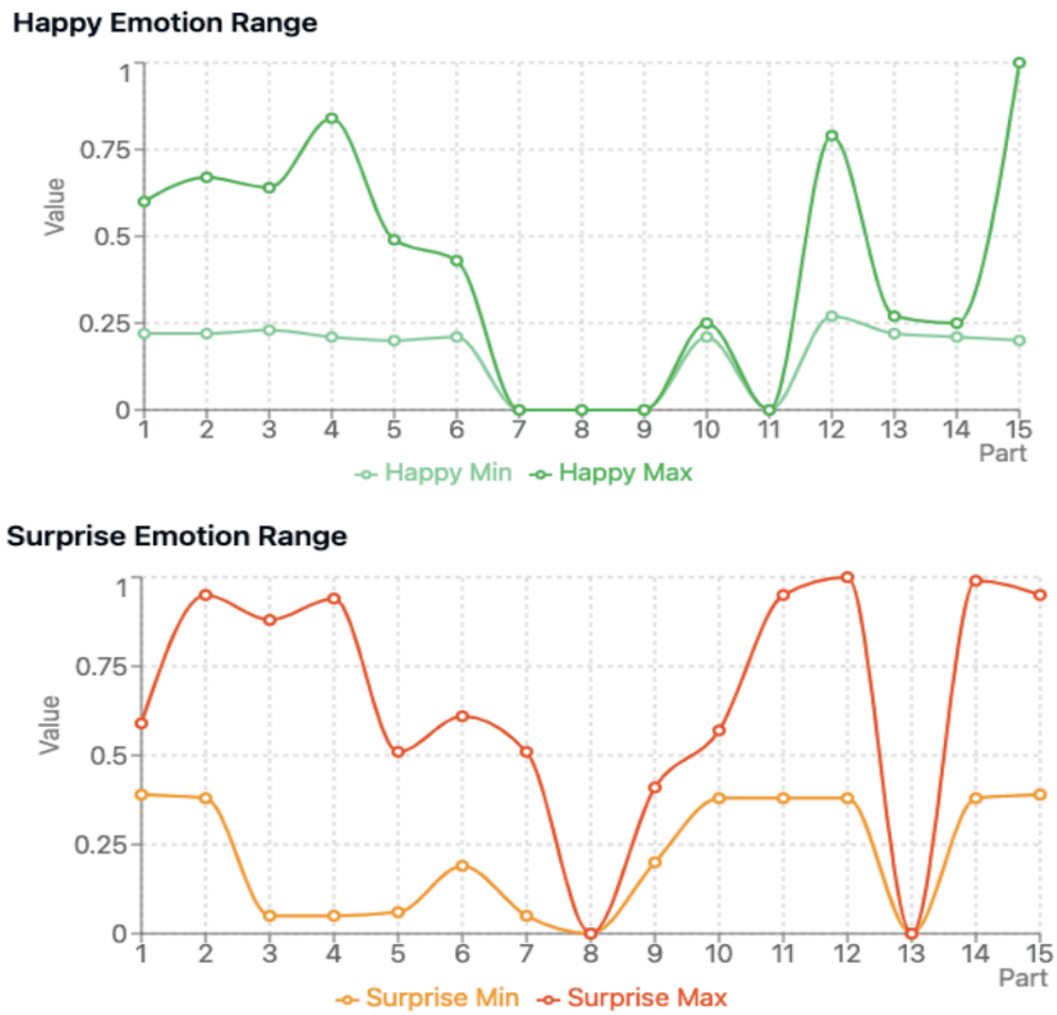

Figure 7. The range of happiness and surprise levels in static media

Attention metrics present more variability through the varied results of the mean raw attention ranging between 0.09 and 0.61, with participants achieving 0.61, 0.43, and 0.49 as the most attentive. The attention raw and normalized varied between (-1 to 0.86) and (-5.69 to 3.30), respectively, emphasizing and highlighting the notable significant variations and differences in how audiences engaged and interacted with the three static designs.

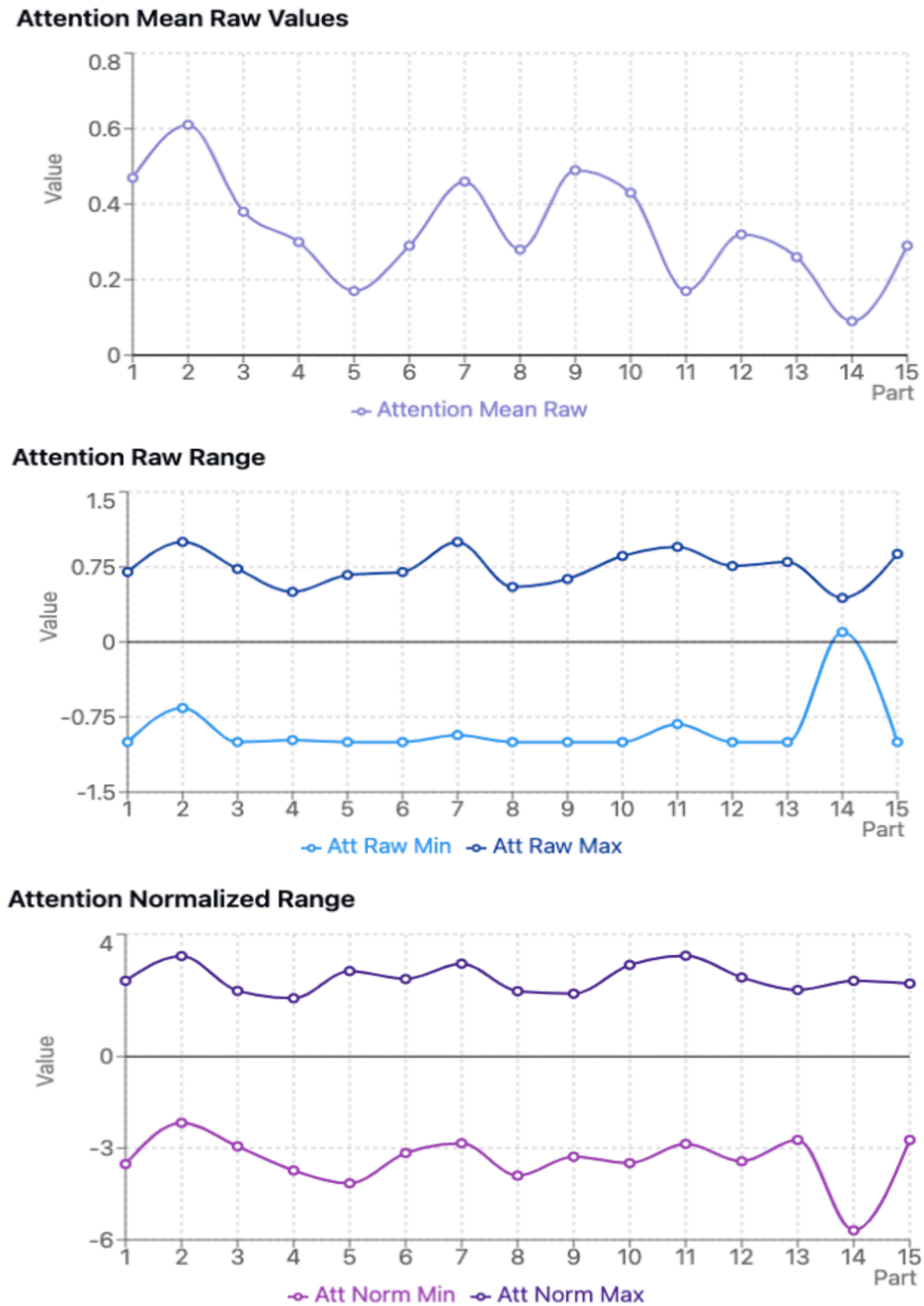

Figure 8. The range of attention levels in static media

These findings strongly support **H1**, aligning with the assertion that motion elements effectively capture attention due to the human visual system's evolutionary predisposition to detect movement. The significantly higher fixation counts and longer engagement times for dynamic content confirm Federico's[10] observation that motion not only attracts initial attention but sustains it through narrative flow and dynamic changes. As Holmqvist[7] noted, these eye-tracking metrics provide objective insights into users' visual attention patterns, offering quantifiable evidence of engagement differences. The consistency in average fixation duration (0.3-0.4 seconds) across both formats, coupled with the stark differences in total fixations, indicates that viewers maintain similar processing depth while engaging more frequently with dynamic content.

C. Comparative analysis between 30 movie's static posters and dynamic trailers through Instagram

Popular social media platforms like Instagram have 2 billion active users in the rapidly evolving digital media landscape. Audience behavior and engagement metrics are essential to understanding, framing, and analyzing various visualised media content formats through static posters and dynamic trailers. Thirty movies have been selected to be examined through viewers' number of likes on the official authorised pages of each film, leading to more strategic, engaged, personalised media content development by professionals, businesses, and organizations.

Movie	Static poster likes	Dynamic Trailer likes
M3gan	18,600	24,300
After Yang	1,141	22,400
Blade Runner	3,374	7,523
Matrix	33,400	6,430
Upgrade	536	11,100
West World	71,100	374,000
Terminator	12,900	58,200
Deadpool	93,900	162,000
Captain America	68,700	248,000
SpiderMan	65,300	19,800
Superman	14,000	27,700
Titanic	45,900	56,500
TheGodFather	136,000	19,800
LordOfRings	5,656	25,900
Oppenheimer	35,100	65,300
The Whale	4,814	45,100
Tenet	6,654	45,000
Nope	76,200	285,000
Jojo rabbit	15,600	143,000
Knives Out	20,600	188,000
Mission Impossible	955,000	188,000
Little Mermaid	7,184	39,600
Joker	129,000	23,100
Mufasa LionKing	219,000	924,000
The Angel Has Fallen	4,176	7,660

Movie	Static poster likes	Dynamic Trailer likes
Get Out	1,426	51,800
1917	4,785	40,300
Interstellar	42,300	334,000
A Star is born	52,600	304,000
A Ghost Story	2,965	830

Table 6. IG Comparative Analysis Between 30 Movies' Likes on Static Posters and Dynamic Trailers

The table represents detailed quantitative numerical data to assess and compare the differences between likes on 30 movie static posters and dynamic trailers. Generally, the static posters' likes varied between 536 and 965,000, with a mean of 71,597 (SD = 174,257), while the dynamic trailers' likes varied between 830 and 924,000, with a mean of 124,945 (SD = 187,019). Movies like Mufasa the Lion King and Interstellar showcase and draw attention to the dominant and overwhelming preference for dynamic trailers, with engagement metrics exceeding and outpacing static posters by four times. Conversely, films such as Joker, a static poster, achieved 129,000 likes and just 23,000 likes for the dynamic trailer. Movies like (A Ghost Story) show low engagement metrics for static and dynamic media formats, reflecting and demonstrating the movie's niche and appealing to a specific audience through promotional, advertising, and marketing strategies. Exceptionally, the Mission Impossible movie gathered 900k for its poster, surpassing the trailer's 250k likes, highlighting the complex assessment of audience engagement in the digital media landscape.

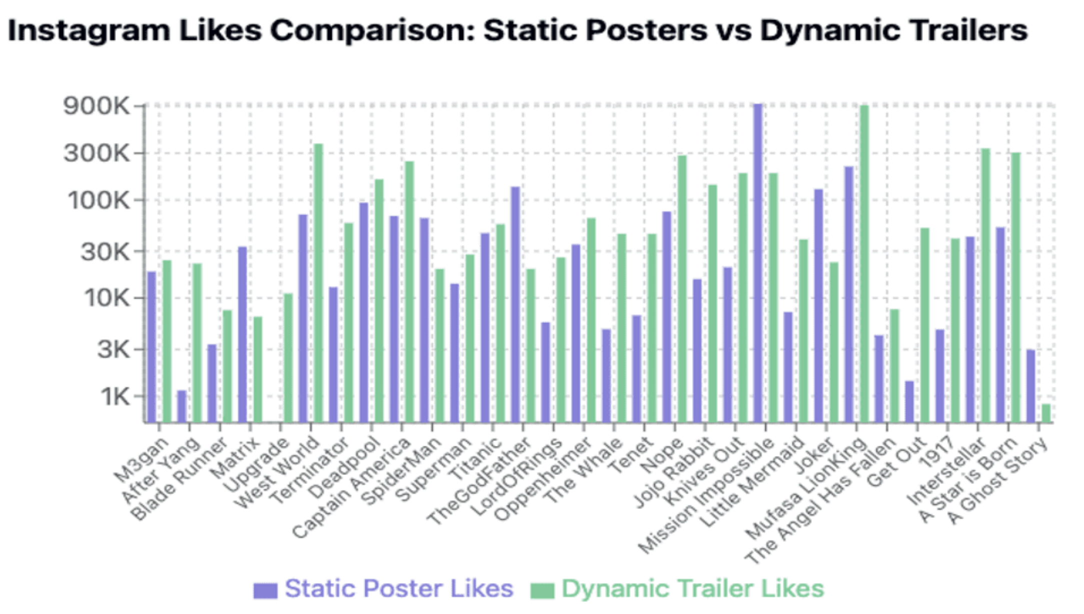

Figure 9. Instagram engagement metrics analysis of 30 movies.

The bar chart is a numerical statistical analysis of audience engagement between static posters and dynamic trailers, as the data was collected in the previous table. The bars in green reveal the number of likes for the trailers, while the bars in purple represent the number of likes for the static posters. The chart shows consistent outperformance of dynamic trailers over static posters, as Mufasa the Lion King achieved 219,000 likes for the poster, while almost 924,000 likes for the trailer. Additionally, West World shows the same outpacing for dynamic trailers, with 374,000 likes and 71,000 likes for posters. Also, the Nope movie gathers 285,000 likes for the trailer and just 76,200 likes for the static poster. Meanwhile, Mission Impossible gathered over 900k likes for the static poster, surpassing the dynamic trailer's 250k likes. The comparative analysis through IG engagement metrics highlights the significant difference and the importance of developing audiovisual media content for professionals, companies, and organizations in engaging their targeted viewers and audience by leveraging their preferences on visual storytelling techniques and formats, even though static posters still play a core and fundamental role in promotional advertising and marketing campaigns, highlighting the complex assessment of audience engagement.

These findings largely support **H2**, consistent with Habibi's[23] observation that dynamic media formats consistently outperform static content in eliciting interaction across social platforms. The exceptions align with Dai's[26] assertion that credibility and accessibility increase perceived behavioral control, making users more likely to engage. For example, the Joker poster became an iconic cultural symbol, potentially increasing its perceived value and shareability despite being static. The findings also reinforce Pittman's[22] analysis connecting engagement levels to cognitive load, suggesting that users employ heuristic cues to evaluate content credibility and form engagement intentions. The predominantly higher engagement with dynamic content supports Truong's[3] finding that ease of access and perceived value are strong predictors of digital engagement.

D. SPSS

1) Normality tests through One-Sample Kolmogorov-Smirnov Test

The normality test has been utilized through the Kolmogorov-Smirnov test within the sample size (N=15) for the number of fixations between static and dynamic media content measurements. Consequently, the test statistic was recorded as 0.161, indicating the significant difference between the observed and expected distributions consistently across absolute, positive, and negative categories and groups. The p-value of 0.200 affirms and validates that the data were normally distributed. Additionally, the same test was conducted to verify and support the normal distribution where the total time of fixations for both static designs and dynamic audiovisuals was examined as the test statistic equals 0.168 with a maximum positive difference of 0.107 and a maximum negative difference of -0.168 through the most significant and maximum absolute deviation and discrepancy between the empirical and theoretical cumulative distribution functions. The p-value again equals 0.200, indicating and revealing that the data were normally distributed. However, despite the normality assumption being validated through the Kolmogorov-Smirnov test, the small sample size (N=15) necessitates the use of a non-parametric approach to ensure the reliability of comparative statistical analysis. Therefore, the Wilcoxon Signed-Rank Test was employed to compare the number and duration of fixations between static and dynamic media content.

2) Paired T-test (Wilcoxon Signed Rank Test)

The Wilcoxon Signed Ranks test indicated significant differences between the number of fixations and the total time of fixations in static and dynamic media content. The test statistic Z equals -3.408, and $P < 0.001$, suggesting the absolute deviation and differences statistically.

doi.org/10.32388/F16VXK

		N	Mean Rank	Sum of Ranks	Test Statistics	
					Z	P Value
Static fixations and Dynamic fixations	*Negative Ranks*	15^a	8.00	120.00		
	Positive Ranks	0^b	.00	.00	-3.048^b	<0.001
	Ties	0^c				
	Total	15				
Average duration fixation in static and average duration fixation in dynamic	*Negative Ranks*	15^d	8.00	120.00	-3.408^b	<0.001
	Positive Ranks	0^e	.00	.00		
	Ties	0^f				
	Total	15				

Table 7. Results of Wilcoxon Signed Rank Test

E. Application of Theory of Planned Behavior (TPB) and Cognitive Load Theory (CLT)

1) Theory of Planned Behavior

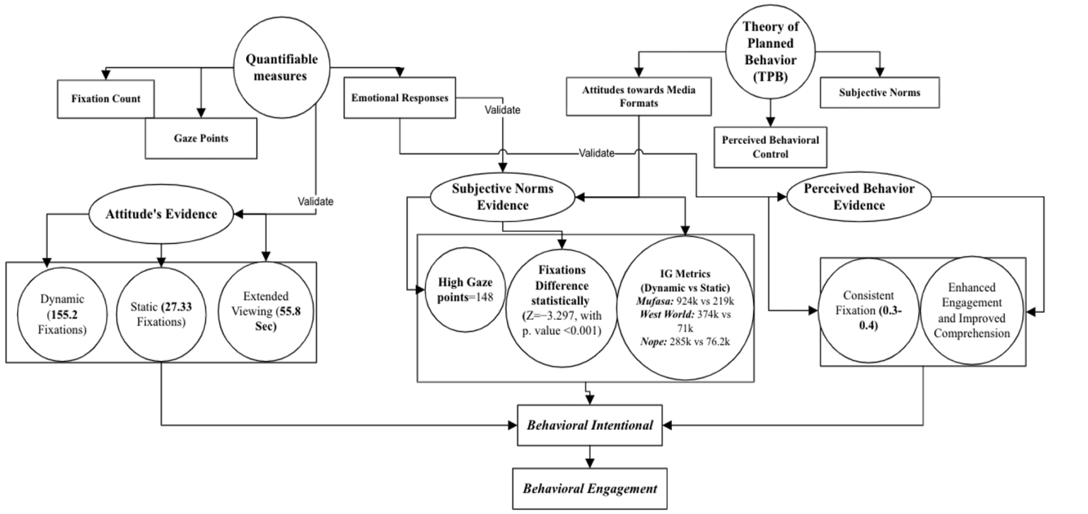

Figure 10. Application of the Theory of Planned Behavior (TPB).

The Theory of Planned Behavior (TPB) serves as a critical framework lens for analyzing audience engagement by analyzing attitudes, subjective norms, and the perceived controlled behavior to different examined media formats as dynamically or statically through measurable factors such as numbers of fixations, the total time of fixations, and the emotional and attention measures. The research findings revealed a strong preference for dynamic audiovisual over static through a higher average number of fixations of 155.2 and 27.33. Also, the extended total time of fixations on dynamic is 55.8 seconds. Consistent fixation durations (0.3 to 0.4 seconds) and the significant differences in normalized attention scores ($Z = -3.297$, $p < 0.001$), **IG metrics (dynamic vs static) where** Mufasa movie: 924k vs 219k likes, West World movie: 374k vs 71k likes, and Nope movie: 285k vs 76.2k likes, confirm and validate the positive attitude toward the interactive content and visual appeal formats as more effective and impactful in the context of advertising, electronic journalism, marketing, cinema, and media production.

These findings support **H3**, demonstrating significantly higher eye-tracking metrics for dynamic content. The results align with Fielden's[4] extension of TPB, showing that media elements can shape audience attitudes and trust. The more consistent emotional responses to dynamic content reflect Zhang's[18] and Shesterina's[19] findings that emotionally resonant content enhances viewer satisfaction and promotes engagement behavior. The K-Coefficient analysis reveals that dynamic content facilitated more focused processing, suggesting that viewers found it easier to follow and process; a key element of perceived behavioral control in TPB. This supports Mishra's[17] finding that emotionally engaging content enhances viewer satisfaction, which further reinforces positive attitudes toward the content.

2) Cognitive load theory (CLT)

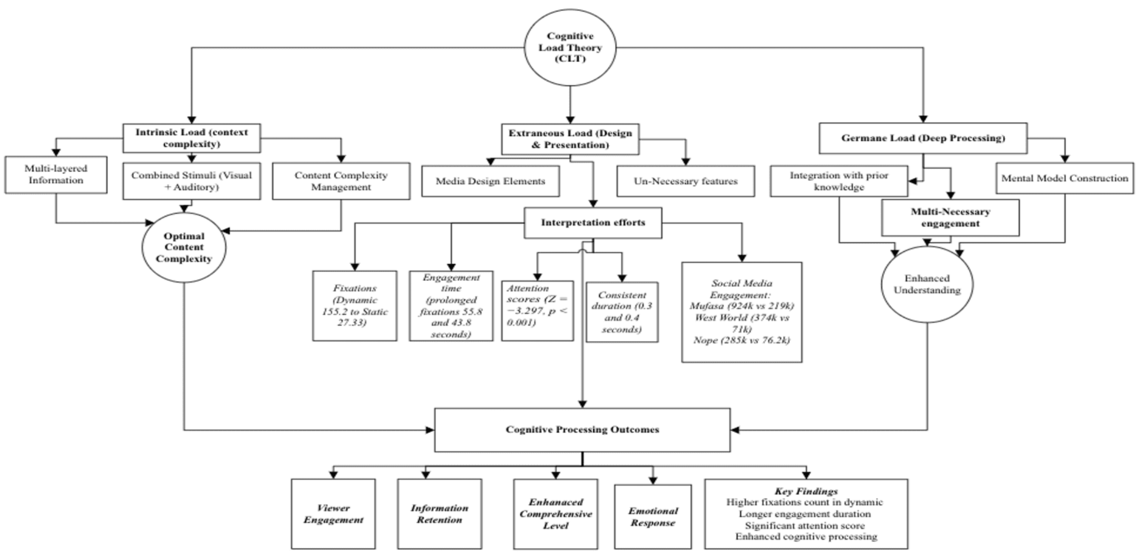

Figure 11. Application of the Cognitive Load Theory (CLT).

Cognitive Load Theory (CLT) was applied to evaluate the effects of intrinsic (complexity of the media content), extraneous (which arises from media design and presentation), and germane cognitive loads (the cognitive effort required for deeper learning) through the eye-tracking comparative experimental case study findings as number of fixations, total time of fixations, emotional and attentional findings such as consistent fixation durations across participants (0.3–0.4 seconds), fewer fixation counts and gaze points (e.g., 27.33 fixations for static designs compared to 155.2 for audiovisual), longer engagement times, such as 43.8 seconds on dynamic content, prolonged fixation durations observed in participants like (55.8 and 37.8 seconds, respectively), and higher normalized attention scores ($Z = -3.297$, $p < 0.001$), **IG metrics (dynamic vs static) where** Mufasa movie: 924k vs 219k likes, West World movie: 374k vs 71k likes, and Nope movie: 285k vs 76.2k likes, supports meaningful cognitive processing, which is vital for learning and comprehension, and further affirms the effectiveness of dynamic audiovisual content in promoting engagement and deeper cognitive connection, facilitating adequate attention and information retention.

These findings support **H4**, consistent with Sweller's[5] and Plass's[6] assertions that dynamic audiovisual content can reduce extraneous load by guiding viewers through visual sequences. The eye-tracking data revealed that dynamic content facilitated more efficient cognitive processing, allowing viewers to engage more deeply with the material. This aligns with Pittman's[22] research showing that media with lower cognitive demands typically result in higher user satisfaction and behavioral engagement. The correlation between normalized attention scores and Instagram engagement metrics supports the CLT prediction that content optimizing cognitive load will generate a stronger user response.

Merging and consolidating TPB and CLT theories with numerical quantifiable measures provides a holistic, comprehensive framework for analyzing the significant differences between static and dynamic media content affecting the audience's perception and engagement. The Theory of Planned Behavior illuminates adjusting and calibrating media content development with the audience's attitudes and norms. In addition, CLT reveals how cognitive load management and strategising can improve and enhance attention and emotional behavioral engagement.

5. Conclusion

The eye-tracking findings for the dynamic audiovisual media contents evoke a higher number of fixations ranging between 120 and 189 fixations, and a longer total time of fixations varying between 32.4 and 55.8 seconds within a consistent average fixation duration of 0.3 to 0.4 seconds. On the other hand, the findings for the static designs showed a lower number of fixations, 18 to 36, and a lower total time of fixations ranging between 19 and 29.9 seconds. The results revealed that the dynamic audiovisual format effectively preserves and sustains audience engagement. K-Coefficient analysis demonstrates dominance and prevalent attention to focused processing ($K > 0$) in dynamic content, distinguished by longer fixations and shorter saccades, in contrast to varied processing patterns in static designs.

The findings for the emotional and attentional responses to the dynamic audiovisual reveal greater flexibility, as happiness and surprise levels ranged between 0 to 0.83 and 0.05 to 0.99, respectively. In comparison, the results for the static evoked lower emotional engagement within higher frequencies of 0 values. The metric findings for the audience's attention verify the higher engagement and interaction in the dynamic media content format within raw attention measures, reaching 0.39 and a broader normalized range between -4.59 and 3.06, in contrast to the static, which displayed less consistent and reduced attention reactions and responses.

The statistical analysis through the Kolmogorov-Smirnov test confirmed that the data for the number of fixations and the total fixation time in static and dynamic followed a normal distribution with a P-value of 0.200. Finally, the Wilcoxon Signed Ranks test declares and approves the significant differences between the metrics of the number of fixations and total fixation time in static and dynamic media formats with a test statistic $Z = -3.408$ and $P < 0.001$.

The comparative analysis of IG engagement metrics through the number of likes between 30 static posters and dynamic trailers for selected movies demonstrates more engagement for dynamic trailers through films like The Lion King and Interstellar by substantial considerable gaps and margins, even though anomalies like the Joker movie, where the number of likes for the static poster surpassed and exceeded the dynamic trailer. Movies like A Ghost Story accumulated low engagement, and both posters and trailers showcase that variations were based on the audience's preferences and perception, the quality of the film, and marketing and advertising strategies. While static posters persist as a core element of advertising campaigns in the digital media and cinema landscape, the research study highlights the significance of understanding the psychological and cognitive responses of audience engagement to effective media content development.

a) Possibilities

The findings of the eye-tracking experiment through the dynamic audiovisual media content, where the heatmaps and gaze points demonstrate accurate fixations on famous football stars and branding logos like the South Korean Son, the French Kareem Benzema, and Indigoo Oooaals, suggest the audience's attention is drawn to significant figures, familiar faces, and product branding. The Consecutive Eye Movement Patterns highlight the celebrity and brand accreditation in effective engaging strategies and enhancing brand recall for communication, advertising, and media.

doi.org/10.32388/F16VXK

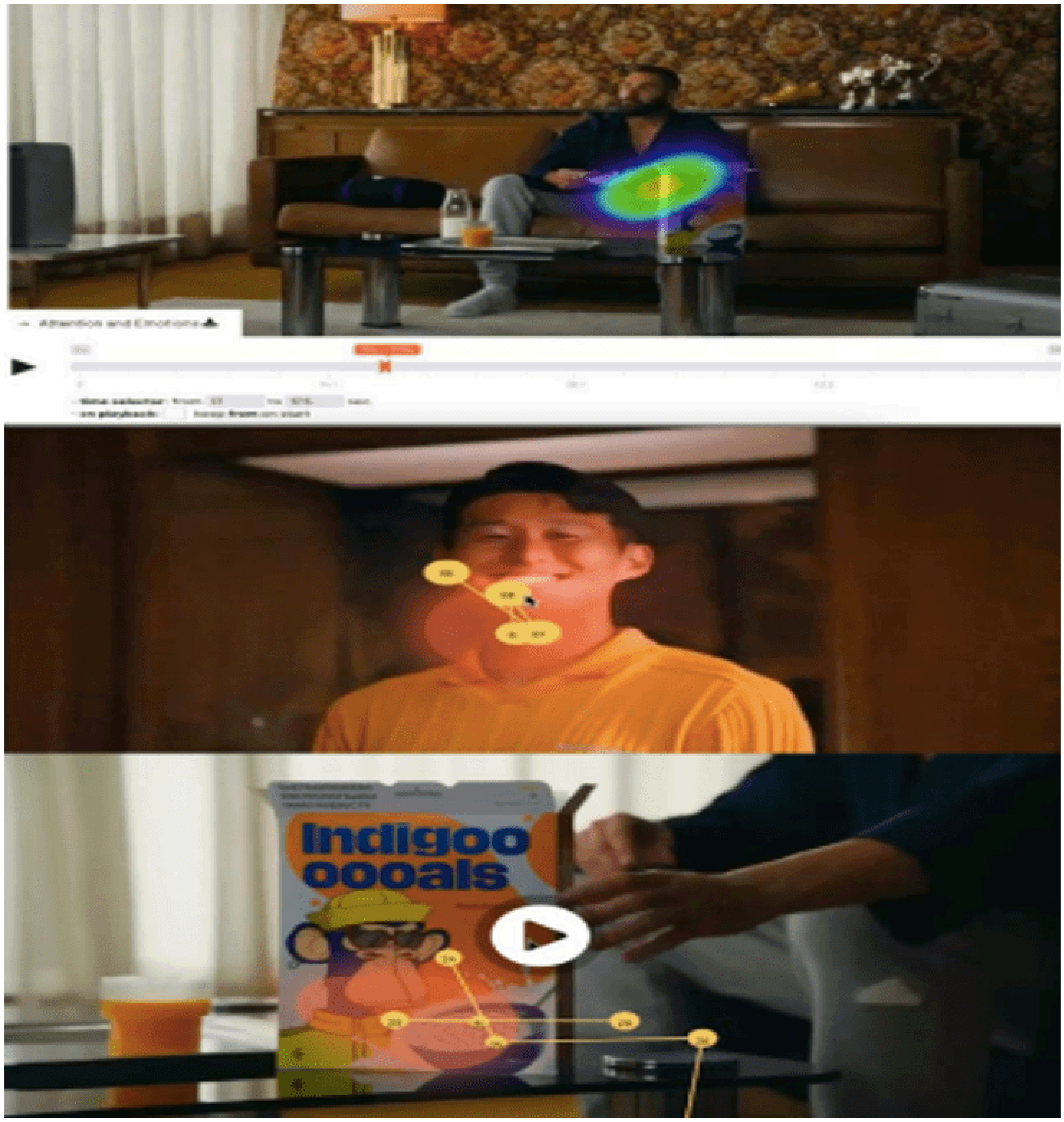

Figure 12. Accurate fixations and gaze points.

Realeye.io showed valuable technical capabilities, validating its utility as an eye-tracking tool for researchers, advertisers, media professionals, and marketers through gaze, fixations, and eye movement within approximately 110 pixels and a frequency of up to 60 Hz through options such as an online analytical dashboard and exporting detailed Excel sheets, facial coding, surveys module, API access for data export, and online panellists remotely via webcam as a scalable and cost-effective solution. The level of accuracy allows professionals to analyze individual design principles, elements, and visual stimuli,

doi.org/10.32388/F16VXK

enhancing the development of more effective and engaging media communication formats and strategies.

The possibilities of this study extend to multiple domains, offering valuable insights for both academic research and practical applications in media production, marketing, and communication strategies. The integration of eye-tracking technology and social media engagement metrics provides a methodological framework that can be expanded to analyze user interaction across diverse media platforms, including virtual reality, augmented reality, and interactive digital experiences. Additionally, by establishing a theoretically grounded approach through TPB and CLT, this study sets a foundation for future research to explore the cognitive and behavioral impacts of evolving media formats. The findings can inform content creators, advertisers, and user experience designers in optimizing visual content to maximize audience engagement, retention, and cognitive processing efficiency.

b) Limitations

While there is a nuance of accurate findings and measures, limitations such as webcam calibration, lighting conditions, and participant distractions can lead to the figure above showing all the fixations clustered in the bottom-left corner, far from any related subjects and objects such as the road, the bus, and the football stars, highlighting the crucial need and necessity of following a controlled experimental environment to ensure accurate and reliable findings are collected.

Figure 13. Inaccurate fixations.

The limitations of the study can be summarized as follows: the relatively small sample size in the eye-tracking experiment may limit the generalizability of the findings, as the engagement patterns observed may not fully represent a broader audience. Additionally, the use of Realeye.io as a single eye-tracking tool introduces potential constraints regarding calibration accuracy and environmental factors that may affect fixation and saccade measurements. The reliance on Instagram engagement metrics as an indicator of audience interaction presents another limitation, as likes and shares do not fully capture cognitive engagement or deeper emotional responses. Moreover, the study does not account for demographic variations, cultural differences, or content preferences, which could influence engagement with static and dynamic media content.

The following can be recommendations for future directions and research:

Future research should incorporate a larger sample of participants from diverse demographics and sectors to improve the generalizability and applicability of the results and findings, offering a broader and more expansive lens on patterns for more effective engagement.

Employing more neuroscience techniques and data analytics, such as EEG headbands, fMRI, stress level, and even heart rate measures, will demonstrate a wider array of metrics offering detailed analysis of audience perception.

Utilizing more media formats to be analyzed, such as interactive media, augmented reality, and virtual reality, could expand the scope beyond static and dynamic, providing valuable findings and metrics for audience engagement.

More social media engagement metrics, such as Twitter (X), Facebook, and TikTok, will be combined through more profound comments and sentiment analysis.

Conducting longitudinal studies to reveal the metrics and analysis over time, especially with repeat exposure to specific media formats.

Exploring the role of culture, demographics, and organizational contexts in shaping the audience's engagement and perception of media content can help identify and analyze these variables.

Statements and Declarations

Conflicts of Interest

The authors declare no conflicts of interest related to this study. No financial, personal, or professional relationships have influenced the research design, data collection, analysis, or interpretation of results. The study was conducted independently, with no external funding or commercial affiliations affecting its outcomes. Any potential biases have been addressed to ensure objectivity and transparency in the research process.

Ethics

This research was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and followed the NMSBA Code of Ethics, particularly relevant to behavioral and neuromarketing research practices.

This study received formal approval from the Social, Humanities and Administrative Sciences Ethics Subcommittee at Eastern Mediterranean University (Ref No: ETK00-2024-0197), dated 27 November 2024.

Informed Consent

All participants voluntarily took part in the eye-tracking experiments after providing informed consent. The study involved non-clinical behavioral research with adult participants, and care was taken to ensure full anonymity and confidentiality of all collected data.

References

1. [a, b] *Li PP, Zhong F (2022). "A study on the correlation between media usage frequency and audiences' risk perception, emotion and behavior." Frontiers in Psychology.* ***12****.*
2. [a, b, c] *Ajzen I, Schmidt P (2020). "Changing behavior using the theory of planned behavior." The handbook of behavior change. 17–31.*
3. [a, b, c] *Truong Y (2008). "An evaluation of the theory of planned behaviour in consumer acceptance of online video and television services." The Electronic Journal Information Systems Evaluation.* ***12****(2):177–186.*
4. [a, b, c] *Fielden N, Holch P (2022). "Exploring the influence of social media influencers on intention to attend cervical screening in the UK: utilising the theory of planned behaviour." Cancer Control.* ***29****:Article 10732748221079480.*
5. [a, b, c, d] *Sweller J, Van Merrienboer JJ, Paas FG (1998). "Cognitive architecture and instructional design." Educational Psychology Review.* ***10****:251–296.*
6. [a, b, c, d] *Plass JL, Kalyuga S (2019). "Four ways of considering emotion in cognitive load theory." Educational Psychology Review.* ***31****:339–359.*
7. [a, b, c] *Holmqvist K, Nyström M, Andersson R, Dewhurst R, Jarodzka H, Van de Weijer J (2011). Eye tracking: A comprehensive guide to methods and measures. Oxford: OUP Oxford.*
8. [a, b] *Wisiecka K, Krejtz K, Krejtz I, Sromek D, Cellary A, Lewandowska B, Duchowski A (2022). "Comparison of webcam and remote eye tracking." 2022 Symposium on eye tracking research and applications. 1–7.*
9. [^] *Klimmt C, Vorderer P (2003). "Media psychology “is not yet there”: Introducing theories on media entertainment to the presence debate." Presence.* ***12****(4):346–359.*
10. [a, b, c] *Federico G, Ferrante D, Marcatto F, Brandimonte MA (2021). "How the fear of COVID-19 changed how we look at human faces." PeerJ.* ***9****:e11380.*
11. [^] *Miller A, Leshner G (2007). "How viewers process live, breaking, and emotional television news." Media Psychology.* ***10****(1):23–40.*
12. [^] *Wang X, Hickerson A (2016). "The role of presumed influence and emotions on audience evaluation of the credibility of media content and behavioural tendencies." Journal of Creative Communications.* ***11****(1):1–16.*
13. [^] *Duchowski A, Duchowski A (2007). "Eye tracking techniques." Eye tracking methodology: Theory and Practice. 51–59.*
14. [^] *Wielgopolan A, Imbir KK (2024). "More than just ambivalence: the perception of emotionally ambiguous words on the spaces of origin and activation indexed by behavioural and webcam-based eye-tracking correla*

tes." Language and Cognition. ***16****(2):401-424.*

15. ^*Rahal RM, Fiedler S (2019). "Understanding cognitive and affective mechanisms in social psychology through eye-tracking." Journal of Experimental Social Psychology.* ***85****(103842).*
16. ^*Beesley T, Pearson D, Le Pelley M (2019). "Eye tracking as a tool for examining cognitive processes." Biophysical measurement in experimental social science research. 1–30. Academic Press.*
17. a, b*Mishra E, Nikam P, Vidhyadharan S, Cheruvalath R (2022). "An affect-based approach to detect collective sentiments of film audience: Analysing emotions and attentions." Acta Psychologica.* ***230****.*
18. a, b*Zhang Q (2022). "RESEARCH ON THE INFLUENCE OF NEWS COMMUNICATION ENTERTAINMENT ON AUDIENCE PSYCHOLOGY UNDER THE BACKGROUND OF NEW MEDIA." Psychiatria Danubina.* ***34****(suppl 4): 255–255.*
19. a, b*Shesterina A, Zvereva E (2023). "Means of emotional impact on the audience in user media content." Media Education. (1):179-189.*
20. ^*Dias P, Jorge A (2016). "Audiences experiencing emotions in the contemporary media landscape." Journal of Audience & Reception Studies.* ***13****(1):431-445.*
21. ^*Córdoba-Tlaxcalteco ML, Benítez-Guerrero EI (2024). "A systematic literature review on vision-based human event recognition in smart classrooms: identifying significant events and their applications." Proceedings of the Institute for System Programming of the Russian Academy of Sciences.* ***36****(1):175-198.*
22. a, b, c, d*Pittman M, Haley E (2023). "Cognitive load and social media advertising." Journal of Interactive Advertising.* ***23****(1):33–54.*
23. a, b, c*Habibi SA, Salim L (2021). "Static vs. dynamic methods of delivery for science communication: A critical analysis of user engagement with science on social media." PLoS One.* ***16****(3).*
24. ^*Mittal T, Chowdhury S, Guhan P, Chelluri S, Manocha D (2024). "Towards determining perceived audience intent for multimodal social media posts using the theory of reasoned action." Scientific Reports.* ***14****(1). 10606.*
25. ^*Pozharliev R, Rossi D, De Angelis M (2022). "A picture says more than a thousand words: Using consumer neuroscience to study instagram users' responses to influencer advertising." Psychology & Marketing.* ***39****(7):1336–1349.*
26. a, b*Dai X, Wang J (2023). "Effect of online video infotainment on audience attention." Humanities and Social Sciences Communications.* ***10****(1):1-18.*

Declarations

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.