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Attention Metrics in Advertising: a Comparative Analysis between Academic Theory and Industry Practice

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Abstract

Measuring advertising effectiveness has represented a central challenge in the advertising industry for a long time. Traditional exposure-based metrics, while scalable and standardized, fail to capture whether advertising stimuli are actually cognitively processed by consumers. In response, both academic research and practitioners have increasingly turned to studying attention as a key explanatory mechanism of advertising effectiveness. This thesis investigates the significant divergences between academic literature and industry practice in the understanding of human attention and its practical operationalization. The question this study aim to answer consist in the identification of the differences in the application of techniques and derived metrics to study advertising between academic theory and market practitioners, in order to outline potential direction to improve the current attention metrics market. To address this research question, the study adopts qualitative research, including a comprehensive review of both academic and grey literature. The final part of the work consists of a structured discussion of the differences between theory and practice, based on the application of the Klein and Lawrence (2012) framework of attention, which intersects modes of attentional control with the domains of space, time, sense, and task. The findings reveal substantial discrepancies between the two approaches, leading to important implications that affect both the validity of practitioners' methodologies and the overall development of the attention metrics market. The thesis concludes with recommendations aimed at bridging the current division between theory and practice, including stronger alignment with cognitive frameworks, more rigorous validation studies, and enhanced methodological transparency.

Key-words: attention metrics, advertising effectiveness, biometric measurement techniques, eye tracking, neuromarketing, advertising accountability.

Abstract in italiano

Misurare l'efficacia della pubblicità rappresenta da tempo una sfida fondamentale nel settore pubblicitario. Le tradizionali metriche basate sull'esposizione, sebbene scalabili e standardizzate, non riescono a cogliere se gli stimoli pubblicitari siano effettivamente elaborati cognitivamente dai consumatori. In risposta a ciò, sia la ricerca accademica che i professionisti nel mercato si sono sempre più orientati verso lo studio dell' attenzione come meccanismo chiave per spiegare l'efficacia della pubblicità. Questa tesi indaga le significative divergenze tra la letteratura accademica e la pratica industriale nella comprensione dell'attenzione umana e nella sua operatività pratica. La domanda a cui questo studio mira a rispondere consiste nell'identificare le differenze nell'applicazione delle tecniche e delle metriche derivate per studiare la pubblicità tra la teoria accademica e i professionisti del mercato, al fine di delineare una potenziale direzione per migliorare l'attuale mercato delle metriche dell'attenzione. Per affrontare questa domanda di ricerca, lo studio adotta una ricerca qualitativa, che include una revisione completa sia della letteratura accademica che di quella grigia. La parte finale del lavoro consiste in una discussione strutturata delle differenze tra teoria e pratica, basata sull' applicazione del quadro di riferimento dell'attenzione di Klein e Lawrence (2012), che interseca le modalità di controllo dell'attenzione con i domini dello spazio, del tempo, dei sensi e dei compiti. I risultati rivelano discrepanze sostanziali tra i due approcci, con importanti implicazioni che influenzano sia la validità delle metodologie dei professionisti sia lo sviluppo complessivo del mercato delle metriche di attenzione. La tesi si conclude con raccomandazioni volte a colmare l'attuale divario tra teoria e pratica, tra cui un maggiore allineamento con i quadri cognitivi, studi di validazione più rigorosi e una maggiore trasparenza metodologica.

Parole chiave: metriche di attenzione, efficacia pubblicitaria, tecniche di misurazione biometrica, tracciamento oculare, neuromarketing, responsabilità pubblicitaria.

Contents

Introduction

Quantifying advertising effectiveness has always been a fundamental question for advertisers Morgan et al. (2022). From one point of view, a grate share of advertising investment may fail to generate meaningful impact; from the other one, the attribution of which parts of the investments are effective or ineffective has always been, and continues to be, very complicated (Berman, 2018; Hartnett et al., 2025; Valenti et al., 2023).

To find an answer to this important question, both academic research and industry practitioners have increasingly turned their effort to the concept of attention as a key mechanism to understand advertising effectiveness (Berman, 2018). Unlike traditional exposure metrics that measure the opportunity of a person to see an advertisement, attention metrics objective is to quantify actual attentional processing, whether consumers genuinely notice and focus on an advertising content (Hartnett et al., 2025; Orquin and Wedel, 2020). Academic literature is full of studies about attention and attention measurement applied for advertising research and dozens of measurement companies now offer attention solutions, employing a vast range of technologies and related biometric metrics (ARF, 2024a, 2024b; IAB and MRC, 2025). Despite that, when looking into detail how these relatively new approaches are applied by attention metrics providers, it becomes evident how their methodologies diverges significantly with the studies present in the academic literature. This reflects a deep disconnection between these two worlds: the academic research tradition, grounded in decades of cognitive psychology and neuroscience that conceptualizes attention as a complex, multidimensional construct; and on the other hand, the practitioner measurement industry, constrained by operational realities of scalability, cost, and real-time deployment, prefer simplified proxies and proprietary scoring systems.

Against this background, this thesis investigates the extent to which contemporary attention measurement practices align with established theoretical frameworks of attention. The central research question guiding this work is:

How do advertising practitioners define and measure attention, and to what extent do current attention metrics align with academic theories of attention?

To address this question, the study first explores the theoretical foundation of attention by reviewing the evolution of attention research, its core definitions, and its principal dimensions as discussed in academic literature. Particular emphasis is placed on the different types and mechanisms of attention and on the biometric techniques traditionally used to study them. After that, the study analyzes how attention is measured by industry practitioners, tacking information from researches and industry reports. The fourth chapter starts with a structured discussion, built upon a theoretical framework, on how practitioners' techniques adapt or not to academic standards. This part is finally followed by the implications and recommendations that follow the results of the discussion.

1 Chapter one

This introductory chapter aims to introduce biometric measurements of attention in the field of advertising, which represents one of the main objectives of this work. To do so, it will first address the concept of advertising accountability, explaining how it constitutes a fundamental part of the marketing performance measurement system, and then retrace the evolutionary stages of the metrics related to advertising accountability. Finally, the chapter will outline the importance of biometric measurement techniques for assessing attention.

1.1. Introduction to Advertising Accountability

Marketing (and so advertising) accountability has long been a central topic in both the marketing literature and practice (Katsikeas et al., 2016). Historically, the marketing function has faced consistent demands to prove its value, often struggling to link its expenditures and activities to tangible financial outcomes. This challenge is intensified by recent developments, including the enormous explosion of data generated through digital channels, the widespread adoption of marketing automation, and the growing focus on customer experience as a primary firm priority (Morgan et al., 2022). The concept of accountability is directly related to the broader framework of the marketing performance measurement system (MPMS), which serves as the organizational mechanism for achieving accountability (Lamberti and Noci, 2010). Lamberti and Noci

(2010) explored the characteristics of MPMS and identified its dimensions from literature. These dimensions refer to five typologies of performances found in literature that are related to marketing actions: marketing efficiency, customer relationship management, internal consistency, supply-chain interface and intellectual capital and knowledge-based asset management. For the purpose of this research, particular attention will be devoted to the first dimension, as it is the most directly connected to advertising accountability. Marketing efficiency refers to the firm's ability to efficiently transform marketing inputs into marketing outputs (Clark, 2000, 1999; Clark and Ambler, 2001; Morgan et al., 2002; O'Sullivan and Abela, 2007). Within this view, advertising accountability represents the concrete application of the efficiency principle to the communication domain: it concerns how advertising investments are measured, evaluated, and optimized to ensure that resources are effectively converted into brand and business performance outcomes (Morgan et al., 2022).

1.2. Advertising-Related Metrics

For decades, marketing has faced sustained pressure to demonstrate its contribution to firm performance and shareholder value. This constant challenge of marketing accountability has driven a continuous evolution in measurement approaches, moving from basic metrics to increasingly advanced and complex methodologies (O'Sullivan and Abela, 2007). As organizations have increasingly demanded for a clear evidence of marketing's return on investment, both scholars and practitioners have worked to improve the tools and metrics used to evaluate marketing effectiveness (Morgan et al., 2022). This effort has produced a gradual but significant movement in the measurement paradigm moving away from output-focused measures (Clark and

Ambler, 2001), toward more sophisticated methodologies capable of capturing attitudinal shifts and cognitive responses to marketing stimuli (Morgan et al., 2002).

1.2.1. Reach, Frequency, Gross Rating Points (GRP)

Among the earliest and most important metrics developed for the evaluation of advertising effectiveness are reach, frequency, and gross rating points (GRPs). These measures emerged in the mid-20th century as the advertising industry aimed at standardized and scalable tools to justify media investments, particularly in mass media contexts such as television, radio, and print. Their development reflects an era in which marketing accountability was conceptualized primarily through exposure, operating under the assumption that greater and more efficient exposure would translate into improved sales and brand outcomes (Bonoma and Clark, 1988; Clark and Ambler, 2001).

Reach can be defined as the number of people or households, or the percentage on the target audience, that will be exposed to an advertising schedule at least once over a specified period of time (Aaker et al., 1992). It quickly became central to advertising evaluation because it captured the breadth of exposure, aligning with the assumption that persuasion begins with contact (Naples, 1992). Media specialists consistently ranked reach among the most important criteria when selecting media vehicles for national campaigns (King et al., 1997).

$$Reach\ (\%) = \frac{Number\ of\ unique\ individuals\ reached}{Total\ target\ audience} \times 100$$

In contrast, frequency measures the number of times that an individual is exposed to a particular advertising message in a given period of time (Novak and Hoffman, 1997). Historically, frequency was conceived to capture the repetition necessary for message comprehension, memory encoding, and subsequent behavioral change (Naples, 1979). The early literature identified substantial debate regarding optimal frequency levels. Effective frequency stands for the number of times an individual should be exposed to an advertisement in order for it to become effective (Cannon and Riordan, 1994). Following this logic, effective reach indicates the number of people reached with an effective frequency. Naples (1979) argued that most advertising messages require at least three exposures to generate meaningful impact, an argument that shaped media planning practices for decades. However, subsequent research challenged the universality of this threshold, demonstrating variation depending on message complexity, competitive clutter, consumer involvement, and category dynamics (Cannon and Riordan, 1994). Despite these critiques, frequency remained a core planning metric because it reflected exposure depth, complementing the breadth measured by reach.

$$Frequency = \frac{Total\ exposures\ (impressions)}{Number\ of\ people\ reached}$$

The combination of reach and frequency led to the development of Gross Rating Points (GRPs), calculated as reach (expressed as a percentage of prospects in the target market exposed to the vehicles carrying the ad) multiplied by average frequency. GRPs provide an aggregate measure of the total volume of advertising impressions delivered on a weekly or monthly basis, regardless of duplication (Novak and Hoffman, 1997). They became a standard currency for buying and evaluating media schedules, especially in television advertising, allowing planners to compare alternative media plans on a common scale and enabling cost-efficiency analysis that supported the broader marketing productivity paradigm (Morgan, Clark & Gooner, 2002).

$$GRP = Reach\ (\%) \times Frequency$$

These metrics treated advertising as a numbers game: greater exposure and higher frequency were expected to increase the likelihood of influencing attitudes and behavior. This logic drew support from information-processing perspectives suggesting that repeated exposure facilitated message encoding and recall (Aaker et al., 1992; Naples, 1979). However, subsequent research exposed significant limitations in this exposure-driven paradigm. Studies of media specialists revealed that exposure quantity alone proved insufficient: advertisers increasingly recognized the need to reach the right audiences (effectiveness) rather than merely large, undifferentiated populations (efficiency; King et al., 1997; Nowak et al., 1993).

1.2.2. Affinity Index

The limitations of volume-based metrics such as reach, frequency, and GRPs revealed that large quantities of exposure did not necessarily translate into meaningful advertising effects. Consequently, advertisers shifted their focus toward audience quality metrics that emphasized the efficiency of reaching intended targets rather than mass audiences. Among these measures, the affinity index emerged as particularly influential. It is a ratio comparing the concentration of a brand's target audience within a media vehicle to its concentration in the general population, thus higher index indicates higher efficiency of media channel for reaching target market of company (Rossiter and Percy, 1998; Sissors and Baron, 2010).

$$AI = \frac{Percentage\ of\ the\ medium's\ audience\ that\ belongs\ to\ the\ target}{Percentage\ of\ the\ target\ in\ the\ total\ population} \times 100$$

1.2.3. The Digital Era

The arrival of the digital era fundamentally shifted advertising evaluation and measurement, moving the industry from metrics based on estimated broad exposure in mass media to precise, individual-level measurement focusing on engagement, accountability, and causal impact. This evolution was driven by both the changing media landscape and increasing concern for demonstrating the return on advertising investments (Lewis et al., 2013). With the introduction of the Internet and the advertiser-supported web site new digital measures emerged: unlike traditional media, digital environments generate detailed, real-time data on how individuals interact with advertising content, enabling advertisers to move beyond proxies such as GRPs or affinity indices (Lewis and Rao, 2015). A notable example of new index was the *Click-Through Rate (CTR)*, which measures the percentage of users who click on an advertisement, offering a measure of consumer response (Novak and Hoffman, 1997). Other early digital metrics included Ad Views, Page Views, and Site Visits (Lewis et al., 2013; Novak and Hoffman, 1997).

Digital measurement standards evolved rapidly to address the critical gap between a served ad and an ad actually viewed by a person: an important metric in this sense was *viewability*. Viewability is a foundational measurement of an ad's condition, formalized by the IAB and MRC (2014), determining whether sufficient pixels of an ad are visible for a minimum duration, thus providing the opportunity to see the ad (IAB and MRC, 2014). Following the requirements for viewability (MRC/IAB Standards), for standard digital display ads, 50% of the pixels must be on an in-focus browser tab in the viewable space for a minimum of one continuous second, for video ads, the standard is 50% of the pixels in view for a minimum of two continuous seconds and for large display ads (242,500 pixels or greater), a threshold of 30% of pixels for one continuous second may apply (IAB and MRC, 2025, 2014).

Another significant development was the widespread adoption of *completion rate* in video advertising. This metric measures the proportion of viewers who watch an ad to its end and is often interpreted as a sign of user engagement or tolerance (Belanche et al., 2017; IAB and MRC, 2025; Teixeira, 2014). The importance of digital metrics lies in their ability to overcome the limitations of traditional exposure- and composition-based measures. Digital behavioral metrics provide direct evidence of how users respond to advertising. However, these metrics also exposed a critical gap: while they capture action, they do not necessarily capture attention (Belanche et al., 2017). A click may be accidental, a "like" may be habitual, and a completed video view may occur without any cognitive engagement (Lewis et al., 2013; Lewis and Rao, 2015; Wright and Campbell, 2008). This realization set the stage for the next phase in advertising measurement: the rise of attention metrics, which seek to quantify the cognitive and perceptual processes that occur during exposure rather than the behaviors that follow it (Hartnett et al., 2025).

1.2.4. Attention Metrics

Lately, the advertising industry has experienced significant pressure due to rising costs and declining consumer engagement, which prompted the search for new measurement currencies (Hartnett et al., 2025). These new currencies have been identified as attention metrics, which are derived from biometric measurements of various physiological signals that aim to quantify the attention a subject allocates during ad exposure (Harris et al., 2019; IAB and MRC, 2025; Mole, 2024; Orquin and Wedel, 2020). The contemporary attention framework encompasses multiple measurement approaches designed to capture user exposure, engagement, focus, and cognitive-emotional impact (IAB and MRC, 2025). These include data signals (such as time-in-view, scroll depth, and interaction patterns), visual tracking technologies (eye tracking, gaze tracking, facial coding), physiological and neurological observations (heart rate, blood pressure, EEG), and panel-based survey methods capturing brand recall and emotional response (Bell et al., 2018; Calvert and Brammer, 2012; Hartnett et al., 2025; IAB and MRC, 2025).

The ultimate objective of attention measurement is to develop predictive models based on deterministic data coming from biometric measurement that can estimate expected attention outcomes for advertising campaign (Bell et al., 2018; Hartnett et al., 2025; IAB and MRC, 2025; Zhang et al., 2009). This approach aims to ensure consistency and reliability across the advertising ecosystem, representing the industry's most sophisticated attempt yet to bridge the gap between advertising exposure and actual cognitive processing.

1.3. Importance of Biometric Measures in the Measurement of Attention

Biometric measurements are becoming increasingly important in advertising evaluation because they provide objective and real-time insights into consumers' neurological response that traditional methods and metrics cannot capture (Guerreiro et al., 2015; Ohme et al., 2009; Read et al., 2024). Their importance lies in several key contributions to understanding and optimizing advertising effectiveness.

First, biometric measures capture unconscious and objective consumer responses, moving beyond the limitations of other techniques (Colomer Granero et al., 2016; Guerreiro et al., 2015). While subjective methods such as questionnaires rely on qualitative behavioral assessment, biometric approaches monitor physiological signals that often represent unconscious drivers of decision-making (Colomer Granero et al., 2016; Zaltman, 2007). For example, one study found that an advertisement elicited higher Electrodermal Activity (EDA), indicative of arousal, in the participants, even though they reported no conscious awareness of the subtle difference in the ad version (Ohme et al., 2009). Second, biometric tools operationalize critical psychological processes relevant to advertising theory, such as arousal, interest, attention, and affective reaction (Read et al., 2024). These measurements also enable granular temporal analysis. Some permit to capture consumers responses as they develop in real-time, enabling advertisers to identify reactions frame by frame (Read et al., 2024; Vecchiato et al., 2011). Finally, these data provide new insights for predicting advertising success beyond traditional measures (Bell et al., 2018; Venkatraman et al., 2015; Vezich et al., 2017).

Biometric measurements are very important because they provide a rich, detailed, and objective picture of consumer interaction with advertising, moving beyond simplistic exposure metrics to capture the underlying mechanisms of attention, emotional engagement, and memory formation that lead to consumer behavior. This improvement in measurement capability allows advertisers to optimize content and media spending based on empirical and science based evidence of how advertisements are truly processed by consumers (IAB and MRC, 2025; Read et al., 2024; Vecchiato et al., 2011).

2 Chapter two

Before examining in detail the techniques currently employed to measure human attention to advertising, it is necessary to introduce and clarify what is meant by attention from both psychological and neuroscientific perspectives. In this section, the general concept of attention will be defined, its various types and sensory modalities will be outlined, and the main cognitive theories will be presented to explain how advertising captures and directs attention within the advertising context.

2.1. What is Intended for Attention from a Psychological and Neuroscientific Perspective

2.1.1. Definition

The concept of attention lies at the heart of cognitive science and perception, yet defining it precisely has historically been a difficult challenge due to its multifaceted nature. Since it is certainly not a clear or unambiguous concept, numerous definitions of human attention from a psychological perspective can be found in literature. Writing at the dawn of experimental psychology in the book *The Principles of Psychology*, William (James, 1890, pp. 917–918) captured the seemingly intuitive understanding of the concept by asserting: *Everyone knows what attention is. It is the taking possession by the mind, in clear, and vivid form, of one out of what seems several* *simultaneously possible objects or trains of thought*. Indeed, what we experience, perceive, and remember is profoundly influenced by which aspects of this we choose to attend.

Consequently, a widely accepted modern conceptualization frames attention in terms of resource management, recognizing that the human capacity for processing information is intrinsically constrained (Kahneman, 1973; Lindsay, 2020). In this context, Lindsay (2020) defined attention as *the flexible control of limited computational resources*, thus referring to the cognitive process used to identify and select relevant events over competing distractors. In contexts such as advertising, attention is often conceived as the controlled, but also the automatic, focusing of limited cognitive resources on external stimuli. This selection mechanism can be first divided into distinct attentional functions: automatic (bottom-up) processes that serve to attract attention, and controlled (top-down) processes that serve to maintain attention to relevant stimuli (Fritz et al., 2007; Hartnett et al., 2025; Klein and Lawrence, 2012; Venkatraman et al., 2015).

2.1.2. Bottom-up vs. top-down

Bottom-up attention is the mechanism of attention that is automatic, sound-based, or stimulus-driven (Read et al., 2024). This is an automatic process in which attention is captured by salient stimuli that "pop out" from the surrounding environment without conscious effort. These processes do not require conscious effort or processing to be identified and are likely the result of feature detectors built into the sensory system (Hartnett et al., 2025; Lindsay, 2020; Onișor and Ioniță, 2021; Orquin and Wedel, 2020). For instance, a prominent picture in an ad can automatically capture bottom-up attention. This form of attention is also highly responsive to stimuli with emotional or perceptual salience, such as smiling faces (Fernández-Martín et al., 2026; Harris et al., 2019)

On the other hand, top-down control refers to the influence of internal psychological factors on attention allocation. Theories about top-down control take into account the effect of personal goals and preferences on eye movements, the effect of search styles, or the implications for decision. This form of attention is goal directed, controlled, voluntary, and more deliberate and effortful than bottom-up processing. It reflects a person's current tasks, knowledge, motivations, and interests (Orquin et al., 2013; Orquin and Wedel, 2020).

An interesting aspect highlighted by an experiment conducted by Orquin et al. (2013) is that when humans are faced with a choice for the first time, bottom-up control predominates in the implementation of the choice over top-down control, as external factors capture more attention. However, when this choice is repeated, it has been observed that top-down control gradually becomes more important, as the participants in the experiment learned to base their choices on the attributes they considered important, rather than those that were merely the most salient or visually attractive. These two control type of attention are related with the concepts of high and low attention (Lavie, 2005, 1995).The theoretical link between these two forms of attentional control and the concepts of high and low attention hinges entirely upon the limited capacity of the cognitive system and the resulting degree of processing engagement (Kahneman, 1973; Lang, 2006, 2000). In conditions of high attention, the primary task involves high perceptual load, meaning it requires processing a large amount of heterogeneous information or demands complex perceptual operations (Lavie, 1995; Lavie et al., 2004). Thus, high attention is achieved when the top-down intention to focus is supported by a demanding task that consumes all available resources, eliminating the capacity for bottom-up capture. However, when attention is low, the system use automatic processing, allowing bottom-up elements to be processed, potentially influencing behavior and choice even if the stimuli were presented outside the focus of conscious attention (Cowan, 1995; Mack and Rock, 1998;

Sokolov and Cacioppo, 1997). Overall, bottom-up and top-down control can be looked at as mechanisms that operate under different levels of attentional engagement: high attention emerges when strong top-down control is sustained by high perceptual load, whereas low attention reflects conditions in which limited task demands allow bottom-up, stimulus-driven processes to dominate (Lavie et al., 2014).

2.1.3. Overt vs. Covert attention

Another important differentiation can be made when talking about attention, this is the distinction between overt and covert attention. From the literature, we know that overt attention involves the physical movement of the eyes to focus the fovea, the part of the retina with the highest visual resolution, on a specific point or object of interest. This is a shift in attention that is visible from the outside. The main mechanism of overt attention is saccades, which is a small, rapid jump of the eyes from one position to another. The periods when the eye is relatively still between saccades are called fixations, and it is during this time that information is extracted from the visual field. Therefore, this type of attention is easily measurable, particularly through eye tracking techniques. The study of overt attention helps researchers understand what automatically attracts attention (bottom-up processing) and how specific tasks influence gaze patterns (top-down processing; Fernández-Martín et al., 2026; Lindsay, 2020; Orquin and Wedel, 2020).

In contrast, covert attention is the process of mentally shifting the focus of attention to a specific spatial location in the visual field without moving the eyes. This allows for processing of information in peripheral vision while maintaining a central fixation point, and, as some theories suggest, covert helps to guide overt attention (Lindsay, 2020; Posner, 1988).

2.1.4. Brain Areas Involved in Attention

Posner and Petersen (1990) proposed a tripartite model of attention, according to which the human attention system is composed of three anatomically distinct networks that perform different functions: alerting, orienting, and executive control (Posner and Petersen, 1990).

The ***alertness network*** is responsible for achieving and maintaining a state of high sensitivity to incoming stimuli, that is called sustained attention. Its function is to prepare the brain to process high-priority signals, improving the speed of orientation and response to a target event. It is responsible for both phasic alertness (a brief change in alertness, often triggered by a warning signal) and tonic alertness (prolonged alertness over a longer period, (Petersen and Posner, 2012). Anatomically, this network is strongly lateralized in the right cerebral hemisphere, that is the one related to sustained vigilance. It involves the arousal systems of the brainstem, particularly the *locus coeruleus*, which is the source of the neuromodulator norepinephrine (NE). Key brain areas involved include the *thalamus* and regions of the *right frontal and parietal cortex*. The alertness system is influenced by the release of NE, which, as some pharmacological studies show, affects alertness but not orientation, suggesting a double dissociation between the alertness and orientation networks (Lindsay, 2020; Posner, 2008).

The ***orientating network*** is responsible for shifting attention toward particularly informative sensory inputs, mainly by selecting a specific mode or location. This mechanism is often described as the “spotlight” of attention. Subcortical regions such as the superior colliculus and the lateral pulvinar nucleus of the *posterior thalamus* contribute to this network by supporting both covert and overt shifts of spatial attention (Posner and Petersen, 1990). Studies have identified two key systems within this network: a *dorsal attention network (DAN)* and a *ventral attention network* (*VAN*; Corbetta et al., 1991; Corbetta and Shulman, 2011, 2002). The former is associated with top-down control of attention and includes the *frontal eye fields (FEF)* and the *intraparietal sulcus/superior parietal lobe (IPS/SPL)*. Activity in this network is typically observed when subjects voluntarily orient attention according to internal goals or cues, for instance when following directional arrows or anticipating a target location (Corbetta et al., 1991; Corbetta and Shulman, 2002). In contrast, the latter is strongly right-lateralized and is involved in bottom-up, stimulus-driven attention, such as reorienting attention to unexpected events, and includes the *temporo-parietal junction (TPJ)* and *ventral frontal cortex (VFC)*. It is activated when attention must be reoriented to unexpected, behaviorally relevant events or salient stimuli (Corbetta and Shulman, 2002; Shulman et al., 2009).

The third and final network identified by the authors is the ***executive network***. It is involved in voluntary control of thoughts and actions, especially in situations that require planning, decision-making, error detection, and conflict resolution. This network is responsible for monitoring and resolving conflicts between conflicting responses, regulating cognitive and emotional functions, and top-down control. It is activated by a wide range of demanding tasks, including pain perception, reward processing, and error detection. The core of this network involves the medial frontal areas, particularly the *anterior cingulate cortex (ACC)*. In their 2012 article Petersen and Posner (2012), the authors explored this system in greater depth, proposing two distinct executive control networks. The first is the *cingulo-opercular network* (which includes the ACC) and is thought to maintain stable control of tasks during trials. The second, the *frontoparietal network* (which includes the lateral frontal and parietal regions of the prefrontal cortex (PFC), is associated with the initiation and regulation of moment-to-moment control. In particular, the *dorsolateral prefrontal cortex (dlPFC)*, is specifically involved in cognitive control and working memory and it is crucial for holding the target of attention (Desimone and Duncan, 1995).

A key component of executive control is inhibitory control, which refers to the ability to control one's attention, behavior, thoughts, and emotions, making it possible to suppress unwanted or inappropriate responses (Carlson et al., 2002; Diamond, 2013; Hoek et al., 2022). In other words, this ability is often referred to as self-control or self-regulation (Petersen and Posner, 2012). This function is particularly relevant in advertising contexts, where exposure to persuasive stimuli requires individuals to resist immediate affective or impulsive reactions (Hoek et al., 2022). Moreover, disruptions in inhibitory control processes have been observed in individuals with alcohol use disorder when exposed to alcohol-promoting commercials, suggesting that deficits in this executive mechanism can increase vulnerability to advertising cues (Ueno et al., 2025).

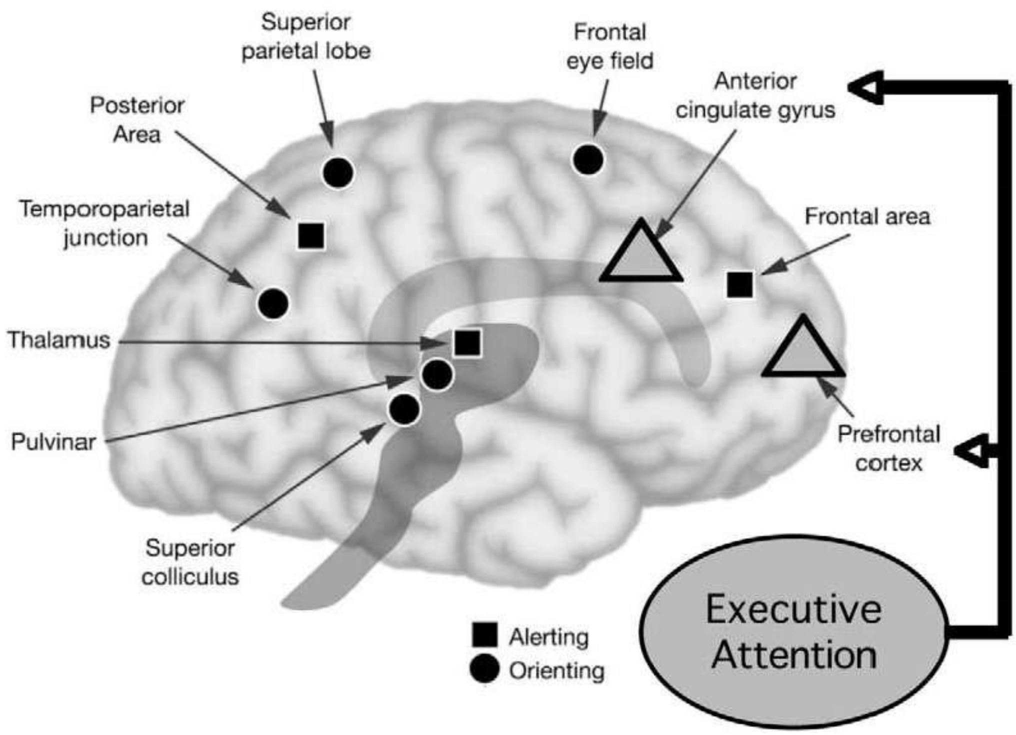

Figure 1: Anatomy of three attentional networks (Posner and Rothbart, 2007)

For what concern the distinction between covert and overt attention, fMRI studies has demonstrated that covert and overt shifts of attention involve similar areas (Corbetta et al., 1998). However, there is a different cells involvement in the two distinct situations. In essence, attention control operates like a unified system where the high-level brain areas (FEF, PFC) compute a "priority map" for selection, where covert attention is majorly involved. If that selection results in a physical movement, the same circuitry executes the initial stages of the motor program (FEF), leading to overt attention (eye movement; Petersen and Posner, 2012).

2.1.5. Types of attention

Attention can be classified into some functional typology, each defined by its specific constraints, functions, and underlying mechanisms. These are called selective attention, divided attention, sustained attention (alerting/vigilance) and temporal attention.

Selective attention is the ability to focus on what is important while simultaneously ignoring or suppressing irrelevant information. It acts primarily as a filter that selects and admits certain channels of information from the environment for further processing, while excluding others (Onișor and Ioniță, 2021; Santoso et al., 2022). This type of attention has been the most studied by the relevant cognitive theories of the last decades. A crucial modern distinction in research concerning selective attention is whether irrelevant stimuli are processed due to actual flaws in the filter or due to attentional shifts. These events are called *leakage* and *slippage*. Leakage occurs if semantic processing of irrelevant items "leaks" through the attentional filter, even when attention is strictly focused elsewhere. On the other hand slippage refers to when attention is unintentionally allocated to irrelevant items due to inadequate control (an attentional "slip"; Lachter et al., 2004).

Selective attention is supported by a distributed network of cortical and subcortical structures, with major mechanisms involving biasing sensory processing. The shared frontoparietal network underlies the control of both visual and auditory spatial attention. In the parietal cortex, part of the dorsal attention network, the superior parietal lobe (SPL) and posterior parietal cortex show enhanced responses to salient stimuli responses to salient stimuli and are involved in orienting, while the lateral intraparietal area (LIP) processes bottom-up attention, culminating in a saliency map (Lindsay, 2020). Also the frontal cortex areas, as for example the frontal eye field (FEF) contribute to attentional orienting while the prefrontal cortex (PFC), as it is part of the executive control, plays a critical role in tracking task goals, biasing sensory cortices toward task-relevant stimuli (Fritz et al., 2007). For this type of attention multiple experiments both in the auditory and visual field have been historically made. In modern auditory research, paradigms based on **Event-Related Potentials** (ERPs) are heavily utilized, particularly those measuring mismatch negativity (MMN). The MMN is an event-related potential (ERP) component that occurs when infrequent deviant stimuli are inserted in a series of standard stimuli. The MMN component is crucial because it is largely resistant to the influences of focused attention and thus reflects automatic, preattentive processing of acoustic features, including complex language features like lexical, semantic, and syntactic information (Bronkhorst, 2015). For visual attention the **Posner Cueing paradigm** (Posner, 1980) remains a foundational tool for studying the spatial control of attention, specifically covert orienting (shifting attention without eye movement). In this paradigm subjects are asked to detect as quickly as possible a target that appears either to the left or right of the fixation shortly after a briefly flashed central cue, which could be valid, neutral or invalid (Petersen and Posner, 2012). Another group of experimental paradigms are the **filtering** ones. In these studies, irrelevant stimuli (often called distractors or flankers) are typically presented in a different location than that of the target. Participants are assumed to devote their attention to the target and thus away from these irrelevant stimuli

(Lachter et al., 2004). The measure for these studies is the time required to find the target as a function of the number of distractors and the target-distractor confusability. Another major class of paradigms centers on **supervisory control** and the monitoring of visual displays. In these environments, operators are confronted with a wide array of dynamic information sources known as areas of interest (AOIs), such as altimeters, speedometers, or warning lights. The experimental task requires the operator to monitor these AOIs, controlling some variables while monitoring others for potential deviations and the measurement of selective attention in this context is accomplished by predicting visual scanning behavior using computational frameworks like the SEEV model (Salience, Effort, Expectancy, and Value). The primary metric of measurement in these studies is the percentage dwell time (PDT) or the percentage of scans allocated to each AOI, typically measured via eye-tracking, serving as a proxy for selective attention (Wickens, 2021). A closely related paradigm is the investigation of **noticing** discrete, sudden events. This requires studying phenomena like change blindness or inattentional blindness, where the former term refers to a failure to notice wherever the change event is in the visual field; the latter term specifically applies to an event or change which was within foveal vision at the time it occurred. The core task in this domain involves measuring noticing times in response to the discrete visual event and the experimental manipulation often involves controlling for retinal eccentricity, the visual angle separation between the current fixation point and the location of the event, as well as the salience and expectancy of the event itself.

Divided attention refers to the concept of attention as a limited resource needed to enable subsequent information processing, specifically constrained by the demands of multiple tasks performed concurrently (multi-tasking). Conceptually, divided attention can manifest either sequentially through discrete task switching or in parallel through continuous resource allocation (Wickens, 2021). It is one of the two main concepts of attention discussed in cognitive theory, contrasting with selective attention, which acts as a filter for choosing relevant channels of incoming information. For what concern the neural mechanism supporting divided attention, it primarily involves higher-order cortical regions responsible for executive control and resource allocation, rather than modulation within individual sensory cortices. First of all, researchers, employing neuroimaging studies with fMRI (Johnson and Zatorre, 2006), have established a neural distinction between selective attention and divided attention, particularly in bimodal settings. While bimodal selective attention (when participants are instructed to attend only one sense) tends to increase activity in the relevant sensory cortices (e.g., visual cortex if visual stimuli are selected) and simultaneously decrease activity in the irrelevant sensory cortex, bimodal divided attention (participants are instructed to attend both senses at the same time) recruits areas like the dorso-lateral prefrontal cortex (dlPFC) and the anterior cingulate cortex (ACC). This suggests that divided attention utilizes a different set of neural processes for resource management compared to selective attention (Fritz et al., 2007).

The fundamental method for investigating divided attention is the **dual-task paradigm**, which examines performance when two tasks are performed simultaneously. The main metric used by scholars to investigate divided attention is the attention operating characteristics (AOC). A typical AOC study consists of two tasks. Baseline conditions measure how well each task is done alone; if two tasks can be done simultaneously without loss, the joint performance is the same as that in the baseline conditions. On the contrary, if the two tasks make competing demands on attention, the joint performance is worse than that in the baseline conditions (Zhong-Lin, 2008). A more focused paradigm is **bimodal divided attention**, where subjects are required to process inputs from two different sensory modalities simultaneously, such as listening to novel melodies and viewing geometric shapes. To better explained this concept, it is possible to take as reference the experiment explained in Johnson and Zatorre (2006). During a 10-s trial, instructions were displayed on the screen corresponding to four conditions: attend to melodies and ignore shapes (auditory selective), attend to shapes and ignore melodies (visual selective), attend to both melodies and shapes (bimodal divided), or as a baseline, passively listen to melodies and view shapes (bimodal passive). In studies investigating attentional spillover effects, a dual-task setting is used where one task is designated as primary and the other as secondary. This setup implicitly creates a condition of resource scarcity for the secondary task (Yechiam and Hochman, 2014).

In addition, ***sustained attention***, also referred to as vigilance or alerting, is a fundamental type of attention defined by the ability to maintain a state of readiness and focus over an extended period (Lindsay, 2020). In particular, it refers to two related concepts: vigilance, that is the specific ability to sustain attention often measured during long and typically boring tasks, and directed attention (effortful focus), that involves the deliberate and effortful control of attentional resources to maintain focus on a goal-relevant task, despite fatigue or distraction (Kaplan, 1995).

The control of sustained attention relies on the alerting network (Petersen and Posner, 2012). Studies employing fMRI in subjects performing vigilance tasks have uniformly demonstrated the overriding importance of areas within the right cerebral hemisphere in managing this type of attention. In the specific, findings associated the activation in the frontal cortex with vigilance tasks (Posner and Petersen, 1990). This area showed high activity during auditory discrimination, visual, and somatosensory vigilance conditions during the experiments(Cohen, 1988; Deutsch et al., 1988). At the same time, when high metabolic activation is observed in the right prefrontal cortex during these tasks, it is accompanied by reduced activation in the anterior cingulate cortex (ACC; (Cohen, 1988). This reduction in ACC activity is theoretically significant because the ACC is strongly associated with executive attention and target detection (Goldberg et al., 2006; Gottlieb, 2007). This means that in vigilance scenarios, where an operator must suspend most internal cognitive activity while waiting for low probability signals, the observed deactivation is interpreted as a strategic mechanism to avoid thinking that might interfere with signal detection (Petersen and Posner, 2012).

Operationalizing and quantifying sustained attention presents a challenge, as attention itself is notoriously difficult to measure precisely, particularly regarding its intensity and duration (Fritz et al., 2007). The approach used to investigate this type of attention is the utilization of long and typically monotonous tasks (Oken et al., 2006). Historically, these vigilance tasks emerged from practical concerns, such as monitoring displays where signals occur infrequently and must be detected over long periods of time, mirroring the workload faced by radar operators looking for near-threshold changes. In performance-based studies, vigilance is assessed by monitoring changes in accuracy and reaction times throughout these long tasks .

Finally, ***temporal attention*** refers broadly to the function of attention concerning time, including focusing on events projected to occur at a specific future moment, the dynamics and time course of attention shifts, and the processing of information that unfolds across time. From a psychological and neuroscientific perspective, temporal attention involves the capacity to focus on an event expected to occur at a particular moment and to manage attention shifts dynamically (Fritz et al., 2007). The shift of attention is also important, while exogenous stimulus-driven shifts occur within 50-100 milliseconds, the endogenous ones are normally slower, between 150 and 500 milliseconds (Lachter et al., 2004).

There is evidence that the neural basis for temporal expectancies and discrimination is supramodal, meaning it applies across sensory modalities, and involves prefrontal cortex (with dlPFC also involved), basal ganglia, and cerebellum (Fritz et al., 2007). Even if the dimension of time is recognized as a comparatively recent addition to the psychological research agenda, some experimental paradigms are present in the literature (Nobre and Coull, 2010; Nobre and Van Ede, 2018). One primary way is the Attention Reaction Time (ART) paradigm, developed by Reeves and Sperling (1986).

In this experiment, subjects monitor two adjacent rapid serial visual presentations (RSVP): a stream of letters, containing an embedded target letter, and a stream of numerals. Participants are instructed to initially focus their attention on the letter stream, and immediately upon detecting the target, swiftly switch their attention to the numeral stream to report the earliest possible numeral they perceive (Reeves and Sperling, 1986; Zhong-Lin, 2008). Similarly, the phenomenon of intermittent attention is discovered using the RSVP technique. In fact, if a second target appears too close to the first one (specifically, between approximately 200 ms and 500 ms later), subjects often fail to perceive it. Studies employing this method, which introduces a brief temporal interval between two targets, investigate the attentional dwell time, the period during which an object consumes processing capacity (Chun and Potter, 1995; Duncan et al., 1994; Ward et al., 1997, 1996). Findings have suggested that interference can persist for several hundred milliseconds, supporting models where processing capacity is occupied for longer durations rather than short, high-speed scanning (Desimone and Duncan, 1995; Zhong-Lin, 2008). The operation of temporal attention is primarily quantified through metrics related to speed, accuracy, and changes in perceptual capacity (Zhong-Lin, 2008).

Type of Attention	**Network**	**Regions**	**Modality of Attention**	**Experimental Paradigm**	**Metrics**
Selective Attention	Orienting Network: Ventral Attention Network	TPJ,VFC	Bottom-up	Posner Cueing Paradigm; Noticing Sudden Events / Inattentional Blindness	Eye-tracking saccade latency
	Orienting Network: Dorsal Attention Network	FEF, IPS/SPL	Top-down	Posner Cueing Paradigm; Filtering Task; Supervisory Control	RT difference between valid/invalid cues (Posner), Accuracy/error rates, ERP N1/P1

	Executive Network	Anterior Cingulate Cortex (ACC)	Top-down		amplitude modulation (early sensory enhancement), Eye-tracking (Fixation Count, Dwell Time on AOIs, Time to First Fixation)
		Prefrontal Cortex (PFC)	Top-down		
		Dorsolateral Prefrontal Cortex (dlPFC)	Top-down		
		Ventromedial Prefrontal Cortex (vmPFC)	Top-down		
Divided Attention	Executive Network	Prefrontal Cortex (PFC)	Top-down	Dual-task Paradigm; Attention Operating Characteristic (AOC); Bimodal Divided Attention; Multiple Object Tracking	Dual-task cost, Accuracy loss vs. baseline, EEG theta/alpha, Pupillometry, Heart rate
		Dorsolateral Prefrontal Cortex (dlPFC)	Top-down		
Sustained Attention	Alerting Network	Locus Coeruleus (LC)	Bottom-up	Continuous Performance Test; Vigilance Task; Necker Cube Control	RT, Vigilance decrement, EEG alpha suppression, Pattern Control Score
		Thalamus	Top-down		
		Right Frontal and Parietal Cortex	-		
Temporal Attention	Executive Network	Prefrontal Cortex (PFC)	Top-down	Attention Reaction Time (ART); Rapid Serial Visual Presentation (RSVP)	Attentional Blink magnitude, EEG oscillations
		Dorsolateral Prefrontal Cortex (dlPFC)	Top-down		

Table 1: Types of Attention

2.1.6. Sensory Modalities of Attention

When thinking about attention, the first thing that comes to mind is the visual dimension, which is also the modality most extensively covered in scientific literature (Kanwisher and Wojciulik, 2000; Lindsay, 2020). However, it is essential to consider that attention is not limited to sight, but can be activated through all the senses, each with its own specific mechanisms and implications.

Visual spatial attention is a multifaceted process that enables us to select information from specific locations using visual channel. It can be overt, involving physical eye movements, or covert, involving mental shifts of focus. A different thing is the *visual feature attention*. It is a type of covert, selective attention where individuals direct their focus to a particular visual characteristic, such as a specific color, shape, or orientation, across the entire visual field, rather than to a specific spatial location. Unlike spatial attention, which prioritizes information from a specific location, feature-based attention operates globally. This means that when you attend to a particular feature (e.g., the color red), the brain modulates the activity of neurons representing that feature everywhere in the visual space, not just in one spot (Lindsay, 2020). In addition to visual attention, the other most important mode is *auditory attention*. This modality of attention consist in a set of cognitive and neural mechanisms that allow people to select, initiate, and maintain focus on a specific sound in a complex auditory environment. It is a fundamental component of attentional processing, as it allows the auditory system to extract important information from a mix of simultaneous auditory inputs. This is a challenge that concerns selective attention and is highlighted by the cocktail party problem. This problem describes the difficulty of focusing on and understanding the speech of one speaker in a crowded room that is brimming with multiple competing speakers and other noises. In these contexts, the listener must divide the relevant auditory stream from competing voices or background noise, relying on both bottom-up and top-down mechanisms to guide selection (Bronkhorst, 2015).

From a neurophysiological perspective, auditory attention functions as a searchlight that dynamically enhances the neural representation of relevant sounds while discarding irrelevant ones (Fritz et al., 2007). Though the "cocktail party problem" is traditionally stated in the auditory domain, growing evidence is demonstrating that auditory attention is strongly vision-driven and reveals the cross-modal nature of attentional processes. Vision, in particular, has been demonstrated to affect sound localization and segregation and thus how good listeners can discriminate a specific auditory stream from many interfering streams. A classic example of this effect is the visual bias of auditory location, otherwise referred to as the ventriloquism effect. The ventriloquism effect describes the propensity of the perceived spatial location of a sound to shift in the direction of a simultaneous visual stimulus. Experimental paradigms have shown that if the listeners are asked to monitor one of two superimposed speech passages from a single loudspeaker, they perform well if the image of the target talker producing the target speech is displayed on a screen located behind the loudspeaker, rather than in front of it. The visual cue effectively pulls the perceived auditory source towards the distant face, hence space-separating it from the interfering noise. This perceptual transfer assists attention selection and speech comprehension by allowing the listener to isolate the target stream from distractors. Surprisingly, this visual effect is accomplished even when the task does not require spatial localization. Individuals need to make no judgments of space, and yet their performance on recognition is still affected by a shift in the apparent source of sound due to visual information. This finding implies that the ventriloquism effect is a pre-attentive and automatic spatial bias, rather than the result of voluntary or conscious compensation. It documents how visual information can influence auditory perception unconsciously, with a focus on the interconnectedness of sensory modalities in directing attention and building comprehensive perceptual scenes (Bertelson and Aschersleben, 1998; Bronkhorst, 2015; Fritz et al., 2007; Macaluso et al., 2004).

2.2. Main Cognitive Theories of Attention

In the following paragraphs the major cognitive theories regarding attention will be introduced. Although the earliest controversy regarding this matter began even in the first decades of the twentieth century, the first accounts of actual models that helped shape the modern concept of the phenomenon began even in the 1950s. For that reason, this review will highlight theory developments towards the mid-point of the previous century.

Early studies on selective attention in the early 1950s focused solely on auditory attention, starting with the cocktail party problem (Cherry, 1953), a problem that has already been explained above. Over time, various theories have been formulated: some derive from the evolution of previous models, while others arise in contrast to them. The first group of models derives essentially from the work of Broadbent, who proposed an early selection filter capable of blocking irrelevant auditory stimuli on the basis of physical characteristics. Psychologists attempting to produce a theory of attention in the nineteen sixties and seventies were highly influenced by Donald Broadbent's picture of attention and their first objective was to locate this attentional bottleneck (Mole, 2024). This group of theories is called capacity-limitation theories and is divided into three main groups that differ in the phase in which the filtering of unattended stimuli occurs: Early Selection theory, Late Selection theory, and Attenuation theory (Treisman, 1964). Parallel to these developments, theorists proposed models specialized for visual processing; the first important theory was Feature Integration theory (Treisman and Gelade, 1980), which stated that simple visual features (e.g., color, orientation) are recorded preattentively in parallel across the entire visual field.

2.2.1. Early selection theory

The first very important contribution was Donald Broadbent's (1958) theory. It was a fundamental contribution to cognitive psychology, introducing the concept of bottleneck in information processing and establishing a dominant paradigm for attention research for decades (Lachter et al., 2004).

The central idea of Broadbent's selective filter theory is the existence of an early selection model structured around two successive and qualitatively different stages of perceptual processing, separated by a selective filter (Driver, 2001; Figure 2). The first stage is called *Preattentive Parallel Processing* and consists of identifying and extracting the physical properties (e.g. the position or the tone of a sound) of incoming stimuli. Representations of these physical features are briefly held in an immediate memory store. This temporary storage allows an observer to attend and process two simultaneously presented stimuli sequentially via rapid switching of attention. In the middle between the first and the second stage, the selective filter is present, also called bottleneck. It operates on the physical properties extracted in the first stage and selects one specific "channel" or physically definable stream of information to be passed in the following position. Therefore, the main function of this bottleneck is to protect the second step from overload. The second level is also called *Limited Capacity Processing* because only selected information passes through the filter to the second phase, which has a lower capacity. (Broadbent, 1958; Driver, 2001; Lachter et al., 2004; Mole, 2024; Wickens, 2021).

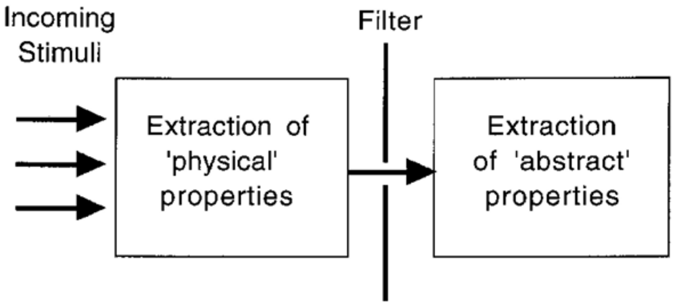

Figure 2: Early Selection Theory

This theory was highly innovative at the time and formed the basis for many subsequent studies that focused on both its positive and negative aspects. Criticisms and problems with this theory fall into three main categories: empirical evidence contradicting strict filtering, issues with the estimated speed of processing, and architectural rigidity. The primary empirical challenge was the demonstration that unattended information could sometimes be processed beyond simple physical features to the level of meaning or identity, a phenomenon that implied the filter was "leaky" or incomplete. For example, several experiments using indirect measures suggested a semantic processing of the irrelevant messages (Lachter et al., 2004). Another significant issue identified later was Broadbent's estimation of the time needed to shift attention: he argued that shifts of attention required about one half a second (500 ms or more) because he believed attention shifts were slow. Subsequent research revealed that involuntary (exogenous) shifts of attention can happen rapidly, in less than 100 ms. This revised understanding allows critics to argue that the previous evidence for semantic processing of unattended stimuli (which refuted Broadbent's theory) was actually caused by slippage (unintentional allocation of attention to the irrelevant item) rather than leakage (semantic processing occurring while attention remained focused elsewhere (Lachter et al., 2004).

Finally, this model's ultimate issue was its very simplistic and static architecture: it treated attention as if it were a single, fixed bottleneck and thereby neglected the true complexity of cognitive processing (Driver, 2001; Lachter et al., 2004; Wickens, 2021).

2.2.2. Late selection theory

The first major theoretical departure from Broadbent's framework is the late-selection theory proposed by Deutsch and Deutsch (1963). Their theory hypothesized the selection process occurs late in the processing stream, acting upon the results of this extensive analysis. The bottleneck was thus recast not as a protector against sensory overload during initial identification (stage one), but rather as a gating mechanism regulating access to further processes, such as memory storage and whatever else it may be that leads to awareness (Deutsch and Deutsch, 1963; Lachter et al., 2004). In simple words the selection of the stimuli happens only after their elaboration (Figure 3).

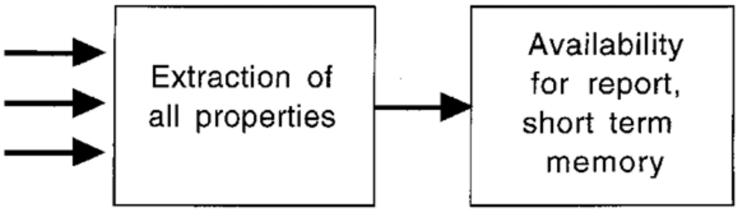

Figure 3: Late Selection Theory

Deutsch and Deutsch conceptualized this late selection as a comparison process: they hypothesized the existence of a diffuse and nonspecific system that takes up a fluctuating board that acts as a standard. The level of this board is determined by the most important stimulus arriving at each time. If the level of this diffuse system is above that of a particular discriminatory mechanism (which represents an incoming stimulus), that mechanism will not register information in memory or motor adjustment. This process ensures that the most important message to the organism will have been selected. Their work, based on behavioral findings, aimed to propose a system that could explain various features of attentional behavior and considered tentative hypotheses concerning the neural identification of this system, even discussing neurophysiological results that claimed to demonstrate a neural blockage of rejected messages at lower levels (Deutsch and Deutsch, 1963).

The strict late selection position, which argues that attention operates only on the results of identification and has no effects on initial perceptual processing, has been largely discredited. Subsequent neurophysiological research, often driven by advancements in brain imaging, provided strong evidence of early attentional modulation. They demonstrated that attention, through mechanisms like stimulus enhancement and external noise exclusion, affects perception itself, rather than just post-perceptual memory or response selection (Driver, 2001; Lachter et al., 2004; Petersen and Posner, 2012).

2.2.3. Attenuation theory

Despite the elegance of the Late Selection solution in accommodating semantic breakthrough, it quickly became evident that this framework suffered from a critical drawback: it appeared to be an overcorrection. If all messages are processed fully at the semantic level automatically, as late selection claimed, then the widespread empirical finding that listeners know surprisingly little about the content of the non-shadowed message becomes highly problematic (Moray, 1959). To solve this dichotomy between the two theories of early selection and of late selection, Anne Triesman proposed a crucial intermediate approach: the Attenuation Theory.

In her work, Treisman (1964) suggested a less drastic revision of Broadbent's filter model with respect to Deutsch and Deutsch (1963). She maintained the basic idea of an early filter but proposed that its operation was not absolute: the filter did not completely block or exclude the input from the irrelevant, non-attended channels, but instead merely attenuated or weakened the strength of the signal (Figure 4).Thus, unlike Broadbent's filter, which acted like an on/off switch, Treisman's attenuator acted like a volume knob turned down low. Treisman argued that some words have lower thresholds as a result of being important (such as a person's own name) or contextually appropriate. Consequently, even an attenuated signal could activate these words (Driver, 2001; Lachter et al., 2004; Treisman, 1964). This attenuated signal proceeds to the second stage of processing, where they are analyzed at the semantic level, but receives weaker input compared to the attended channel. For most words in the attenuated channel, the weakened signal is insufficient to trigger identification, and thus the subject remains unaware of the content. However, Treisman argued that thresholds are not fixed universally. Certain stimuli are characterized by a permanently low threshold for activation due to their inherent importance to the listener, as for instance the person's name (Driver, 2001; Lachter et al., 2004; Treisman, 1964).

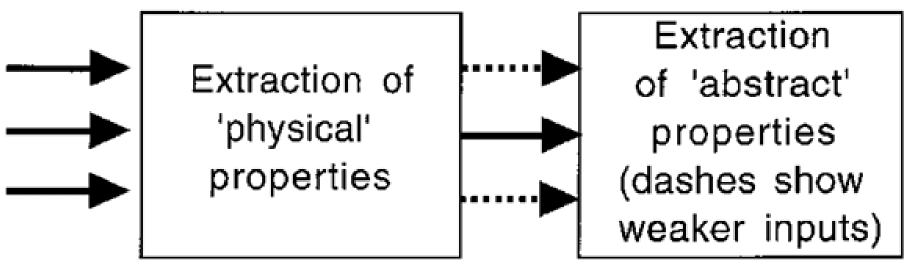

Figure 4: Attenuation Theory

Attenuation theory thus provided a successful theoretical compromise: it accounted for the general lack of awareness of unattended input (supporting the early selection stance against full semantic processing for every input) while simultaneously explaining the exceptions based on relevance and context (refuting the idea of a total early block). In this model, selection operates effectively during the process of verbal and semantic analysis, manipulating signal strength and identification criteria rather than simply acting as a binary exclusion device at the periphery or a late gate solely controlling entry into consciousness.

2.2.4. Feature Integration theory

The three theories outlined above mainly concern auditory attention. As already mentioned, it took some years for scholars to shift their focus to the study of visual attention. The first major and fundamental contribution in this field was made by Anne Triesman and Garry Gelade, who in 1980 proposed the famous and widely recognized Feature Integration Theory of Attention with a paper where theoretical conclusion are accompanied with nine experimental results. This new theoretical proposal aimed to answer a fundamental question neglected by the filter models of auditory attention: how does the cognitive system successfully merge the disparate streams of sensory data, such as color, orientation, and size, into the coherent, unified perception of an object? This challenge is known as the binding problem (Driver, 2001; Mole, 2024; Treisman and Gelade, 1980; Wolfe, 2020).

FIT proposed a structured, two-stage architecture of visual perception to resolve the binding dilemma (Driver, 2001; Figure 5).

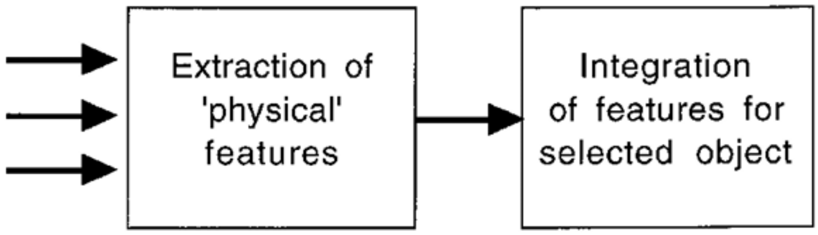

Figure 5: Feature Integration Theory

During the initial stage, termed *preattentive processing*, simple, fundamental features of the visual scene, such as color, orientation, size, brightness, and direction of movement, are registered rapidly and simultaneously across the entire visual field. Preattentive processing operates without the need for focused, serial scrutiny and is powerful enough to carry on low-level perceptual organization tasks like texture segregation and figure-ground grouping (Driver, 2001; Treisman and Gelade, 1980; Wolfe, 2020). The second layer of the model is the *focused attention stage*, which is introduced specifically to tackle the binding problem. Treisman proposed that, in order to recombine these separate feature representations and ensure their correct synthesis into a recognizable percept, stimulus locations must be processed serially by focal attention (Driver, 2001; Treisman and Gelade, 1980; Wolfe, 2020).

The feature integration theory provided the conceptual basis for much subsequent research on perceptual integration and the binding problem, and it also influenced the neuroscience of attention and eye-tracking studies; suffice it to say that by 2020 the 1980 paper had over 13,000 citations on Google Scholar (Wolfe, 2020). Despite its foundational influence, FIT faced sustained critique, primarily focused on the rigidity of its proposed serial mechanism and its failure to account for the influence of perceptual organization and contextual knowledge (Driver, 2001; Wolfe, 2020). Specifically, three main criticisms were directed at this theory: the falsification of strictly serial conjunction search, the neglect of perceptual grouping and object-based effects, and certain limitations regarding early feature coding (Driver, 2001).

2.2.5. From serial filtering models to dynamic, distributed, and contextual models: the capacity model.

The models described so far focus on identifying a framework of attention conceived as a filtering process. A crucial shift away from strictly defining the location of this bottleneck began with the introduction of the concept of limited cognitive resources. Daniel Kahneman's *Capacity Model* (1973), introduced in Attention and Effort, became essential by arguing that attention could be identified with the limited mental effort or resources available for cognitive work (Bruya and Tang, 2018). Kahneman (1973) criticized the singular focus on fixed structural bottlenecks, proposing instead that attention is a shared resource pool that must be allocated among concurrent tasks (Kahneman, 1973; Yechiam and Hochman, 2014). The model assumes attention can be allocated with considerable freedom among concurrent activities, moving the focus from what information is selected (the core issue of the filter debate) to how much mental energy is available and where it is distributed (Bruya and Tang, 2018; Yechiam and Hochman, 2014). This resource-based perspective directly paved the way for Nilli Lavie's *Load Theory of Selective Attention*. Lavie's framework offered a dynamic resolution to the decades-long early/late selection debate by positing that the perceptual load of the primary task determines if the selection happens early or late (Driver, 2001). Concurrently, other researchers challenged the assumption of a single filter, leading to new different architectures. *The Biased Competition Model* (Desimone and Duncan, 1995) views attention not as a filter or a separate process, but as the emergent property of competitive interactions occurring simultaneously among stimuli throughout distributed neural systems. Selectivity arises because multiple stimuli compete to drive the activity of neurons in visual cortex (a "winner-takes-all" mechanism), a competition which is then biased top-down by the subject's goals and relevance (Mole, 2024).

Parallel to this, Wolfe's *Guided Search Theory* (1989, 1994, 2007) re-described visual attention as a guided process by the constant interplay between bottom-up salience and top-down goals. Stepping away from parallel vs. serial search dichotomy, Wolfe proposed a hybrid mechanism by which visual attention is dynamically regulated towards objects with maximum activation on a priority map integrating sensory distinctiveness, expectations, and task relevance. This model combined feature-based and goal-directed theories, demonstrating that attention was not necessarily a passive filter but an adaptive system that actively select information based on perceptual and cognitive cues (Wolfe, 2021, 2007, 1994; Wolfe et al., 1989).

Overall, these models reflect the move from early concepts of attention as a serial, capacity-limited filter to one of attention as a dynamic, distributed, and goal-dependent system that can integrate perceptual, cognitive, and neural aspects.

2.2.6. Load Theory of Selective Attention

The Perceptual Load Theory (PLT), developed by Nilli Lavie, provided a crucial conceptual tool to resolve the historical discrepancies between the earlier theories previously exposed in this work, proposing that the location of selection is not fixed, but rather dynamic, entirely dependent upon the processing demands of the task-relevant information.

This theory operates based on two core assumptions synthesized from the opposing historical positions: first, that perceptual capacity is fundamentally limited (Bruya and Tang, 2018), and second, that perceptual processing is automatic in the sense that any available capacity must be utilized and cannot be deliberately withheld (Lachter et al., 2004; Lavie, 1995). The fundamental principle of PLT is that the degree of processing of irrelevant information depends on the perceptual load imposed by the primary task to which an individual must pay attention:

- ***High Perceptual Load***: When the primary task is highly demanding, the processing capacity is exhausted by the relevant input. Since there is no residual capacity available for ancillary processing. This outcome replicates the predictions of traditional early selection.

- ***Low Perceptual Load***: If the primary task is simple and requires only a small fraction of the available capacity, the spare capacity automatically spills over to the irrelevant stimuli.

After the publication of the 1995 work, Lavie kept active her research to extensively review and expand the theory. With the publication *Blinded by the load: attention, awareness and the role of perceptual load* of 2014, she broadened the theory's reach, linking perceptual load not only to selective attention but also to conscious visual awareness and providing crucial neuroscientific verification. Another, but important, refinement documented in the 2014 paper addresses the underlying mechanism of capacity allocation. While the original 1995 paper described the effects of capacity exhaustion and spillover, the later work clarified that PLT does not necessarily suggest a serial two-stage model where relevant information is processed first, followed by a spillover of residual resources. Instead, the theory can be fully explained by a simultaneous parallel processing model, where the limited capacity is allocated simultaneously across all competing inputs in the visual field, with processing weights reflecting the priority of the task-relevant stimuli. High load ensures that the capacity resources are saturated by the heavily weighted relevant items, effectively shutting out irrelevant stimuli in parallel. This refinement ensures the model remains robust against critiques suggesting that attention acts primarily as a facilitator rather than a suppressive filter, aligning PLT with modern views, such as the biased competition model, where networks compete for limited capacity (Lavie et al., 2014).

2.2.7. The Biased Competition Model

The Biased Competition Model (BCM), primarily elaborated by Robert Desimone and John Duncan (1995), presents a comprehensive neurobiological framework for understanding selective attention (Mole, 2024). The core assertion of the BCM is that, since the nervous system does not have unlimited capacity to process all sensory input simultaneously, stimuli compete against each other to dominate the neural response (Driver, 2001). Moreover, the model suggests that the neural competition for selection is biased. Attention works by biasing this competition toward the stimulus that is the target of attention. The biases can be a bottom-up biases or a top-down. The first refers to factors in the stimulus that automatically favor certain inputs in the competition. The latter, on the other hand, originates from the requirements of the current task and the person's goals, guiding the system to direct attention toward relevant information (Desimone and Duncan, 1995; Lindsay, 2020).

2.2.8. The Guided Search Theory

While most of the theories discussed so far have focused primarily on when attention operates or how much information it can process, Guided Search Theory (1989, 1994, 2007, 2021) concentrates on how attention is spatially directed within complex visual environments. In this sense, the Guided Search model was explicitly introduces by Wolfe as an alternative to the FIT (Wolfe, 1994). FIT enforced a rigid dichotomy in visual search performance: if a target could be defined by a single unique feature, search would be effortless, producing quick reaction times (RTs) largely independent of the number of distractors (set size). On the contrary, a search for a target defined only by a conjunction of features required serial attention to check each item in turn to solve the binding problem, leading to search times that increased steeply and linearly with set size (Driver, 2001). The fact that multiple reports demonstrated that this strict parallel dichotomy of FIT was empirically untenable led directly to the formulation of this model in 1989 (Wolfe, 2020). The first version of 1989 (GS1), retained the two-stage structure of FIT (preattentive parallel stage and a serial attentive stage), introducing the concept of guidance of the serial deployment of attention acted by the first stage. According to GS1, the efficiency of visual search depended on the quality of this guidance: feature searches, where preattentive signals strongly highlight the target, are highly efficient and largely independent of set size, while conjunction searches show intermediate slopes as attention is probabilistically biased toward likely target items rather than randomly distributed across the field (Wolfe et al., 1989).

In the year 1994, the model was reformulated to capture a continuum between purely parallel and purely serial searches. The concept of activation map was introduced, meaning an integration within bottom-up salience with top-down control. Attention is deployed to the item with the highest peak on this integrated map, progressively suppressing distractors through inhibition of return (Wolfe, 1994). A later review of the model proposed the real-world analogy of the visual search with a carwash. As cars enter and leave in a serial manner but multiple cars are washed at the same time, the items are selected entering the process and are recognized in a way in which time between selection is shorter than the time required for recognition (Wolfe, 2007). Finally, the latest revision of the model dates to 2021. In this version the author expands the model to reflect contemporary understanding of attention as a multi-source, adaptive system. The essential points are that selective attention selects one item at a time, but the time between selections is shorter than the time needed for recognition, ensuring multiple items are processed concurrently. Also, this revision addresses the issue of memory for rejected distractors. Unlike previous versions, which stated that visual search had no memory for distractors, this latest model assumes that there is a modest memory for a small number of previous distractors (about four to six). This limited memory helps avoid immediate reselection without requiring the system to track every rejected item, thus maintaining computational efficiency (Wolfe, 2021).

Across its evolution, the guided search framework has progressively shifted from a static two-stage model to a dynamic, computational architecture integrating perceptual, cognitive, and motivational sources of guidance. It now stands as one of the most comprehensive models of visual attention, bridging the gap between basic feature-based theories and real-world, context-dependent visual behavior.

3 Chapter three

Chapter two provided an overview of the concept of attention, how it has evolved in terms of cognitive theories, and the different classifications that can be made when discussing this broad concept. Following this overview of the theoretical foundations of attention as a cognitive process, this chapter will focus on how attention can be quantified, distinguishing between the processes and attention metrics described in academic literature and those used in industry. This chapter is therefore divided into two main sections. The first presents the most relevant academic methods used to measure attention, emphasizing their theoretical rationale and technical features. The second examines how these principles have been operationalized by attention metrics porviders, comparing academic and industry measurement approaches.

3.1. Academic Biometric Measurement Techniques

This section will discuss the main biometric attention measurement techniques, with the resulting attention metrics, theorized and used by academic researchers in the marketing and advertising field. These measures are categorized in literature based on whether they assess activity in the central nervous system (brain and spinal cord) or the peripheral nervous system (Read et al., 2024). Specifically, the two main central measures are brain electrical activity, assessed using electroencephalography via electrodes placed on the scalp, and the presence of oxygenated blood in the brain, measured using functional magnetic resonance imaging (fMRI). On the other hand, the main peripherical measures are: Electrocardiography (ECG) and Cardiac Activity, Electodermal Activity (EDA) or Galvanic Skin Response (GRS), Facial

Electromyography (fEMG), Eye Tracking (ET) and Facial Expression Analysis (FEA; (Read et al., 2024).

The following Table 2 will provide an overview of the advantages, disadvantages and attention metrics of these central and peripherical measures.

Biometric Measure	**Biological Mechanism**	**Primary Advantage**	**Primary Drawback**	**Attention Metrics**
EEG	Neural electrical activity	Temporal precision, Gold standard	Limited spatial precision	ERP
				Memorization Index
				Pleasantness Index
				Interest Index
fMRI	Blood oxygenation level- dependent (BOLD) signal	Spatial resolution	Low temporal precision, cost prohibitive	BOLD signal
ET	Eye movement (and fixation), pupil dilation, blink response	Can distinguish between bottom-up and top-down	Only measure overt attention	Fixation Duration or Dwell Time (DT)
				Fixation Count (FC)
				Time to First Fixation (TFF)
				Heatmap
				Gaze Plots
				Pupil Dilatation
				Blink Rate/Duration
ECG & Cardiac Activity	Electrical activity and Beats of the heart	Relatively easy to collect	Susceptible to artifacts	Heart Rate Variability (HRV)
				LF/HF Ratio
				Beats Per Minute (BPM)
				Orienting Response
EDA		Very effective in determining the	Cannot determine the	Skin Conductance Level (SCL)

	Conductance of externally generated potential	intensity of an emotion	valence (positive or negative) of an emotion	Skin Conductance Response (SCR)
fEMG	Facial muscle electrical activity	Assesses visually indistinguishable facial muscle movement	Can be complicated to interpret	Amplitude of Electrical Activity Zygomaticus Major Activity Corrugator Supercilii Activity
FEA	Visible facial muscle activity	Relatively noninvasive	Requires visible facial muscle movement	Index of Emotional Engagement

Table 2: Biometric Techniques

3.1.1. EEG Signals

Electroencephalography, or EEG, is a fundamental technique within neuropsychology-oriented research, serving as an objective method for monitoring and analyzing the electrical activity produced by the central system (Colomer Granero et al., 2016). This techniques consists on acquiring voltage fluctuations or electrical potentials on the scalp that are caused by the concomitant electrical activity and synchronization of a large population of neurons, referred to as the electrogenic capacity (González-Morales, 2020). This signals are collected by placing electrodes on the human scalp following standardized disposition to ensure consistent and replicable data collection. The two main standardized positions are the 10-20 system, which consists of 30 electrodes, and the 10-10 system, which involves placing additional scalp electrodes at half distance between the standard electrodes of the 10–20 system. Once the electrical activity is recorded over time (a time series), the raw EEG trace must be subjected to processing steps, which may include filtering and segmentation, before analysis (Aminiroshan et al., 2023; Harris et al., 2019; Kane et al., 2017).

The electrical activity produced by neurons firing in the brain is often organized into rhythmic patterns, known as neural oscillations or brainwaves. The major canonical frequency bands identified in EEG recordings are five: Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ). In terms of frequency analysis in the attention research related to advertising, two specific bands power are completely linked to attention. The first is the Alpha Activity (8-13 Hz) and the second is the Theta Activity (4-7 Hz). Alpha power in the frontal region of the brain is negatively related to attention, this means that an increase in attention is therefore correlated with a decrease in alpha power, a phenomenon that consists on the reduction of the alpha amplitude and is called alpha desynchronization or alpha blocking (Klimesch, 2012). This blocking indicates that active cognitive processing is occurring. On the other hand an increase in theta power, often observed alongside alpha desynchronization, has been shown to indicate both attention and an increase in episodic memory encoding (Aminiroshan et al., 2023; Harris et al., 2019; Read et al., 2024). The other bands are less related to attention measurement and can be studied in other types of research or in advertising research in the context of individual preferences and commercial success. For example, Delta activity (1-3 Hz) is commonly the focus of research in sleep studies, while Beta (13-30 Hz) waves have been linked to cognitive processing during consumer decision making. Finally, Gamma activity (>35 Hz) is associated with memory processes, specifically encoding, and selective attention. Increased activity in the gamma band has been observed, alongside theta, during the observation of commercials that were remembered (Briesemeister et al., 2013; Donoghue et al., 2022; Fischer et al., 2018; Vecchiato et al., 2010).

Although researchers can analyze EEG data in different ways, the two most often used techniques in advertising research are event related potentials (ERPs) and frequency band analysis. *Event-related potentials* are systematic fluctuations in the brain's electrical activity that are associated with events and they consist of systematic positive and negative voltage deflections in the EEG. The ERPs can be analyzed for amplitude and latency, with the former indicating the intensity of the response and the latter indicating the timing of the response (Read et al., 2024). The other type of EEG data interpretation used by advertising researchers is the *frequency bands analysis*. The standard method of quantifying frequency band oscillations is the power spectrum analysis or power spectral density (PSD), which mathematically describes the distribution of signal power, or the "frequency content", across different frequencies (Dressler et al., 2004). In quantitative research, analysis goes beyond simply examining the power within these bands and researchers extract features to synthesize the data into meaningful metrics (Colomer Granero et al., 2016). One commonly used metric is the Global Field Power (GFP), which quantifies the moment-to-moment spatial variability of the EEG signal across electrodes. It reflects the standard deviation of potentials across all sensors and therefore indicates the strength of the electric field at the scalp (Lehmann and Skrandies, 1980). High GFP values correspond to stronger, more synchronized neural responses across cortical regions. Since absolute power levels vary widely between individuals, the GFP is often normalized to a baseline period to produce a Z-score index. This Z-score indicates how much the power during the stimulus deviates from the average basal cerebral activity (Vecchiato et al., 2010). Colomer Granero et al. (2016) suggest an approach to compute this two indexes, in this paper the GFP is calculated with the following formula:

$$GFP = \sqrt{\frac{\sum_{i=1}^{N_e} \sum_{j=1}^{N_e} \left(u_i - u_j\right)^2}{N_e}}$$

where u_i is the potential at the electrode i (over time), u_j is the potential at the electrode j (over time) and N_e is the total number of electrodes employed to compute the GFP. Following this computation the authors suggest the following method to compute the Z-score:

$$Zscore = \frac{GFP_i - \overline{GFP_B}}{\sigma(GFP_B)}$$

where GFP_i is the Global Field Power during the ad under analysis, GFP_B is the Global Field Power during a period of 2 minutes. Researchers also created other indexes used in the frequency band analysis. Examples of these measures are the Memorization Index (MI), the Pleasantness Index (PI), and the Interest Index (II; Colomer Granero et al., 2016; Vecchiato et al., 2011).

The *Memorization Index* is designed to measure a stimulus's capacity to be remembered, it is calculated using GFP from the theta and alpha bands, since these bands are associated with attention and the human memorization process (Vecchiato et al., 2010). Colomer Granero et al. (2016), consider these index to implicitly relates attention (and consequent encoding effort) to later recall of brands in advertising. Also the Pleasantness Index is strongly correlated with attention because the alpha power it measures is the signature of cortical activation and resource allocation (Briesemeister et al., 2013). This index provides continuous information about moments that are pleasing who is watching an advertisement. Its core mechanism relies on *Frontal Alpha Asymmetry (FAA)*, which measures the difference between activity in the right and left frontal hemispheres. The computation involves decomposing the raw EEG data into frequency bands, discarding non-alpha or theta activity, applying a natural-log transformation, and finally calculating the metric as the difference between right-hemispheric electrode data minus their left-hemispheric counterparts $\ln(R) - \ln(L)$. Increased left frontal activation is consistently associated with motivation for approach-related behavior, liking, or positive affect. This pattern suggests that stimuli judged as pleasant or attractive receive a greater allocation of attentional resources to the left frontal cortex. Conversely, greater relative right-hemispheric activation (lower alpha power in the right frontal area) is associated with withdrawal-related motivation or negative affect (Briesemeister et al., 2013; Vecchiato et al., 2011, 2010).

EEG main advantage with respect of the other techniques is that it is considered a gold standard for the investigation of attention and of the time course of cognitive and psychological phenomena (Hartnett et al., 2025). This is due to the unique ability to provide direct, real-time neural measurements that overcome the temporal limitations of other imaging techniques and the biases inherent in subjective measurement methods. This characteristic is particularly important in advertising research, since this precision permits to determine, for example, the exact moment and characteristic in which the advertise is effective (Vecchiato et al., 2011). Moreover, EEG devices are typically relatively inexpensive, robust, and becoming increasingly portable and even wearable. This portability allows for data collection outside of controlled laboratory environments, increasing the validity of the findings (Bell et al., 2018). On the other hand, some limitations are present. Firstly this method has a limited spatial resolution compared to fMRI, making it difficult to precisely pinpoint the exact source of specific brain activation (Bell et al., 2018). Also, It is almost impossible to acquire the electromagnetic activity elicited by deep brain structures, such as the amygdala, which are often associated with core emotional processing in humans, using usual superficial EEG electrodes (Colomer Granero et al., 2016; Vecchiato et al., 2014).

3.1.2. Functional Magnetic Resonance Imaging

Functional Magnetic Resonance Imaging (fMRI) is a neuroimaging technique that measures neural activity indirectly by tracking the *Blood Oxygenation Level-Dependent (BOLD)* signal. The fundamental principle of fMRI rests on the physiological response to heightened neural activity: increased activity in brain areas demands more oxygen, leading to metabolic changes. The BOLD signal specifically tracks changes in cerebral blood flow, reflecting the amount of oxygenated blood in different areas of the brain, this means that active brain regions can be pinpointed with detail accuracy. Overall, fMRI has the advantage of having an high spatial resolution, since it can detect deep brain structures, making it ideal in studies where researchers need to know the neural substrates underlying consumer-related processes. This spatial resolution permits also to distinguish between bottom-up and top-down mode of attention, simply identifying the active areas of the brain (Hahn et al., 2006; Lawrence et al., 2019). Table at page 29 highlight which areas are associated with which mode of attention. On the other hand, the main limitation is the poor temporal resolution, since it relies on measuring the cerebral blood flow response, which is delayed following the neural event. Another disadvantage is its cost prohibitiveness and the difficulty to set up an experiment with the machine (Bell et al., 2018; Driver, 2001; Read et al., 2024; Vecchiato et al., 2011).

3.1.3. Eye Tracking

Eye tracking is probably the most widely used and influential physiological and neuroscientific method utilized in applied marketing research and consumer science to study attention. Its equipment can be used to measure changes in pupil size, but it is also used to monitor the direction of gaze in consumer research. Modern eye trackers use specialized sensors to infer viewing direction from the patterns of infrared light reflected by the cornea during normal eye movements. These sensors can be placed on a table top, or in a pair of specialized goggles to allow mobile eye tracking outside of the laboratory; overall this techniques is relatively easy to apply. The underlying assumption of eye tracking is that an individual is visually and mentally processing any stimuli toward which their gaze is directed. Eye tracking thus represents a good measure of visual attention. Importantly, it is useful when aiming to investigate whether and how attention is allocated to stimuli, for instance whether they capture attention or whether attention dwells on them. Measuring eye movements is also helpful in understanding the role of vision in judgment and decision making, motivation and goal pursuit, and preferences (Bell et al., 2018).

Eye movement data are typically categorized into two main types: fixations and saccades. A fixation represents the duration for which the eyes remain continuously directed at a specific location. It occurs when the eye pauses on a specific Area of Interest (AOI) for more than a certain amount of time, often defined as longer than a passing moment or over 200ms or 300md (Management Association, 2019). This is a crucial measurement in ET, as it indicates periods of stable eyes within close proximity, often suggesting visual and mental processing. Analysis of fixations can be used to examine whether attentional resources are preferentially allocated to a particular stimulus over other stimuli and is often also referred to as dwell time. On the contrary, a saccade is the quick, directional, and unimpeded eye movement from one location to another. It records the speed and angle of eye movement and can indicate how quickly a stimulus grabs attention. Simplifying a little, it is possible to say that saccades are strongly influenced by the bottom-up component, while the fixations by the top down (Wolf and Lappe, 2020).

Eye tracking attention metrics are multiple and we can find many in literature since it is the most used technique used for experimental studies. One is the *Fixation Duration or Dwell Time (DT)*, which consists in the total time the eyes are fixed on a specific AOI and reflects how long attentional resources are allocated providing insights into the cognitive processing required by the stimuli (Kim et al., 2022). Another is the *Fixation Count (FC)* which indicates how often a viewer focuses on particular areas and can reveal the relative attractiveness or importance of visual materials (Milosavljevic et al., 2012). Different to this, there is the *Time to First Fixation (TFF)* that measures the time spent from the stimulus until the gaze first lands on a specific AOI (Management

Association, 2019). It is used to assess what attracts a viewer's attention and how long it takes to do so. Then there are metrics that correspond to visualization techniques as display an *heatmap* where more intense colors correspond to where users focus their attention most intensely, helping identifying “hotspots” of interest, or Illustrate the sequence and duration of fixations, providing a chronological map of visual exploration, called *Gaze Plots* (Riswanto et al., 2024). Finally there are others related metrics like *Pupil Dilatation,* which measures changes in pupil size, which reflect the intensity of mental activity and cognitive processing demands (Mathôt, 2018), and *Blink Rate/Duration*, where shorter durations (relative to baseline) suggest high attention and longer durations suggest fatigue or lower attention (Morris and Miller, 1996). These metrics represent only a portion of those found in the existing literature. It is important to note that new measures can always be developed, depending on what researchers consider most relevant or impactful for capturing attention.

One particular feature of eye tracking is that it allows researchers to investigate whether and how attention is allocated to stimuli, differentiating between automatic (bottom-up), often indexed by quick saccades and first fixations, and controlled (top-down) attention, often indicated by measures like total fixation duration and fixation count on areas perceived as highly informative or valuable to the task. Other advantages are that it is an objective measure compared to interviews and questionnaires and that is precise technology, increasingly portable and non-invasive. On the other hand, a major challenge is that eye movements only measure overt attention, while they may not be useful in investigating covert attention, which is the ability to shift focus without moving one's eyes. Moreover, eye tracking inherently generates limited insight into deeper cognitive processes (e.g., what the participant is thinking), and the data should often be paired with other measures (like EEG, ECG, or self-reports) for reliable inferences. Finally, most eye-tracking studies, especially those in controlled settings, typically use small sample sizes due to the expense of equipment and the need for individualized data collection, which can limit external validity (Bell et al., 2018; Gong et al., 2025; Hartnett et al., 2025; Nichifor et al., 2021; Read et al., 2024; Riswanto et al., 2024).

3.1.4. Electrocardiography and Cardiac Activity

Another important peripheral biometric measure is called Electrocardiography (ECG) and it is based on the underlying principle is that the heart's activity reflects the subject's internal emotional state. It consists in the measurement of the electrical activity of the heart. The technique involves registering cardiac activity using two bipolar inputs. Typically, two disposable electrodes are placed on the upper chest: one electrode is positioned below the right clavicle (plugged into the positive terminal of the amplifier) and the other below the left clavicle (plugged into the negative terminal). The ECG signal captures voltage changes corresponding to the heart’s electrical activity, then, the signal must be processed before the extraction of meaningful data (Colomer Granero et al., 2016).

The core output derived from the ECG signal is the *Heart Rate Variability (HRV)*, which is the analysis of variations in the instantaneous heart rate time series using the beat-to-beat RR-intervals (known as the RR tachogram). HRV analysis involves extracting features quantified across both time and frequency domains. In the time domain, metrics include the *maximum (MaxRR)* and *minimum (MinRR) RR intervals* and *MeanRR*. In the frequency domain, researchers examine parameters like absolute and normalized low frequency (LF) and high frequency (HF; Brennan et al., 2002). Specifically, in higher HR values and higher values of the *LF/HF ratio* were observed during the observation of commercial videos that were subsequently remembered or judged pleasant, compared to forgotten or unpleasant content (Vecchiato et al., 2010). Another output is expressed as *Beats Per Minute (BPM)*, or as a Z-score derived by normalizing the cardiac signal against a resting baseline period. This is the measure most often used in marketing research incorporating cardiac activity (Kakaria et al., 2023). In these researches attentional processing is associated with prolonged cardiac deceleration. This means that physiological slowing of the Heart Rate (BPM less than baseline) is hypothesized to indicate high attention as the body temporarily quiets itself to intake external information, a phenomenon that is part of the orienting response. These conclusions are derived from the fact that BPM perform effectively compared to the gold standard of the EEG Alpha as it is shown in the experiment carried on by Hartnett et al. (2025). Advantages of these techniques are related to the facility to collect this kind of data and that heart rate can measure both visual and sound stimuli. However, ECG data are susceptible to artifacts, as non-cardiac bodily processes, such as arm movement, can distort the signal (Hartnett et al., 2025; Read et al., 2024).

3.1.5. Electrodermal Activity

Electrodermal Activity (EDA), also traditionally known as the Galvanic Skin Response (GSR), is a fundamental peripheral physiological technique used in neuromarketing and consumer research to objectively measure the body's autonomic state. It consists of the measurement of the differences in the electrical conductance of the skin resulting from sweat emitted by the eccrine glands, that cover the entire body and are particularly dense on the palms of the hands and the soles of the feet. EDA is unique among some autonomic measurements because it is innervated solely by the sympathetic nervous system (SNS) and is not contaminated by parasympathetic activity. Therefore, increases in skin conductance reliably reflect SNS activity, which is associated with "fight or flight" responses, and heightened alertness, allowing EDA to be used as an objective index of emotional states (Braithwaite et al., 2013; Dawson et al., 2007).

EDA is comprised of two main components: one tonic and the other phasic:

- *Skin Conductance Level (SCL)*: This is the tonic or background component, which reflects the slower-acting, longer-lasting, average SNS arousal over a prolonged period. Changes in SCL are thought to reflect general changes in autonomic arousal.
- *Skin Conductance Response (SCR)*: This is the phasic component, which consists of rapid changes or spikes in electrical conductivity. These rapid changes, known as Event-Related SCRs when linked to a specific stimulus, reflect short-term orienting responses associated with attention.

These two metrics are often quantified by comparing them to a subject's resting baseline. In the context of attention this technique is highly utilized because it serves as an index of arousal reactions induced by emotionally evocative stimuli. Increased arousal, indicated by SCL or SCR greater than a resting baseline, is hypothesized to indicate high attention because more arousing stimuli are presumed to receive greater attention and cognitive processing. Besides the strength of measuring only the sympathetic activity, making the interpretation clearer than measures like ECG, other advantages are that it can reveal consumer responses even when the consumer is not consciously aware of them and that the technology used in the measurement is easily wearable. The main drawback is that EDA measures intensity but cannot independently determine the valence (positive or negative direction) of an emotion. This means that this method must be used in conjunction with one or more different techniques in order to achieve a complete understanding of the results. Additionally, EDA recordings are susceptible to being influenced by many extraneous factors unrelated to the stimulus, such as room temperature, caffeine, medication, and prior physical exercise (Bell et al., 2018, 2018; Guerreiro et al., 2015; Hartnett et al., 2025; Ohme et al., 2009; Read et al., 2024).

3.1.6. Functional Electromyography

Functional Electromyography, or fEMG, is a physiological technique, which consists of assessing the electrical activity generated by facial muscles, used in consumer neuroscience to measure the direction of emotional responses. It is often employed by media researchers in conjunction with EDA, since EDA is useful for assessing the intensity, and fEMG for the direction of the emotional experience. The primary muscle groups monitored are the *Zygomaticus Major* (in the cheek area), which indexes positive engagement and attention, and the *Corrugator Supercilii* (above the eyebrows), which is correlated with negative engagement and attention (Higgins et al., 2025). It is important to notice that fEMG is able to record electrical impulses even when the resulting facial expressions are not visible to the naked eye, this makes fEMG the most accurate facial measure. The metric correlated with this technique is the *Amplitude of Electrical Activity* in the designated muscle groups, which serves as an index of emotional valence. The main limitations are that it is considered relatively invasive because it requires the placement of electrodes on the skin, and it requires skilled electrode placement (Bell et al., 2018; Read et al., 2024).

Facial EMG has been used to assess valence of affect toward products and advertisements (Hazlett and Hazlett, 1999; Poels and Dewitte, 2006). For example, radio adverts with a positive tone evoked more zygomatic activity and those with a negative tone more corrugator activity (Bolls et al., 2001).

3.1.7. Facial Expression Analysis (FEA)

Facial expression analysis is a technique that detects the observable facial muscle movement and microexpression that reflects emotional response, which is associated with attention (Hartnett et al., 2025). The core principle is that facial expressions are fundamental nonverbal cues that convey emotional significance and enable individuals to deduce the emotional states of others, playing a crucial role in interpersonal communication. In this view, facial expressions are considered a basic way that people communicate meaning to each other.

FEA utilizes a video camera to capture facial images. These images are then processed, either manually by a researcher or, more commonly, automatically using computer software. The software maps facial features and calculates emotional expression based on the confluence of visible facial muscle movements, known as Facial Action Units (FAUs). This process involves an algorithmic calculation of these FAUs that indicates the expression of positive, negative, and discrete emotions. As for fEMG, the metrics provided by FEA are primarily focused on the direction of the emotional response but also on the intensity of it. FEA provides an *Index of Eemotional Engagement* by quantifying the prominence, intensity, and valence of observable microexpressions. A significant advantage of FEA is that the data can often be collected covertly, making the technique relatively noninvasive compared to electrode-based methods like fEMG. A major limitation is that it relies on visible facial muscle movement. Unlike fEMG, it cannot detect subtle muscle activity that is not visually apparent. This limitation may result in FEA being less effective for detecting subtle positive emotional responses, also, it can't discriminate between a real and a fake smile. Moreover, automated software requires a clear, well-lit, direct facial image for accurate feature mapping, meaning changes in head position or lighting can complicate analysis (Bell et al., 2018; Danner et al., 2014; Read et al., 2024; Rehman et al., 2025)

3.2. Industry-level attention measurement approaches

The advertising industry's increasing focus on measuring attention has led to the emergence of diverse methods, ranging from subtle physiological recordings to broad digital proxies. Industry efforts, such as the IAB/MRC *Attention Measurement Guidelines*, and the Advertising Research Foundation (ARF) *Attention Measurement Validation Initiative*, organize these methods into several core categories based on the data source and collection technique (ARF, 2024b; IAB and MRC, 2025). The first one represents the first cross-industry attempt to codify a unified framework for the collection, processing, validation, and reporting of attention signals, this includes a minimum eligibility condition, a taxonomy of attention signals, and transparency and auditability requirements (IAB and MRC, 2025). The latter evaluates different attention-measurement companies through controlled tests combining surveys, eye-tracking, facial coding, biometrics, and neuro-scientific tools (ARF, 2024).

The framework proposed in the IAB/MRC document introduces a unified system for defining, measuring, and validating attention. It organizes measurement approaches into a 5-method taxonomy, contextualizes attention through 3 dimensions (content, placement, creative), standardizes metrics into 4 categories (exposure, cognitive load, emotional response, interactions), and sets strict requirements for data quality, user presence, transparency, and predictive modeling. The five methods provide advertisers and media platforms with a comprehensive view of how users engage with ads across multiple dimensions.

- Data Signals: This approach collects various data signals from devices, ad placements, and publisher metadata.
- Visual Tracking: This approach includes eye tracking, gaze tracking, facial coding, presence monitoring, and audio signal analysis.

- Physiological and Neurological Observations: This method tracks physiological and/or neurological responses, such as heart rate, EEG and/or EDA signals.
- Panel and Survey-Based Methods: This approach may use self-reported data from brand health studies, focus groups, and effectiveness surveys or also may directly measure ad media usage, exposure, attention, and behaviors.
- Predictive Models: These methods combine visual tracking, physiological/neurological observations and/or panel and survey-based methods with data signals to produce models that predict expected attention for ad.

The three dimensions are placement, creative and content. Placement concerns where the ad physically appears, for example the position on the page, the type of device and the size. The creative is about how the ad is built and what it contains, so its characteristics in terms of creativity. Otherwise, content relates to the editorial or contextual material surrounding the advertisement. This includes the webpage, article, video, or program adjacent to the ad, as well as the semantic topic of the content, its tone, and emotional intensity.

Finally, the four metrics are the following:

- Exposure: assess conditions such as viewability (measured in percentage or milliseconds), time-in-screen, on-screen duration and audibility. These measures describe the availability of attention rather than actual attention: they indicate that the ad was technically observable, but do not guarantee that it was cognitively processed or noticed.
- Cognitive load: measure the mental effort and processing that occurs during ad exposure. Some examples are fixation duration, number of fixations, and saccadic patterns, EEG indexes and heart rate variability such as the LF/HF ratio.

- Emotional Response: it measures both the intensity and valence (positive or negative) of these reactions. By leveraging facial coding, physiological or , neurological data, or panel-based methods, that reflects what users see and feel about a particular ad or content.
- User Interaction: it focuses on user engagement with the ad or content, capturing how frequently and in what manner users interact with the ad or content. It reflects active participation, including clicks, swipes, and audio and video interactions. It also includes scroll behavior: speed, changes in direction and the number and length of pauses in scrolling.

This proposed framework serves as targets, but it is important to note that it is not currently followed by the providers present in the market analyzed in the ARF document. While there is conceptual alignment with theory in the types of data and measurement approaches used, implementation remains highly heterogeneous, the following Table 3 offers a summary of how the practitioners are aligned to this framework:

Provider	**Methods**	**Dimensions**	**Metric Groups**
Adelaide	Data Signals + Visual + Panel/Surveys + Predictive	Placement + Creative + Content	Exposure + Interaction
Affectiva	Visual + Panel/Survey	Creative	Exposure + Emotion
Amplified Intelligence Technologies	Data Signals + Visual + Predictive	Placement + Creative + Content	Exposure + Interaction
Australian Radio Network (ARN)	Visual + Physiological/Neurological + Panel/Survey	Placement + Creative + Content	Exposure + Cognitive load
Audacy	Physiological/Neurological + Panel/Survey + Predictive	Placement + Creative + Content	Cognitive load + Emotional + Interaction
DoubleVerify	Data Signals + Visual + Predictive	Placement + Creative	Exposure + Interaction
Element Human	Visual + Panel/Survey + Predictive	Creative + Content	Exposure + Emotion

Eye Square	Visual + Survey + Panel/Survey	Placement + Creative + Content	Exposure + Interaction
Immersion Neuroscience	Data Signals + Panel/Survey + Predictive	Creative + Content	Emotional
Lumen	Data Signals + Visual + Panel/Survey + Predictive	Placement + Creative + Content	Exposure + Interaction
Mediaprobe	Physiological/Neurological + Panel/Survey	Content	Cognitive + Emotional
MediaScience	Visual + Physiological/Neurological + Panel/Survey	Creative + Content	Exposure + Cognitive load + Emotion + Interaction
NielsenIQ BASES Neuroscience	Visual + Physiological/Neurological + Panel/Survey	Creative	Cognitive + Emotional
Omnicom Media Group (OMG)	Data Signals +Visual + Physiological/Neurological + Panel/Survey + Predictive	Placement	Exposure + Interaction
Playground XYZ	Data + Visual + Panel/Survey + Predictive	Placement + Creative	Exposure + Interaction
Realeyes	Visual + Panel/Survey + Predictive	Placement + Creative + Content	Exposure + Emotion + Interaction
Tobii	Data Signals + Visual + Panel/Survey	Placement + Creative + Content	Exposure
TVision	Data Signals + Panel/Survey	Placement + Creative + Content	Exposure
XPLN.AI	Data Signals + Visual + Panel/Survey + Predictive	Placement + Content	Exposure + Interaction

Table 3: ARF Proposed Framework

Among the nineteen companies evaluated, most measure both media dimensions (where and how the advertisement is delivered) and creative dimensions (the creative elements and design of the ad). These companies are distributed across three operational models: nine offer both measurement and prediction of attention, nine provide measurement capabilities only, while *XPLN.AI* focuses exclusively on predictive modeling. The methodologies employed differ substantially not only in the biometric techniques utilized and the resulting attention metrics generated, but also in the control variables considered. These typically include factors such as device type, psychographic and demographic characteristics, ad position and placement, exposure duration, and other contextual features that may influence attentional outcomes.

Regarding what is being measured, it becomes evident that only a minority of attention providers explicitly differentiate between types of attention. Thirteen of the nineteen vendors report a single, global attention without decomposing it into underlying components. Among the remaining six, five providers introduce a distinction that broadly aligns with passive (the lowest form of attention without active engagement with the ad) versus active attention (a higher level that goes beyond mere screen or content focus to include some form of engagement). *NielsenIQ BASES Neuroscience* stands apart as the only provider distinguishing between sustained attention (the ability to maintain focus over time) from selective attention (the ability to prioritize relevant stimuli while filtering out competing ones).

Even within biometric approaches, the market remains highly fragmented. Eye-tracking clearly dominates: fourteen providers employ it, and for approximately half, it represents the only biometric input used. Eye-tracking is frequently complemented by facial expression analysis (FEA), which the ARF notes improves the predictive performance of visual tracking alone. Two companies, *Audacy* and *Immersion Neuroscience,* rely exclusively on heart rate or heart rate variability derived from wearable sensors, using physiological arousal as a proxy for attentional engagement. EEG signals are utilized by only five vendors, almost always in combination with eye-tracking, reflecting their higher operational complexity and cost. Finally, electrodermal activity (EDA) appears in merely three cases, confirming its limited adoption due to measurement noise, low scalability and high costs. Finally, it is important to note that the final product is, in the vast majority of cases, a single score which represents an indication of the medium attention that a person put to an adv. This score is rarely well explained in the ARF's work but it is built from the metrics each provider measure and normally it is unique also if the company distinguishes between different types of attention.

4 Discussions

Chapter three outlined how attention is currently measured both in academic research and industry. Building on this foundation, this final chapter returns to the initial research question to critically reflect on what emerges from comparing theory and practice:

How do advertising practitioners define and measure attention, and to what extent do current attention metrics align with academic theories of attention?

In order to carry out a structured analysis capable of highlighting the differences and inconsistencies that emerge from the analysis of attention providers compared to what is found in the literature, the following framework conceived by Klein and Lawrence (2012) will be used. In this way, discussions will be conducted in a scientific and structured manner, taking as a basis a product from an academic article. The framework proposed by the two authors is as follows (Figure 6):

		Mode of allocation	
		Exogenous	Endogenous
Domain of allocation	Space		
	Time		
	Sense		
	Task		

Figure 6: Framework for Attention (Klein and Lawrence, 2012)

It consists in a comprehensive attempt to organize the complex field of attention research and measurement by creating a taxonomy that intersects two fundamental *modes* of control with four distinct *domains* where that control is applied. In complete coherence with the theories and the concept of attention explained in 2.1, the authors argue that living systems, including humans, have limited energy and processing capacity, necessitating efficient systems to allocate resources toward information that is relevant to their immediate or ultimate goals. To operationalize this, they discard the idea of attention as a single, unitary concept and instead describe it as a matrix of processes defined by how resources are allocated and what those resources are acting upon. The core of their theoretical structure lies in the distinction between two opposing modes of allocation: exogenous and endogenous. The authors describe exogenous control as a bottom-up process that is driven by the environment rather than the individual. It acts interrupting current focus to orient the organism toward unexpected, potentially behaviorally relevant events. On the other hand, the endogenous mode represents top-down control. This mode is voluntary, non-reflexive, and allows an individual to deliberately monitor specific stimulus or prepare for expected events. While these two modes function differently, one captures us from the outside, the other directed from the inside, the framework posits that they operate orthogonally, meaning they can function independently or interact within the same domain.

Klein and Lawrence then apply these two modes across four distinct domains of information processing: Space, Time, Sense (or Modality), and Task. In the domain of space, the framework examines how we allocate resources to specific locations in our environment. This is the most historically studied domain, where the authors distinguish between overt and covert attention. Moving to the domain of time, the authors argue that attention is not just about where we look, but when we are ready to process information. Here, the exogenous mode functions through warning signals, a sudden sound or flash that automatically increases alertness and prepares the system for incoming input, a phenomenon often described as the *phasic alerting effect*. Conversely, endogenous temporal attention involves the preparation for a stimulus at a specific moment based on temporal expectations or regularities. The third domain is sense (or modality), it concerns how the brain prioritizes input from different sensory channels. The authors detail how endogenous control allows us to voluntarily shift our focus between modalities. For example, we can choose to listen to a sound while ignoring visual distractions. Lastly, the authors describe the task domain, that refers to the cognitive operations or rules we apply to inputs, such as the difference between naming a color versus reading a word. In this domain, exogenous control might manifest as an automatic tendency to perform a habitual task when triggered by a stimulus (like automatically reading a word because we are literate), whereas endogenous control is required to override that habit and perform a different, goal-directed task. This is frequently studied using *task-switching* paradigms, where the time it takes to reconfigure the mind from one rule set to another is measured (Klein and Lawrence, 2012).

4.1. Space Domain

The spatial domain is certainly the one most represented by the metrics used by practitioners. In fact, most of them use metrics derived from eye tracking measurements, aimed at capturing the specific location where the gaze is directed. Of the nineteen practitioners analyzed, fourteen use this type of biometric detection, and half of them do not combine it with any other technique described in the previous chapter of this thesis. Specifically, only seven out of nineteen use techniques other than eye tracking or facial coding, which is also measured using metrics related to head or eye position or metrics related to visible emotions, which indicate more engagement than attention. It is therefore clear that the main focus studied in this domain is overt attention, as the main effort is aimed at locating where the gaze is directed. In concrete terms, metrics can be divided into two categories. The first consists of "finished products", as for example the final metrics of the providers that are sold, which usually correspond to scores on more or less defined scales that give an attention grade. The second category, on the other hand, consists of the metrics used to calculate them. The latter includes more specific metrics that are consistent with those found in the literature (for more details, see Chapter three). Those concerning eye tracking and the spatial domain are mainly: *eye on screen duration, number and duration of fixations, sequences of fixations,* and *saccadic movements*. From the discussion of eye tracking in Chapter three, we know that in academia, fixations are considered a possible indication of a top-down mode of attention, while saccades are strongly influenced by bottom-up components. This aspect therefore seems to be consistent and to fit with the two modes (endogenous and exogenous) present in the proposed framework. Despite this, it is clear that this distinction is not considered at all from an operational point of view by practitioners, who, rather than distinguishing between them, seem to mix these metrics, usually arriving at a single "attention score" that is calculated using all of them indiscriminately. The only tentative distinctions between types of attention are all derived from eye tracking measurements, but these distinctions are inconsistent with those found in the literature and are measured in very simplified ways. For example, XPLN.AI calculates three final scores: one for active attention, one for passive attention, and one for negative attention. According to this provider, active attention derives from the amount of eye movement present in the measurements, passive attention simply from how long the user has their gaze directed at the screen but in a static manner, and negative attention depends on actively searching for the skip or countdown button to end the ad. Similarly, Realeyes, NielsenIQ BASES Neuroscience, Eye Square, and Adelaide distinguish between positive and negative. Finally, Amplified Intelligence Technologies identifies time spent with eyes closed or looking away from the screen as non-attention. All the others make no distinction and simply provide a generic attention score. It is therefore clear that these products provided by providers using eye tracking as their main form of measurement completely ignore the definition of attention found in the literature as a multifaceted concept, and that they are unable to distinguish between the two modes (endogenous and exogenous) present in the framework with regard to the spatial domain (ARF, 2024a; Klein and Lawrence, 2012).

4.2. Time Domain

Based on the theoretical framework established by Klein and Lawrence regarding the domain of time, and contrasting it with the commercial methodologies profiled in the ARF reports, we can observe a distinct divergence in how this concept is operationalized. In the academic framework that is being used, in coherence with the rest of the literature and with Chapter three of this work, the domain of time is fundamentally about preparation and readiness. This domain is described not merely as a measure of duration, but as the mechanism by which the brain anticipates when to pay attention (Fritz et al., 2007). As for space, also in this domain the distinction between endogenous and exogenous mode is present. Exogenous temporal attention, called *phasic alerting,* is a reflexive readiness triggered by a warning signal like a sudden sound, and endogenous temporal attention, involves the voluntary expectation of an event at a specific moment (Klein and Lawrence, 2012; Lachter et al., 2004).

When we look at the landscape of attention providers, however, the adaptation to this specific theoretical nuance is largely indirect. The industry adapts to the domain of time by measuring duration and maintenance rather than preparation. For the vast majority of providers listed in the ARF reports, such as Adelaide, ARN, Playground XYZ, and TVision, time is quantified as *Time-in-View, Dwell Time, or Attention Time*. In this context, time is treated as a cumulative outcome, a measure of how long the state of attention was sustained, rather than the cognitive mechanism of orienting oneself toward a specific temporal moment as described by Klein and Lawrence.

However, there are ways in which providers implicitly adapt to the exogenous mode of the time domain, even if they do not use those exact terms. For example, regarding exogenous temporal attention, providers like Lumen, MediaScience, NielsenIQ BASES Neuroscience and Tobii utilize second-by-second time-series analysis to track how specific creative elements (sequences of fixations), such as a sudden audio cue or a visual cut, re-engage the viewer. However, the endogenous mode in this domain is not taken into account by providers. In conclusion, even though some providers use metrics to capture the aspect of preparation and readiness in line with the literature, despite the fact that the endogenous part is not considered in any way, it can be said that there is no clear distinction within the output metrics of the various providers that allows this domain to be distinguished. In this case too, there is no clear distinction in the results that the analyses of these players can offer in the domain of time.

4.3. Sense Domain

Authors Klein and Lawrence highlight the phenomenon of visual dominance, observing that humans naturally prioritize visual input over other senses when inputs conflict. The attention measurement industry has overwhelmingly adapted to this biological reality. As already mentioned, the domain most explored by practitioners is the spatial one, so the sense of reference from which most attention metrics and scores originate is certainly that of sight. Klein and Lawrence describe an endogenous control mechanism that allows individuals to voluntarily shift focus between modalities, choosing to listen while ignoring visual distractions, but they note that this incurs a switching cost that slows performance. Most providers do not measure this switching cost directly; instead, they treat audio and visual attention as additive or binary states rather than competing resources. For instance, providers like Realeyes and TVision utilize audio not as a separate channel of cognitive processing to be measured in isolation, but as an exogenous "alerting" mechanism. Only the Audacy focus specifically on the auditory channel, utilizing heart rate variability to measure engagement when the visual sense is not the primary input. This adapts to the framework's acknowledgment that attention can be allocated to non-visual modalities, not do not focus on the constant interplay and potential interference between senses (ARF, 2024a; Klein and Lawrence, 2012).

4.4. Task Domain

In the proposed framework, the task domain is fundamentally about the cognitive rules we apply to inputs, the struggle between automatic, habitual responses (exogenous control) and voluntary, goal-directed actions (endogenous control). The way authors focus on this domain is by measuring task switching costs, the cognitive cost required to reconfigure the mind from one rule set to another, such as overriding the habit of reading a word to instead name its color. When we look at the attention measurement industry, providers do not generally measure task switching costs in this strict neurological sense. Instead, they use the domain by either simulating tasks to test ad effectiveness or by treating the consumption of media itself as the task that advertising must disrupt. A clear adaptation to the endogenous aspect of the framework is found in providers that explicitly utilize task-based methodologies. Realeyes, for instance, defines its PreView platform specifically as "Task-based visual attention measurement" (ARF, 2024a, p. 133). In their methodology, they create a simulated environment where users are given a directive or are engaging with a feed. The measurement assesses the ad's ability to break through that goal-directed behavior. Similarly, Tobii distinguishes between its passive measurement and active studies. In these scenarios, users are explicitly told what to view and when, such as testing packaging or performing specific shopper tasks. This operationalizes the Task domain by measuring how well a user can maintain an endogenous goal (finding a product) against environmental distractors. Conversely, the majority of the remaining providers adapt to this domain implicitly by focusing on the exogenous mode. They operate "in the wild" or use passive panels where the user's primary task is simply consuming content (reading an article, watching a video). In this context, the advertisement functions as the exogenous stimulus interrupting the user's primary task flow to capture attention. These providers measure the success of this interruption via metrics like *dwell time* or *eyes-on-screen*, effectively measuring the failure of the user to stay focused on their primary content task because the ad successfully triggered an exogenous response.

In summary, while the industry does not typically measure the switching costs or neural reconfiguration times central to Klein and Lawrence's academic work, we can make a distinction within two distinct commercial modes. The first is an active task-based measurement, which tests the robustness of endogenous, goal-directed attention. The second is a passive measurement, which treats the ad as an exogenous interruptor designed to break the user's existing task set.

4.5. Implications

The previous sections have identified the main differences between the more practical and scalable approach of practitioners and the more rigorous approach proposed by academic literature. In light of this, it is possible to make some observations on how this gap affects the market. The first important implication derives from how attention is perceived by practitioners. The definitions of attention provided by professionals are largely limited by the technologies used to measure it and often reduce it to a single observable behavior, without considering all the facets, modes, and domains of attention. In this way, advertisers may implicitly assume that all attentive exposure is equivalent, regardless of whether it is driven by reflective, bottom-up capture or voluntary, goal-oriented engagement. When, as is the case with most practitioners, attention is measured using scores derived solely from eye tracking metrics, practitioners are essentially measuring exposure opportunity rather than actual cognitive processing. This means that advertising campaigns, following the indications provided by these scores, could be diverted from their main purpose, which is to provoke an attentive response that is sustained over time and involves genuine emotional processing. This creates a credibility risk as the market matures. As advertisers become more sophisticated users of attention metrics, the lack of transparency around what is actually being measured may reduce trust in proprietary scores. If providers fail to articulate whether their metrics reflect exogenous capture, endogenous engagement, or task disruption may struggle to justify their value beyond descriptive benchmarking.

This information asymmetry can lead to market distortions as the market may become saturated with providers who lack the necessary technical or scientific expertise, lowering the overall quality of the industry. For the same reason, it can also happen that price competition overcome quality competition. This creates incentives for market entry by providers offering low-cost and methodologically weak solutions, potentially driving out more rigorous approaches. Overall, these implications highlight significant challenges for the current attention measurement ecosystem. These observations naturally lead into the following section, which outlines potential future directions and recommendations for enhancing the scientific robustness and practical value of attention metrics moving forward.

4.6. Future Directions and Recommendations

The analysis conducted in this chapter of the thesis highlights numerous discrepancies between the conceptual richness of academic theories and the operational simplicity of most industry-level attention metrics. It is therefore important to highlight possible directions for the future development of attention measurement, together with concrete recommendations. The first point to start with is to begin treating attention as a multidimensional concept. Providers could report separate indicators corresponding to different domains and modes of attention, or at least it should be easily understandable inside the index from which modes and domain it is created. A second suggestion would be to integrate eye tracking metrics, with others coming from different biometric measurement such as EEG, heart rate, and EDA; which are more indicative of an actual cognitive processing. Finally it would be useful to be very transparent on how the final indexes are computed and which aspects of attention they represent. Nowadays many providers offer final indices without clearly specifying which attentional processes they represent, how different signals are weighted, or which theoretical assumptions underlie their construction. This opacity creates information asymmetries between providers and advertisers and may undermine the legitimacy of attention metrics as a decision-making tool. If practitioners were to adapt their processes to the academic literature, the strong heterogeneity of metrics and measurement techniques offered by different providers and their weak interpratetions, could be substantially mitigated. A natural consequence of such convergence would be greater methodological transparency and more rigorous validation practices. At the same time, collaborations between academic researchers and industry practitioners could promote controlled validation studies, helping to identify which metrics are predictive of meaningful advertising outcomes.

Improving methodological transparency and validation would benefit also the advertisers. With clearer information about how metrics are generated and what they represent, buyers would be better equipped to assess the quality and reliability of each provider's offering. This, would strengthen the overall market by raising barriers to entry for underqualified players and fostering the creation of a more credible market. Ultimately, these actions would position attention metrics as a more robust and actionable component of the broader marketing performance measurement system, bridging the gap between advertising exposure and actual consumer attentional effort.

Conclusions

This thesis has investigated the actual landscape of attention measurement in the advertising sector, with a particular focus on the divergences between academic research and industrial practice. The research started by the recognition that traditional exposure-based metrics, such as Reach and Frequency, are no longer sufficient to guarantee advertising accountability in the actual digital environment. By contrasting the academic literature of cognitive psychology and neuroscience with the operational realities of the current attention metrics market, this study has identified significant gaps between how attention is defined and measured scientifically and how it is commercially.

The theoretical analysis established that attention is not a unitary concept but a complex, multifaceted mechanism governed by distinct neural networks and control systems. Academic literature consistently distinguishes between bottom-up processes, which are exogenous and stimulus-driven, and top-down processes, which are endogenous and depends on a person goals and expectations. Moreover, scientific measurement relies on a vast use of different biometric techniques, combining them in order to asses all the shades and typologies of attention. In contrast, the examination of industry practices revealed that commercial providers predominantly favor scalability and simplicity over the academic cognitive precision. In order to use a structured approach to the analysis, a framework for measuring attention created by Klein and Lawrence was applied. The market is currently dominated by eye-tracking technologies, and related metrics, that frequently amalgamate various signals into a single "attention score". While these commercial metrics successfully track overt visual orientation, they often fail to differentiate between the mere visibility of an advertisement and the actual endogenous cognitive processing of the attentional process. These findings have important implications for the validity of the attention measurement market. The lack of standardization and the weak clarity on how proprietary scores are calculated by practitioners create significant information asymmetries between metric providers and advertisers. Therefore, the providers should adapt to improve the theoretical validity of their product in order to be more credible for advertisers. In conclusion, attention metrics hold significant promise for advancing advertising accountability, but only if they are built with robust theoretical foundations and transparent measurement practices.

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List of abbreviations

ACC: Anterior Cingulate Cortex

AOC: Attention Operating Characteristic

AOI: Area of Interest

ART: Attention Reaction Time

BOLD: Blood Oxygenation Level–Dependent

BPM: Beats Per Minute

CTR: Click-Through Rate

DAN: Dorsal Attention Network

dlPFC: Dorsolateral Prefrontal Cortex

DT: Dwell Time

ECG: Electrocardiography

EDA: Electrodermal Activity

EEG: Electroencephalography

ERP: Event-Related Potential

ET: Eye Tracking

FC: Fixation Count

FEA: Facial Expression Analysis

FEF: Frontal Eye Fields

fEMG: Functional Electromyography

fMRI: Functional Magnetic Resonance Imaging

GFP: Global Field Power

GRP: Gross Rating Point

GSR: Galvanic Skin Response

HRV: Heart Rate Variability

IAB: Interactive Advertising Bureau

IPS: Intraparietal Sulcus

LC: Locus Coeruleus

LF/HF: Low Frequency / High Frequency Ratio

MPMS: Marketing Performance Measurement System

MRC: Media Rating Council

NE: Norepinephrine

PDT: Percentage Dwell Time

PFC: Prefrontal Cortex

PSD: Power Spectral Density

RSVP: Rapid Serial Visual Presentation

RT: Reaction Time

SCR: Skin Conductance Response

SCL: Skin Conductance Level

SPL: Superior Parietal Lobule

SNS: Sympathetic Nervous System

TPJ: Temporo-Parietal Junction

TFF: Time to First Fixation

VAN: Ventral Attention Network

VFC: Ventral Frontal Cortex

vmPFC: Ventromedial Prefrontal Cortex