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PREDICTIVE EYE TRACKING IN SOCIAL MEDIA: COMPARATIVE ANALYSIS OF AI PLATFORMS

Accuracy, Technology, and Applicability in Social Media

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ABSTRACT

Visual attention is a scarce resource on social media, characterized by content saturation and rapid interactions. Predictive eye tracking tools based on artificial intelligence promise scalable analysis, although their scientific validity and practical applicability remain heterogeneous. This study comparatively evaluates ten commercial platforms using a multi-criteria methodology, combining technical analysis, validation through the MIT/Tübingen Saliency Benchmark, and applicability assessment in social media. Results reveal significant architectural heterogeneity, a gap between commercially reported and verifiable accuracy, and limited external validation. These findings position predictive eye tracking as an early diagnostic tool, complementary to traditional experimental methodologies.

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1. Introduction

In the current context of audiovisual advertising saturation, competition for the attention of our audiences, and defined by cognitive overload, attention has become a scarce and invaluable resource (Rachmad, 2024). Furthermore, design has evolved from aesthetic expression into a tool that guides attention through cognitive and psychological principles, capturing it efficiently within limited timeframes (Yuan et al., 2025).

This revolution is characterized by interactivity, user-generated content, the integration of different platforms, the rise of personalization, as well as real-time and instantaneous information (Singh & Singh, 2025).

On the one hand, this environment enables companies to shape brand perception and image but, on the other hand, content consumers have an increasing number of choices (Sujanska & Nadanyiova, 2022).

In this respect, companies have created new processes and forms of communication to differentiate themselves, whether through the emergence of new forms and modes of communication or by shifting from a rational to a more emotional narrative (Tapia Frade et al., 2025). The way visual elements are placed, such brand placement, is essential for building the value of the piece as well as improving overall ad effectiveness (Wedel & Pieters, 2000). Thus, it is key to be able to analyze what captures consumers' attention, and in this sense, advances in applied neuroscience—for example, eye tracking—have represented a breakthrough in measuring advertising attention to understand which stimuli generate higher attention and engagement (Saavedra-Montejo et al., 2025).

Moreover, technological advances, particularly those related to artificial intelligence, offer solutions for automation, graphic content generation, image editing, and real-time analysis of publication performance, thereby responding to the need to adapt to dynamic, competitive, and saturated environments (Arias et al., 2025). In this context, it is pertinent to distinguish between two modalities of visual attention measurement: traditional eye tracking and predictive eye tracking, whose characteristics, advantages, and limitations are described below.

1.1. Traditional Eye Tracking in Visual Communication

Eye tracking has been gaining importance because its metrics provide information about visual attention, such as fixations and viewing patterns (Muñoz-Leiva et al., 2019; Espigares-Jurado et al., 2020), since eye movements are a good indicator of visual attention (Wedel & Pieters, 2000). In fact, the research background of Just and Carpenter (1980) in their eye-mind hypothesis pointed out that there is a direct correlation between what a person observes and their cognitive processing.

Traditional eye tracking has established itself as a fundamental methodology for the study of visual behavior and attention, employing specialized hardware to precisely record participants' eye movements (Holmqvist et al., 2011). By using infrared technology to detect pupil position and corneal reflection, it allows researchers to determine where a participant directs his/her visual attention in real time (Duchowski, 2017). This technique provides metrics such as fixations (periods where the gaze remains relatively stable), saccades (rapid movements between fixations), and heat maps that visualize areas of greatest visual concentration (Holmqvist et al., 2011).

This type of eye tracking has been widely used in consumer behavior studies, interface design, and advertising content analysis, demonstrating its validity for understanding attentional processes (Holmqvist et al., 2011). However, it presents significant limitations, as it requires equipment that can be costly and requieres physically present participants to carry out calibration processes that can be laborious; limiting sample sizes and the generalization of results (Van der Cruyssen et al., 2024). Furthermore, Steil et al. (2019) raise privacy concerns associated with the use of this type of device. Furthermore, and especially in contexts such as social media, where the massive volume of content and the dynamic nature of stimuli, can make large-scale analysis using these traditional methods very difficult (Holmqvist et al., 2011).

As a response to these restrictions, predictive eye tracking has emerged.

1.2. Predictive Eye tracking based on AI

Predictive eye tracking, also referred to as "saliency modeling" or "attention prediction," comprises AI-based platforms that use convolutional neural networks and visual saliency models to anticipate attention patterns without the need for real participants (Kümmerer et al., 2017; Bylinskii et al., 2018). These tools promise to democratize access to insights on visual behavior, offering immediate, scalable, and lower-cost analysis.

Predictive eye tracking uses deep learning algorithms to estimate where users will direct their visual attention (Kümmerer et al., 2017). These models are trained with large image datasets containing real eye tracking data, automatically learning visual features that attract human attention (Borji, 2021).

The most recent models have achieved significant levels of accuracy in predicting attentional patterns in certain controlled contexts (Kümmerer et al., 2017). Nevertheless, some recent studies point to important limitations. Most of these models have been trained and validated with static images of natural scenes, which raises questions about their ability to generalize to dynamic contexts (Borji, 2024) due to social and contextual factors such as those found in social media.

Among the advantages of predictive eye tracking, the following ones stand out. First, its scalability in terms of cost and time, as these predictive solutions directly analyze visual stimuli without requiring human participation, allowing design variants to be analyzed in minutes compared to traditional studies that involve samples of individuals with the consequent time and economic cost (Holmqvist et al., 2011; Kümmerer et al., 2016; Blascheck et al., 2017; Linardos et al., 2021). This capability is especially valuable in A/B testing of advertising creatives, where iteration speed can determine the success of a campaign. Second, it offers advantages in terms of privacy protection and regulatory compliance, given that data obtained through traditional eye tracking constitutes particularly sensitive biometric information under the GDPR (European Union, 2016), potentially revealing implicit information about identity, personality traits, ethnic origin, age, gender, emotions, and preferences (Kröger et al., 2020). Predictive eye tracking completely eliminates concerns related to informed consent, secure storage of biometric data, and rights of access to and deletion of personal data (Bozkir et al., 2023; Vallejo-Blanxart et al., 2026). Third, it is particularly valuable during the early phases of design conceptualization and prototyping, allowing concepts to be tested before production, unlike traditional eye tracking whose time cost makes its iterative use during conceptualization nearly impractical.

However, this modality presents important limitations. A fundamental limitation is its dependence on low-level visual features (perceptual saliency), which prevents it from capturing cognitive factors such as specific task goals, the observer's prior knowledge, or semantic context—factors that significantly influence the actual distribution of visual attention (Henderson et al., 2007; Tatler et al., 2011). Likewise, there is a critical dependence on the training dataset, as algorithms may present generalization problems when applied to populations, cultural contexts, or types of visual stimuli that differ significantly from those with which they were trained, compromising the ecological validity of the predictions (Kümmerer et al., 2018; Bylinskii et al., 2018). Finally, predictive eye tracking is limited to estimating visual attention patterns without being able to measure emotional responses, cognitive load, or affective evaluations that drive purchasing decisions—aspects that traditional eye tracking can capture through metrics such as pupil dilation (Holmqvist et al., 2011).

1.3. Visual Attention in Social Media

As explained in previous sections, visual attention is the result of visual activity triggered by visual stimuli. This can be analyzed through eye tracking, offering comprehensive information on attention patterns to determine how consumers interact in the digital medium and identifying which visual elements attract greater attention and influence their behavior (Riswanto et al., 2024). Within this framework, classical models of visual attention distinguish between two types of attention, such as the automatic response to salient stimuli (bottom-up) and goal-driven

attention (top-down) (Posner & Petersen, 1990). Therefore, the measurement of these attentional processes becomes especially relevant, as visual attention constitutes a significant predictor of advertising effectiveness and brand processing (Pieters & Wedel, 2004). The role of selective attention in information processing can be quantified through attention patterns measured with this type of technology (Yuan et al., 2025).

In the context of social media, where competition for attention is particularly intense, this type of approach becomes highly valuable for optimizing the design of advertising content. Digital platforms pose extreme competition among stimuli, where attentional micro-decisions occur in milliseconds (Mayer et al., 2024). For this reason, eye tracking has been used by marketing professionals to evaluate visual attention and create more engaging ads, using metrics such as fixation time, saccades, and gaze patterns that provide precise information on how consumers interact with digital advertisements (Almourad et al., 2025).

Traditional eye tracking studies, exposing subjects to the visualization of stimuli, have been commonly used for different types of evaluations in the digital field, but given the speed of the current context and the methodological complexity, their iterative use in rapid creative cycles is limited (Šola et al., 2024). Taking into account this limitation, predictive eye tracking offers an alternative that facilitates early visual diagnosis by estimating where attention is likely to be directed during the first seconds of exposure, a critical period dominated by stimulus-driven or reactive attention processing (Bylinskii et al., 2018).

Specifically in the field of social media, various eye tracking studies have been conducted to measure attention in relation to presented content. Vraga et al. (2016) analyzed attention differences according to topics and styles in social media content, while Muñoz-Leiva et al. (2019) evaluated advertising effectiveness in terms of visual attention and recall, and Piotrkowicz et al. (2017) investigated how social media became the starting point for users' information. More recent studies have addressed specific areas, such as Li et al. (2025) on social media news or Chen-Sankey et al. (2025) on disposable cigarette advertising on Instagram. Moreover, Gheorghe et al. (2023) highlight how eye tracking can reveal unconscious factors that influence consumer decisions—factors that are not obtained through traditional market research methods such as surveys and focus groups.

Therefore, we can conclude that there is a need for scientific evaluation of predictive eye tracking models for application in social media.

1.4. Commercial Predictive Eye Tracking platforms

Predictive eye tracking is based on models such as the saliency model by Itti et al. (1999), which computationally predict visual fixations without the need for human participants, using low-level features such as color, orientation, and intensity. Technological evolution through deep learning has substantially improved these predictions, demonstrating that internal representations learned by neural networks can be reused to predict fixations with better performance than classical methods (Kümmerer et al., 2016). Unlike traditional eye tracking, which measures fixations under specific conditions with top-down processing oriented toward concrete tasks, predictive eye tracking estimates probabilities based on statistical regularities and primarily models initial bottom-up attention (Torralba et al., 2006).

In the context of social media, where users view posts integrated into a feed with specific expectations about the placement of key elements such as headlines, faces, or calls-to-action (Vraga et al., 2016), these models combine perceptual saliency with global scene understanding (Torralba et al., 2006), proving to be especially useful as a pre-diagnostic and early optimization tool before deeper empirical validations (Šola et al., 2024).

The transition of these technologies to the commercial sphere has generated an ecosystem of platforms that democratize access to visual attention analysis, although a significant gap persists between the high-accuracy claims of these commercial solutions and the scientific evidence supporting them. Recent literature warns about the need for greater methodological transparency and specific validation (Borji, 2024). The scientific validity of these platforms, their ability to replicate empirical results, and their methodological limitations compared to the gold standard of

traditional eye tracking remain open questions, requiring further empirical research on their ecological validity in contemporary digital contexts.

2. Objectives

The present study has as its general objective to comparatively analyze the main commercial predictive eye tracking platforms based on artificial intelligence, evaluating their suitability for content analysis on social media.

Specifically, the following objectives are proposed: (1) to characterize the platforms in terms of scalability, underlying technology, types of output generated, and privacy considerations; (2) to validate the predictive accuracy of the platforms by contrasting them with standardized benchmarks (MIT/Tübingen Saliency Benchmark); and (3) to evaluate the practical applicability of each platform for the analysis of formats characteristic of social media.

3. Methodology

This study employs a multi-criteria comparative evaluation methodology to analyze artificial intelligence-based predictive eye tracking tools applicable to the context of social media content. The methodological design is structured in five sequential phases: platform selection, definition of the evaluative framework, data collection procedure, accuracy validation through external benchmarking, and evaluation of applicability in social media.

3.1. Platform selection

Predictive eye tracking platforms were identified through a review of specialized literature in neuromarketing and visual saliency, industry market analysis, and publicly available technical documentation. The inclusion criteria were: (a) active commercial availability during the 2024–2025 period, (b) technology based on visual saliency models with artificial intelligence, (c) capability to generate predictive attention maps, and (d) declared applicability to digital content or social media analysis. Platforms without accessible technical documentation or without verifiable information about their performance were excluded.

The final sample comprises ten platforms: Attention Insight, Feng-GUI, Clueify, Emotiva AI (Foresight), Forebrain (Attentive AI), expoze.io (alpha.one), Neurons, 3M VAS, EyeQuant, and Brainsight. This selection represents the current spectrum of commercial solutions with relevance in both the academic field and the professional practice of digital marketing.

3.2. Multi-criteria evaluation

The comparative analysis was structured around five evaluative dimensions defined a priori, following the principles of multi-criteria technology selection frameworks (Wątróbski et al., 2019).

Scalability: the capacity to analyze a high volume of graphic pieces efficiently, including API availability, batch processing, and response time per analysis.

Technology: types of outputs generated (heat maps, gaze plots, focus maps, quantitative metrics), architecture of the underlying AI model, and complementary metrics offered.

Accuracy (precision): the predictive capacity of the model to anticipate human eye fixations, evaluated both through metrics reported by the providers and through external validation on standardized benchmarks.

- **Privacy**: data processing requirements (cloud vs. local processing), image retention policies, and compliance with data protection regulations—an aspect especially relevant for confidential corporate content.

Applicability in social media: the suitability of each platform for the characteristic formats of the social media ecosystem (static images, stories, reels, thumbnails), including specific optimizations for mobile environments or vertical feeds.

3.3. Data collection procedure

Technical information was extracted from the official documentation of each platform (corporate websites, whitepapers, API documentation, and published case studies) during the period January–May 2025. For each platform, the following were recorded: the type of visual and analytical outputs generated, commercially declared accuracy, access model (free, freemium, pay-per-use), and supported content formats.

It should be noted that none of the analyzed tools publicly disclose the architectural details of their proprietary AI model, a common limitation in the sector that affects scientific replicability. In general terms, these platforms employ visual saliency models trained with human eye movement data, typically deep neural networks that learn to predict attention maps equivalent to those obtained through traditional eye tracking (Kümmerer et al., 2017).

The present study does not involve training, fine-tuning, or modification of the analyzed models, but exclusively the comparative analysis of publicly available technical information and metrics.

3.4. Accuracy validation through an external benchmark

Given the infeasibility of conducting traditional eye tracking studies for each platform due to cost and time constraints (Duchowski, 2017), a secondary validation approach was adopted using the public results from the MIT/Tübingen Saliency Benchmark, the reference standard in the field of eye fixation prediction (Kümmerer et al., 2018).

Two datasets with held-out human fixations (not publicly available to avoid overfitting) were used:

MIT300 (Judd et al., 2012): 300 natural images of indoor and outdoor scenes with fixation data from 39 observers, a viewing duration of 3 seconds, captured with an ETL 400 ISCAN eye tracker (240 Hz).

CAT2000 (Borji & Itti, 2015): 4,000 images distributed across 20 thematic categories, with fixation data from 24 observers per image, a viewing duration of 5 seconds, captured with an EyeLink 1000 (1000 Hz).

For each platform with published results on these benchmarks, two metrics were collected: the AUC-Judd value (Area Under the ROC Curve), which quantifies the model's ability to discriminate between fixated and non-fixated locations by treating the saliency map as a binary classifier (Riche et al., 2013); and the Gold Standard value, which represents the theoretical upper limit of prediction calculated through Gaussian kernel density estimation over fixations from a hypothetically infinite number of observers.

With these values, a normalized relative accuracy with respect to the human Gold Standard was calculated using the following formula:

$$\text{Relative precision (\%)} = \frac{AUC}{Gold\ Standard} \times 100$$

This metric expresses what percentage of optimal human performance each model achieves, allowing objective comparisons between platforms regardless of the dataset used and controlling for individual differences among observers. Unlike classical classification accuracy, this relative accuracy quantifies the proximity to the theoretical ceiling of human prediction, not the proportion of binary correct answers.

The source of verification was categorized into two types: (a) MIT verification, when the platform appears registered in the official benchmark results (https://saliency.tuebingen.ai), and (b) self-reported, when the figure comes exclusively from commercial documentation without independent audit.

3.5. Evaluation of applicability in Social Media

To assess the practical suitability of each platform in social media environments, a functional analysis was conducted based on the available demo versions and the official documentation of

each provider. Declared functionalities, supported content formats (static images, video, stories), and recommended use cases for different social platforms were examined. In addition, the commercial access model, declared processing speed, and the existence of specific optimizations for mobile or short video formats were recorded.

4. Results

4.1. Technical characteristics of the platforms

All analyzed tools generate as their main output a predictive heat map (heatmap) indicating the regions of the image with the highest probability of capturing visual attention. Beyond this common denominator, the platforms differ substantially in the complementary visualizations and metrics they offer (Table 1).

Attention Insight and Clueify moreover provide focus maps and attention percentages by areas of interest (AOI) defined by the user, facilitating the evaluation of specific design elements (logos, CTAs, main text). Brainsight incorporates simulated gaze plots representing fixation sequences, along with visual clarity scores. Emotiva AI (Foresight) differentiates itself by integrating prediction of basic emotional responses alongside fixation maps, adopting a broader neuromarketing approach. Neurons and 3M VAS include estimated cognitive load metrics and temporal fixation sequences, respectively.

Regarding the architecture of the AI models, the platforms analyzed in Table 1 present diversity in their technological approaches. The majority employ Deep Learning techniques, with convolutional neural networks (CNN) predominating in Attention Insight, Emotiva AI (Foresight), Forebrain (Attentive AI), expoze.io, and Brainsight, while Clueify uses artificial neural networks (ANN) and Neurons AI implements a Bayesian approach with probabilistic predictions. In contrast, Feng-GUI is based on the biological-computational visual saliency model of Itti-Koch, and 3M VAS employs rule-based computer vision algorithms derived from neuroscience. EyeQuant represents a traditional supervised Machine Learning approach.

4.2. Accuracy validation through benchmarking

Table 2 presents the accuracy validation results. Of the ten platforms analyzed, five have verifiable results on the MIT/Tübingen Saliency Benchmark: Attention Insight, Feng-GUI, Clueify, Emotiva AI (Foresight), and Forebrain (Attentive AI). The remaining platforms—expoze.io, Neurons, 3M VAS, EyeQuant, and Brainsight—report accuracy figures solely in their commercial documentation without independent external validation.

Table 1. Technical characteristics of the predictive eye tracking platforms. Commercially reported accuracy is indicated (MIT = benchmark verification; self = self-reported), along with the type of outputs generated and the type of AI algorithm used.

Platform	Reported Accuracy (Source)	Generation Type	AI algorithm
Attention Insight	96% accuracy (benchmark MIT)	Heat maps and visual attention maps, attention percentage by area, and design clarity metrics. Instant reports and design comparisons.	Deep Learning (CNN)
Feng-GUI	92% accuracy (benchmark MIT)	Heat maps, visual path, focus maps, areas of interest reports, aesthetic reports, video reports, ability to compare reports, automatic object detection.	Biological-computational model (Itti-Koch) of visual saliency.
Clueify	92% accuracy (benchmark MIT)	Measurement of attention through critical areas. Heat maps, visual paths, and visual attention maps. Areas of interest to quantify attention.	Deep Learning (ANN)
Emotiva AI (Foresight)	Accuracy is not reported; Exact MIT benchmark figures are provided.	Measurement of attention levels, attention capacity, and emotional engagement. Fixation density, clarity ratio, and attention distribution.	Deep Learning (CNN)
Forebrain (Attentive·AI)	N/D	Heatmaps, advertising metrics.	Deep Learning (CNN)
expoze.io (alpha.one)	95% accuracy (self)	Quantification of attention through areas of interest.	Deep Learning (CNN)
Neurons AI	95% accuracy (self)	Heat maps, fixation maps, clarity metrics, cognitive load.	Deep Learning (ANN bayesian)
3M VAS	92% accuracy (self)	Fixation probability maps, fixation sequences, and heatmap-type maps for static stimuli.	Computer vision algorithms
EyeQuant	90% accuracy (self)	Heat maps, image and video analysis.	Traditional Machine Learning
Brainsight	94% accuracy (self)	Heat maps, gaze tracking, instant visibility maps, and attention and clarity ratios.	Deep Learning (CNN)

Source(s): Own elaboration

A discrepancy is observed between commercially reported accuracy and the relative accuracy calculated from benchmark data. Attention Insight advertises 96% accuracy, while the calculated relative accuracy ranges between 92.5% (MIT300, 2021) and 94.6% (MIT300, 2019). Feng-GUI, with a reported 92%, achieves 88.0% on MIT300 but 92.2% on CAT2000, suggesting variability depending on the type of stimuli. Clueify represents a particular case: with 92% reported, it achieves 94.3% calculated on MIT300 (2023), being the only platform whose verified accuracy exceeds its commercial figure. Emotiva AI (Foresight), evaluated in January 2025, obtains 92.5% (MIT300) and 93.4% (CAT2000). Forebrain (Attentive AI), evaluated in July 2024, achieves 93.9% on CAT2000.

No platform reaches the theoretical 100% of the Gold Standard, due to top-down attention factors and individual differences among observers that current models do not fully capture (Borji & Itti, 2015).

For platforms without external validation, self-reported accuracies range between 90% and 95%, but the absence of published methodological details makes it difficult to assess their comparability (Bylinskii et al., 2018).

Table 2. Accuracy validation through the MIT/Tübingen Saliency Benchmark. Calculated accuracy = (AUC/Gold Standard) × 100. The symbol "–" indicates absence of verifiable data. MIT = benchmark verification; self = self-reported.

Platform	Reported accuracy with verification (source)	MIT benchmark	Calculated accuracy	Gold Standard	AUC	Last test
Attention Insight	96% accuracy (MIT)	MIT300	**92%**	0.9341	0.864	2021/11
		MIT300 (MIT)	**95%**	0.92	0.87	2019/06
Feng-GUI	92% accuracy (MIT)	MIT300 (MIT)	**88%**	0.92	0.81	2018/06
		CAT2000 (MIT)	**92%**	0.9	0.83	2018/06
Clueify	92% accuracy (MIT)	MIT300	**94%**	0.9341	0.8811	2023/03
Emotiva AI (Foresight)	Does not report accuracy data, but does report MIT300 benchmark data.	MIT300	**92%**	0.9341	0.8636	2025/01
		CAT2000	**93%**	0.9159	0.8556	2025/01
Forebrain (Attentive AI)	N/D	CAT2000	**94%**	0.9159	0.8598	2024/07
expoze.io (alpha.one)	N/D - Only self-reported					
Neurons AI	N/D - Only self-reported					
3M VAS	N/D - Only self-reported					
EyeQuant	N/D - Only self-reported					
Brainsight	N/D - Only self-reported					

Source(s): Own elaboration

4.3. Applicability in Social Media

Table 3 presents the access characteristics and format coverage of each platform for social media content analysis.

Regarding the access model, six platforms offer free trial modalities (Attention Insight, Clueify, 3M VAS, EyeQuant, Brainsight) or freemium (expoze.io). Feng-GUI and Neurons operate exclusively under a pay-per-use or subscription model. Regarding supported formats, all platforms analyze static images. Expoze.io and Neurons additionally incorporate video analysis capability. Clueify includes viewing simulation in a mobile environment.

Table 3. Applicability of predictive eye tracking platforms to social media content analysis. The commercial access model, supported content formats, and specific functionalities of each platform are indicated.

Platform	Type of access	Supported Formats	Social media-specific functionalities
Attention Insight	Free Trial	Images	Clarity metrics, % attention per AOI, CTA evaluation.
Feng-GUI	Pay-per-use	Images, video	Saliency metrics, visual contrast.
Clueify	Free trial	Images	Mobile environment simulation (vertical feed). Ideal for A/B testing.
expoze.io	Freemium	Images, video	Frame-by-frame analysis, fast processing.
Neurons	Pay-per-use	Images, video	Models for vertical feed, scroll prediction.
3M VAS	Free trial	Images	Temporal sequence of fixations, first 0.5 sec analysis.
EyeQuant	Free trial	Images	Clarity/visual saturation metrics.
Brainsight	Free trial	Images	CTR prediction, attention scores.

Soure(s): Own elaboration

5. Conclusions and Discussions

The heterogeneity identified among commercial predictive eye tracking platforms has relevant methodological implications for their comparative evaluation. The observed differences are not limited to functionalities or output formats, but rather respond to distinct algorithmic approaches, including Deep Learning models trained with large volumes of human fixations, classical biological-computational visual saliency models, and approaches derived from visual neuroscience principles. This diversity introduces differentiated attentional assumptions that hinder direct comparison between tools. In this context, validation through standardized benchmarks is consolidated as the most defensible common criterion for sustaining cross-platform comparability and distinguishing verifiable evidence from commercial communication, especially when the internal architecture of the models remains opaque (Kümmerer et al., 2018; Borji, 2024). The results also reveal a persistent gap between commercially communicated accuracy (90–96%) and verifiable relative accuracy on the MIT/Tübingen Saliency Benchmark (88–94%), along with a pattern of partial external validation, where only five of the ten platforms analyzed provide independent verification. Taken together, these findings allow positioning predictive eye tracking as an early diagnostic tool, especially valuable for its scalability and speed in social media environments, but not equivalent to the experimental gold standard. Based on these results, differentiated contributions are derived for academic research and professional practice.

5.1 Theoretical contributions

The study contributes, first, to a reconceptualization of predictive eye tracking within a broader methodological continuum of visual attention analysis. In contrast to approaches that position traditional and predictive eye tracking as mutually exclusive alternatives, the results allow them to be situated as complementary modalities, suitable for distinct analytical objectives. While traditional eye tracking retains its role in controlled experimental contexts oriented toward complex cognitive processes, predictive eye tracking proves especially pertinent in early phases of the creative process, in large-scale analyses, and in scenarios where initial stimulus-driven visual attention is the main focus. This distinction allows for the identification of differential application scenarios according to the phase of the creative process, the scale of analysis, and the cognitive and attentional objective, moving beyond approaches focused solely on isolated technical validation (Kümmerer et al., 2017; Duchowski, 2017; Tatler et al., 2011).

Second, this work provides an explanatory reading of the role of algorithmic architecture in the comparative evaluation of commercial predictive eye tracking platforms. The analysis identifies the coexistence of three main approaches: Deep Learning models trained with large

datasets of human fixations to learn statistical attention patterns; classical visual saliency models focused on bottom-up mechanisms (Posner & Petersen, 1990; Itti et al., 1999); and hybrid approaches that incorporate metrics derived from visual neuroscience. These approaches model different levels of attentional processing, present specific limitations of contextual generalization, and can generate similar visual outputs under different cognitive assumptions. Consequently, algorithmic differences do not invalidate comparison between platforms, but they require rigorous methodological contextualization supported by external validation, reinforcing the role of standardized benchmarks as a leveling criterion against the opacity of proprietary models (Torralba et al., 2006; Kümmerer et al., 2016, 2017; Borji, 2024).

A third contribution resides in the proposal of a multi-criteria evaluation framework for commercial predictive eye tracking platforms applied to digital marketing. The model integrates five dimensions of analysis: scalability, technology, accuracy, privacy, and contextual applicability, responding to the absence of systematic frameworks for evaluating commercial technologies based on artificial intelligence in applied contexts. The abstraction of these dimensions further facilitates the conceptual transferability of the framework to the evaluation of other predictive neuromarketing solutions (Wątróbski et al., 2019; Borji, 2024).

Fourth, the research contributes to the conceptualization of the gap between scientific validation and commercial communication in predictive eye tracking tools. The results empirically document the disconnection between the accuracy figures communicated by providers and the available verifiable evidence, highlighting the impact of proprietary algorithms and limited methodological transparency on scientific replicability (Kümmerer et al., 2018; Van der Cruyssen et al., 2024).

Finally, the study situates predictive eye tracking within the specific ecosystem of social media, characterized by dynamic feeds, continuous scrolling, and very short initial attention windows. This contextualization allows linking the literature on visual saliency with the attention patterns inherent to social platforms and conceptualizing predictive eye tracking as an instrument integrated into agile creative processes of contemporary digital marketing, rather than as a conclusive measurement tool (Vraga et al., 2016; Muñoz-Leiva et al., 2019; Mayer et al., 2024; Šola et al., 2024).

5.2 Practical contributions

From an applied perspective, the results allow the derivation of operational criteria for the selection of predictive eye tracking platforms according to the application context. The analysis demonstrates that the suitability of each tool depends on the type of content and the dissemination environment. In the case of static corporate content, such as banners, LinkedIn posts, or display ads, platforms that offer visual clarity and informational hierarchy metrics prove useful, facilitating the evaluation of the prominence of the main message and call-to-action elements. For mobile feed environments with continuous vertical scrolling, tools that incorporate smartphone viewing simulation provide differential value by anticipating the real attentional competition among stimuli (Xie et al., 2024). In dynamic and short video formats, such as stories, reels, or TikTok, platforms with temporal and frame-by-frame analysis allow an approximation of attentional behavior throughout the visual sequence. Finally, in the analysis of thumbnails, especially on video platforms, solutions oriented toward attentional capture in the first few hundred milliseconds prove more suitable for evaluating the initial probability of a click.

Second, the study offers a practical guide for digital marketing professionals by highlighting the need to align tool selection with the balance between iteration speed, level of validation, and access cost. Predictive eye tracking emerges as a valuable solution in early phases of conceptualization and creative prototyping, where speed and scalability take priority over absolute experimental precision. Its use allows for iterating designs, conducting preliminary A/B tests, and optimizing creatives before undertaking larger-scale advertising investments (Šola et al., 2024), reserving more costly experimental methodologies for later phases. In addition, the absence of personal biometric data processing simplifies regulatory compliance in corporate environments with strict data protection policies. Nevertheless, this operational agility does not

exempt from a critical assessment of the metrics provided by each platform, given that commercially communicated accuracy does not always correspond to verifiable evidence through independent benchmarks.

Lastly, the practical implications reinforce the idea that predictive eye tracking should be understood as a complement within agile creative workflows, and not as a substitute for traditional empirical techniques. Integrated in this way, its value lies in facilitating informed decisions under real time and budget constraints, improving the efficiency of the creative process and the visual coherence of content in highly competitive social media environments (Almourad et al., 2025; Mayer et al., 2024; Yuan et al., 2025).

6. Limitations and future lines of research

This study presents several limitations that should be considered when interpreting the results. First, the comparative analysis is based on publicly available technical information and accuracy metrics, which implies an inevitable dependence on self-reported data for those platforms that do not provide independent external validation. Likewise, the use of standardized benchmarks, although necessary to ensure comparability, relies on sets of static images and natural scenes, which may limit the generalization of the results to dynamic and multimodal formats characteristic of social media. Lastly, the opacity of proprietary models prevents a detailed examination of the internal learning mechanisms and their potential biases.

Based on these limitations, future lines of research should move toward specific empirical validations in social media contexts, combining predictive eye tracking with traditional experimental studies to assess their degree of complementarity in real-world scenarios. It is equally pertinent to explore the performance of these models with dynamic, interactive, and personalized content, as well as to analyze their behavior across different cultural contexts and devices. Finally, the development of transparency and auditing frameworks for commercial artificial intelligence platforms emerges as a priority research line to strengthen replicability and scientific confidence in this type of tool.

7. References

Almourad, M. B., Bataineh, E., Hussein, M., & Wattar, Z. (2025). Strategic placement of branding elements in digital marketing: Insights from eye-tracking data. Proceedings of the 27th International Conference on Enterprise Information Systems, 2, 417–423. https://doi.org/10.5220/0013281500003929

Arias, M. A. S., Báscones, G. G. U., Donoso, A. P. V., & Oña, A. O. C. (2025). El impacto de la Inteligencia Artificial en la producción de contenidos para Instagram: Automatización, Creatividad y Engagement. *Revista Científica Multidisciplinar G-nerando*, *6*(1), 6382. https://doi.org/10.60100/rcmg.v6i1.708

Blascheck, T., Kurzhals, K., Raschke, M., Burch, M., Weiskopf, D., & Ertl, T. (2017). Visualization of *eye tracking* data: A taxonomy and survey. *Computer Graphics Forum*, *36*(8), 260-284. https://doi.org/10.1111/cgf.13079

Borji, A. (2024). *Addressing a fundamental limitation in deep vision models: lack of spatial attention*. *arXiv preprint* arXiv:2407.01782.

Borji, A., & Itti, L. (2015). CAT2000: A large scale fixation dataset for boosting saliency research. En *2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)* (pp. 1-4). IEEE. https://arxiv.org/abs/1505.03581

Bozkir, E., Özdel, S., Wang, M., David-John, B., Gao, H., Butler, K., Jain, E., & Kasneci, E. (2023). Eye-tracked virtual reality: A comprehensive survey on methods and privacy challenges. *arXiv*. https://doi.org/10.48550/arXiv.2305.14080

Bylinskii, Z., Judd, T., Oliva, A., Torralba, A., & Durand, F. (2018). What do different evaluation metrics tell us about saliency models?. *IEEE transactions on pattern analysis and machine intelligence*, *41*(3), 740-757. https://doi.org/10.1109/TPAMI.2018.2815601

Chen-Sankey, J., Weiger, C., La Capria, K., Vassey, J., Jeong, M., Phan, L., Unger, J. B., Allem, J.-P., Berg, C. J., & Choi, K. (2025). Young adults' visual attention to features of social media marketing for disposable e-cigarettes and associated perceptions. *Addiction*, *120*(3), 439-451. https://doi.org/10.1111/add.16586.

Duchowski, A. T. (2017). *Eye tracking methodology: Theory and practice* (3rd ed.). Springer. https://doi.org/10.1007/978-3-319-57883-5

Espigares-Jurado, F., Muñoz-Leiva, F., Correia, M. B., Sousa, C. M. R., Ramos, C. M. Q., & Faísca, L. (2020). Visual attention to the main image of a hotel website based on its position, type of navigation and belonging to Millennial generation: An *eye tracking* study. *Journal of Retailing and Consumer Services*, *52*, 101906. https://doi.org/10.1016/j.jretconser.2019.101906

European Union. (2016). Reglamento (UE) 2016/679 del Parlamento Europeo y del Consejo, de 27 de abril de 2016, relativo a la protección de las personas físicas en lo que respecta al tratamiento de datos personales y a la libre circulación de estos datos (Reglamento general de protección de datos). Diario Oficial de la Unión Europea, *L 119*, 1–88. Bruselas. https://eur-lex.europa.eu/eli/reg/2016/679/oj

Gheorghe, C. M., Purcărea, V. L., & Gheorghe, I. R. (2023). Using eye-tracking technology in Neuromarketing. *Romanian Journal of Ophthalmology*, *67*(1), 2-6. https://doi.org/10.22336/rjo.2023.2

Henderson, J. M., Brockmole, J. R., Castelhano, M. S., & Mack, M. (2007). Image salience versus cognitive control of eye movements in real-world scenes: *Evidence from visual search.* Eye Movements Research, 12(3), 537–562.

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 University Press.

Itti, L., Braun, J., Lee, D. K., & Koch, C. (1999). Attentional modulation of human pattern discrimination psychophysics reproduced by a quantitative model. *Advances in Neural Information Processing Systems*, 11, 789–795.

Just, M. A., & Carpenter, P. A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review*, *87*(4), 329-354. https://doi.org/10.1037/0033-295X.87.4.329

Judd, T., Durand, F., & Torralba, A. (2012). *A benchmark of computational models of saliency to predict human fixations* (MIT-CSAIL-TR-2012-001). Massachusetts Institute of Technology, Computer Science and Artificial Intelligence Laboratory. http://hdl.handle.net/1721.1/68590

Kröger, J. L., Lutz, O. H.-M., & Müller, F. (2020). What does your gaze reveal about you? On the privacy implications of *eye tracking*. *Privacy and Identity Management*, 576, 226–241. https://doi.org/10.1007/978-3-030-42504-3_15

Kümmerer, M., Wallis, T. S. A., & Bethge, M. (2016). *DeepGaze II: Reading fixations from deep features trained on object recognition* (arXiv:1610.01563). arXiv. https://arxiv.org/abs/1610.01563

Kümmerer, M., Wallis, T. S. A., Gatys, L. A., & Bethge, M. (2017). Understanding low- and high-level contributions to fixation prediction. *Proceedings of the IEEE International Conference on Computer Vision*, 4789–4798. https://doi.org/10.1109/ICCV.2017.513

Kümmerer, M., Wallis, T. S. A., & Bethge, M. (2018). Saliency benchmarking made easy: Separating models, maps and metrics. *Computer Vision – ECCV 2018*, 11210, 770–787. https://doi.org/10.1007/978-3-030-01270-0_47

Li, X., Tse, Y. K., & Bu, X. (2025). Examining corporate social irresponsibility in manufacturing: An eye-tracking study of social media news. *International Journal of Production Economics*, *281*, Article 109539. https://doi.org/10.1016/j.ijpe.2025.109539

Linardos, A., Kümmerer, M., Press, O., & Bethge, M. (2021). DeepGaze IIE: Calibrated prediction in and out-of-domain for state-of-the-art saliency modeling. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 12919–12928. https://doi.org/10.1109/ICCV48922.2021.01268

Mayer, A.-T., Ohme, J., Maslowska, E., & Segijn, C. M. (2024). Headlines, pictures, likes: Attention to social media newsfeed post elements on smartphones and in public. *Social Media + Society*, *10*(2), Article 20563051241245666. https://doi.org/10.1177/20563051241245666

Muñoz-Leiva, F., Hernández-Méndez, J., & Gómez-Carmona, D. (2019). Measuring advertising effectiveness in Travel 2.0 websites through eye-tracking technology. *Physiology & Behavior*, *200*, 83–95. https://doi.org/10.1016/j.physbeh.2018.03.002

Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing*, 68(2), 36–50. https://doi.org/10.1509/jmkg.68.2.36.27794

Piotrkowicz, A., Dimitrova, V., Otterbacher, J., & Markert, K. (2017). Headlines matter: Using headlines to predict the popularity of news articles on Twitter and Facebook. *Proceedings of the International AAAI Conference on Web and Social Media*, 11(1), 656–659. https://doi.org/10.1609/icwsm.v11i1.14951

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, *13*, 25–42. https://doi.org/10.1146/annurev.ne.13.030190.000325

Rachmad, Y. E. (2024). Attention-attracting strategy theory. In *Digital marketing theories: From gimmicks to loyalty*. PT Sonpedia Publishing Indonesia..

Riche, N., Duvinage, M., Mancas, M., Gosselin, B., & Dutoit, T. (2013). Saliency and human fixations: State-of-the-art and study of comparison metrics. *Proceedings of the IEEE International Conference on Computer Vision* https://doi.org/10.1109/ICCV.2013.147

Riswanto, A. L., Ha, S., Lee, S., & Kwon, M. (2024). Online reviews meet visual attention: A study on consumer patterns in advertising, analyzing customer satisfaction, visual engagement, and purchase intention. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(4), 3102–3122. https://doi.org/10.3390/jtaer19040150

Saavedra-Montejo, Á., Blanco Moreno, S., & Ballester, E. (2025). Neurociencia e influencers al servicio de la atención. *Investigación y Marketing*, (161), 56–61.

Singh, P., & Singh, A. K. (2025). *The digital revolution: exploring new media in the 21st century*. Crown Publishing.

Šola, H. M., Qureshi, F. H., & Khawaja, S. (2024). Predicting behaviour patterns in online and PDF magazines with AI eye-tracking. *Behavioral Sciences*, *14*(8), Article 677. https://doi.org/10.3390/bs14080677

Sujanska, L., & Nadanyiova, M. (2022). *Online marketing communication as a key tool to capture the attention of Generation Z*. *Ekonomicko-Manazerske Spektrum*, *16*(2), 81–90. https://doi.org/10.26552/ems.2022.2.81-90

Tapia Frade, A., Martín Guerra, E., & Romano de Pedro, C. (2025). *Attention and emotion in spots: An analysis from a neuroscience perspective*. *Vivat Academia*, *158*, 1–20. https://doi.org/10.15178/va.2025.158.e1606

Tatler, B. W., Hayhoe, M. M., Land, M. F., & Ballard, D. H. (2011). Eye guidance in natural vision: Reinterpreting salience. *Journal of vision*, *11*(5), 5-5. https://doi.org/10.1167/11.5.5

Torralba, A., Oliva, A., Castelhano, M. S., & Henderson, J. M. (2006). *Contextual guidance of eye movements and attention in real-world scenes: The role of global features in object search*. Psychological Review, 113(4), 766–786. https://doi.org/10.1037/0033-295X.113.4.766

Vallejo-Blanxart, A., Peláez, A., Gonzalez-Ibáñez, D. & Villoro, J. (2026). Privacy-centric marketing: managerial insights for compliance and competitive differentiation. Rev Manag Sci. https://doi.org/10.1007/s11846-026-00976-4

Van der Cruyssen, I., Ben-Shakhar, G., Pertzov, Y., Guy, N., Cabooter, Q., Gunschera, L. J., & Verschuere, B. (2024). *The validation of online webcam-based eye-tracking: The replication of the cascade effect, the novelty preference, and the visual world paradigm*. Behavior Research Methods, 56(5), 4836–4849. https://doi.org/10.3758/s13428-023-02221-2

Vraga, E. K., Bode, L., & Troller-Renfree, S. (2016). *Beyond self-reports: Using eye tracking to measure topic and style differences in attention to social media content*. Communication Methods and Measures, 10(2-3), 149–164. https://doi.org/10.1080/19312458.2016.1150443

Wątróbski, J., Jankowski, J., Ziemba, P., Karczmarczyk, A., & Zioło, M. (2019). *Generalised framework for multi-criteria method selection*. Omega, 86, 107–124. https://doi.org/10.1016/j.omega.2018.07.004

Wedel, M., & Pieters, R. (2000). *Eye fixations on advertisements and memory for brands: A model and findings*. Marketing Science, 19(4), 297–312. https://doi.org/10.1287/mksc.19.4.297.11794

Xie, W., Lee, M. H., Chen, M., & Han, Z. (2024). *Understanding consumers' visual attention in mobile advertisements: An ambulatory eye-tracking study with machine learning techniques*. Journal of Advertising, 53(3), 397–415. https://doi.org/10.1080/00913367.2023.2258388

Yuan, S., Wei, J., & Chen, C. (2025). *An eye-tracking study of attention capture efficiency in commercial poster design*. Applied Sciences, 16(1), 291. https://doi.org/10.3390/app16010291