JOURNAL OF BUSINESS IN THE DIGITAL AGE

Vol. 7 Issue 2 2024

eISSN: 2651-4737 *dergipark.gov.tr/jobda*

Research Article

ANALYZING TURKEY'S PREMIER E-COMMERCE MARKETPLACES BY PREDICTIVE EYE TRACKING METHOD

TÜRKİYE'NİN ÖNDE GELEN E-TİCARET PAZARYERLERİNİN TAHMİNE DAYALI GÖZ TAKİBİ YÖNTEMİYLE ANALİZİ

Dinçer Atlı[1]

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Article Info:
Received: May 26, 2024
Revised : August 20, 2024
September 15, 2024
November 14, 2024
November 17, 2024
Accepted: November 19, 2024

Keywords:
neuromarketing
eye tracking
artificial intelligence (AI)
predictive eye tracking
AI-Based eye tracking

Anahtar Kelimeler:
nöropazarlama
göz izleme
yapay zeka (YZ)
tahmine dayalı göz izleme
yapay zeka destekli göz takibi

DOI:
10.46238/jobda.1490101

ABSTRACT

Artificial intelligence (AI) is a rapidly evolving and intensely debated discipline over the last decade. AI has the potential to impact many industries, including neuromarketing. Today, many scholars and academic studies emphasize AI's enormous marketing opportunities. Likewise, neuromarketing is a rapidly expanding discipline in marketing. Neuromarketing often aims to use neuroscientific ideas and marketing strategies and integrate them into marketing domains. Neuromarketing uses electroencephalography, functional magnetic resonance, eye tracking, galvanic skin response, and facial coding to assess subjects' neurophysiological responses to various stimuli. In this study, an analysis was performed with an eye tracker. Eye tracking is the most widely used neuromarketing technology in market research. Today, predictive eye tracking, or AI-based eye tracking, has started to be used as a tool in the neuromarketing field of artificial intelligence. This framework uses many images from device- and subject-based eye-tracking studies to train complex deep-learning algorithms. These algorithms can better predict people's neuroscientific preferences as more data is fed to them. The accuracy of academic visual saliency prediction models is about 90%, with a small margin of error. However, this is expected to improve over time. This study analyzed five web pages in the coffee machine category of Turkey's leading e-commerce marketplaces, www.amazon.com and www.trendyol.com, with cognitive demand and clarity metrics, using Neurovision software. As a result of the analysis, it was determined that the overall cognitive demand metric score of these marketplaces' web pages was acceptable; the overall clarity metric score had the best score on the scale, and the websites in question had very user-friendly designs.

ÖZ

Yapay zeka (YZ), son on yılda hızla gelişen ve yoğun bir şekilde tartışılan bir disiplindir. YZ, nöropazarlama da dahil olmak üzere birçok sektörü etkileme potansiyeline sahiptir. Günümüzde birçok akademisyen ve akademik çalışma, yapay zekanın pazarlama için sunduğu muazzam fırsatları vurgulamaktadır. Aynı şekilde, nöropazarlama da pazarlama alanında hızla gelişen bir disiplindir. Nöropazarlama genellikle nörobilimsel fikirleri ve yöntemleri pazarlama stratejilerinde kullanmayı ve bunları pazarlama alanlarına entegre etmeyi amaçlamaktadır. Nöropazarlama, deneklerin çeşitli uyaranlara verdikleri nörofizyolojik tepkileri değerlendirmek için elektroensefalografi, fonksiyonel manyetik rezonans, göz takibi, galvanik deri tepkisi ve yüz kodlamasını kullanır. Bu çalışmada göz takip cihazı ile bir analiz gerçekleştirilmiştir. Göz izleme, pazar araştırmalarında en yaygın kullanılan nöropazarlama teknolojisidir. Günümüzde tahmine dayalı göz takibi, ya da Yapay Zeka Destekli Göz Takibi yapay zekanın nöropazarlama alanı için bir araç olarak kullanılmaya başlanmıştır. Bu çerçeve, karmaşık derin öğrenme algoritmalarını eğitmek için cihaz ve denek tabanlı göz izleme çalışmalarından elde edilen birçok görüntüyü kullanır. Bu algoritmalar, kendilerine daha fazla veri beslendikçe insanların nörobilimsel tercihlerini daha iyi tahmin edebiliyor. Akademik görsel belirginlik tahmin modellerinin doğruluğu, küçük bir hata payıyla birlikte yaklaşık %90'dır. Ancak bunun zaman içinde iyileştirilmesi beklenmektedir. Bu çalışmada, Türkiye'nin önde gelen e-ticaret sitelerinden www.amazon.com ve www.trendyol.com'da kahve makinesi kategorisinde yer alan beş web sayfası, Neurovision yazılımı kullanılarak bilişsel talep ve belirginlik metrikleri ile analiz edilmiştir. Analiz sonucunda, bu pazar yerlerinin web sayfalarının genel bilişsel talep metriği puanının kabul edilebilir düzeyde olduğu; genel anlaşılırlık metriği puanının ölçekteki en iyi puana sahip olduğu ve söz konusu web sitelerinin oldukça kullanıcı dostu tasarımlara sahip olduğu tespit edilmiştir.

1 | INTRODUCTION

Artificial intelligence (AI) and neuromarketing have emerged as promising subjects that have garnered significant attention and extensive research in recent years. AI can revolutionize marketing by opening new avenues for researchers and professionals (Rawnaque et al., 2020). Integrating AI technology with neuromarketing has yielded novel tools and methodologies that offer deeper insights into customer preferences and decision-making processes (Mashrur et al., 2022). The marketing discipline is increasingly adopting a data-driven approach and embracing AI (Chintalapati & Pandey, 2022). The applications of AI in marketing enable the understanding and prediction of human behavior. Machine Learning (ML), a branch of artificial intelligence, facilitates predicting strategic marketing activities by creating a computer system that can learn and self-adjust independently (Thontirawong & Chinchanachokchai, 2021).

Eye tracking is a widely used method in neuromarketing and enables researchers to analyze how consumers visually interact with marketing stimuli (Ćosić, 2016; Lavdas et al., 2021). Researchers can learn about consumer attention and decision-making processes using an eye tracker that detects and records eye movements. This data provides a better understanding of human behavior and opens up opportunities for innovative applications such as mood prediction through biometric analysis (Lim et al., 2022). In this context, recent advances in AI have significantly improved eye-tracking technology, enabling the development of algorithms that can accurately predict changes in eye movement patterns. These AI-supported algorithms offer new possibilities for neuromarketing research and applications by providing precise and reliable results (Frey et al., 2021).

Predictive eye tracking, a cutting-edge methodology that integrates eye-tracking data with AI algorithms, is advancing significantly in predicting individuals' neuroscientific preferences by analyzing their eye movements (Schneider et al., 2022). Deep learning systems, based on extensive eye-tracking data, enable researchers to achieve remarkable levels of accuracy in predicting client behavior. Currently, visual saliency prediction models attain an accuracy rate of 90%, showcasing the methodology's exceptional level of precision.

This study uses predictive eye-tracking technologies to analyze online pages' cognitive demand and clarity on popular e-commerce websites in Turkey. Overall, the measurements showed that the web pages met the required standards. The analysis revealed that these online pages prioritized user-friendly design and provided convincing evidence of effectiveness. This study emphasizes the importance of creating visually appealing and simply understandable content to attract and sustain consumers' interest. Furthermore, this study demonstrates the potential of predictive neuromarketing techniques to improve user experience.

Besides that, this study aims to address the following research question. To what degree do AI-based predictive eye-tracking measures, particularly cognitive demand and clarity, impact the user experience and usability on the prominent e-commerce platforms Amazon Turkey and Trendyol in Turkey?

2 | OVERVIEW OF NEUROMARKETING AND AI

According to Philip Kotler, one of the doyens of the marketing field, marketing has gone through five different periods. Accordingly, in Marketing 1.0, the focus was on the product itself. In the next phase, Marketing 2.0, the focus became the customer with increased interaction and market segmentation. Marketing 3.0 considered consumers' emotional and social aspects, brands connected with consumers on a deeper level, and corporate social responsibility came to the fore. Marketing 4.0 was a phase that embraced digital technologies and focused on online channels, data analytics, and omnichannel marketing. Marketing 4.0 also represents a stage where neuromarketing techniques are used to analyze cognitive and emotional processes while seamlessly integrating digital strategies. This is a period of personalized marketing campaigns based on neurological responses to digital stimuli (Koch et al., 2022; Kotler et al., 2021; Ma, 2023; Muna, 2023; Tang & Pienta, 2012; Zammarchi & Conversano, 2021). Marketing 5.0 is the latest evolution in marketing. It combines advanced technologies with a human touch, utilizing big data, predictive analytics, contextual marketing, augmented marketing, and agile marketing to enhance consumer experiences. In the present era, marketing 5.0 focuses on the customer, creating meaningful connections, and providing personalized experiences. Businesses can gain insights into consumers' subconscious responses, emotions, and decision-making processes by utilizing techniques not just like EEG analysis, eye tracking, and neuroimaging but also predictive neuromarketing analytics (Bajaj, 2023; Kotler et al., 2021; Panda, 2024; Šola, 2024).

Discussing the origins of neuromarketing in this matter is crucial. During the early 2000s, an academic subfield emerged, and a new industry focused on comprehending marketing processes through the lens of the consumer's underlying brain mechanisms. This included studying how the brain processes sensory inputs, encodes and retrieves memories, and evaluates different options when making choices. Neuromarketing, also known as the use of neuroscience in the scientific and business fields, results from the increasing recognition of the importance of neuroscience (Atlı, 2015; Cenizo, 2022; Levallois et al., 2019a).

The term "neuromarketing" was first coined in 2002 by Ale Smidts, Professor of Marketing at the Rotterdam School of Management (Atlı et al., 2018; Bazzani et al., 2020; Cenizo, 2022; Levallois et al., 2019a). This was followed by the emergence of BrightHouse and SalesBrain, the first two consulting firms specializing in research and consulting services using neuromarketing techniques. This development solidified the integration of neuroscience-based technologies into business and marketing (Fisher et al., 2010). In 2008, Hubert and Kenning suggested using the term "consumer neuroscience" as a definition in academic literature while reserving the term "neuromarketing" for industrial use (Hubert & Kenning, 2008; Levallois et al., 2019a).

Neuromarketing seeks to investigate consumer behavior by analyzing neural responses and utilizing this information to shape purchasing decisions and attitudes (Akbarialiabad et al., 2021). Neuromarketing is a specialized field in neuroeconomics that addresses marketing-related matters by drawing on knowledge from brain research (Hubert & Kenning, 2008). Following that, the inaugural neuromarketing research organization was founded, and by 2008, neuromarketing was employed in many marketing research endeavors (Monica et al., 2019). The rise of neuromarketing may be traced back to the convergence of commercial and scientific cultures, where academia and business have played crucial roles in their progress (Levallois et al., 2019).

On the other hand, during the 1990s and early 2000s, the initial functional AI applications surfaced in the market, delivering significant corporate benefits (Peeters et al., 2021). Ever since, neuroscience and AI have expanded considerably and offered terrific tools for understanding the human nervous system, primarily making it feasible to perform emotion detection utilizing improved algorithms (Fotini-Rafailia, 2021). Today, AI has immense opportunities to create value for neuromarketing research. In this regard, machine learning and deep learning methods, as a subset of AI, have demonstrated impressive performance in a wide range of AI-based applications (Zhou et al., 2021).

By looking at physiological and brain signals in interaction with customers and marketing strategies, the partnership of AI and neuromarketing gives us essential insights and a deeper understanding of how people behave (Kusá, 2023; Ramirez et al., 2022). Combining neuromarketing with AI presents a cutting-edge marketing strategy incorporating science and technology to create personalized experiences that establish strong client connections. The study revealed substantial advancements in neuromarketing and AI in marketing (Chowdhury, 2024).

The application of AI techniques in the field of neuromarketing has made a substantial contribution to the design of products, the creation of brands, and the production of influential commercials (Solomon, 2018). AI assists in the investigation and prediction of neurological processes within the subject of neuromarketing. It provides vital insights for comprehending customer responses to marketing stimuli. Moreover, it has an impact on customers (Greguš, 2023). Currently, AI algorithms have improved our capacity to comprehend underlying subconscious processes. These mechanisms directly influence consumers' cognitive processes while making decisions (Ramirez et al., 2022). Integrating neuromarketing information with AI capabilities empowers marketers to develop highly targeted programs. These marketing campaigns evoke strong emotional responses. This effectively captivates clients on a deep level (Chowdhury, 2024).

3 | EYE TRACKING TECHNOLOGY IN MARKETING RESEARCH

Eye-tracking technology has evolved significantly, with its historical roots dating back to the late 1800s and early 1900s. Researchers began developing equipment to detect eye movements during reading or visual perception tasks (Tuwirqi, 2024). This evolution has widespread use in diverse industries, including marketing, design, gaming, medical practice, health and consumer research, cognitive evaluation, architecture, and usability assessments (Afifi & Abdo, 2022; Gordieiev et al., 2021). For instance, eye tracking is a valuable tool in market research, serving various objectives such as product design tests, web page and email communications tests, and marketing communication tests (Gheorghe et al., 2023; Holmqvist et al., 2011).

An eye-tracking system uses an infrared camera to collect corneal and pupillary light responses from a subject's eyes. This occurs when the subject looks at a visual stimulus on a computer screen. Obtained data allows for precise detection of the direction of eye movement at any moment. It has high accuracy in both spatial and temporal dimensions. The calibration of the device is crucial before the experiment. This ensures the highest accuracy level (Gheorghe et al., 2023).

Eye-tracking devices provide researchers with a variety of metrics and measurements. They capture the position of the eye at various frequencies. Frequencies range from 25 Hz. to 2000 Hz. This enables the detection of a significant amount of data points. The typical method for analyzing gaze data involves identifying specific sections of stimulus. Sections of the visual field analyzed are referred to as regions of interest. Areas of attention are ROIs or AOIs (King et al., 2019a).

Visual behavior assesses various factors. These include exposure duration, cognitive processing, and salience visual attention. It encompasses measurement and analysis of gaze state movement. Communication science scholars have observed notable growth in eye-tracking techniques in recent years. Advances in technology rendered eye-tracking devices more affordable. Eye-tracking devices have become increasingly accessible for interested researchers in academia. This surge in accessibility augmented the likelihood of further expansion in eye-tracking research (King et al., 2019b).

Eye-tracking technology is employed in neuromarketing to analyze consumer intentions and preferences. It optimizes product development. It enhances marketing strategies. Moreover, it improves user experience. Navigation systems benefit from this technology. One of the primary methods is eye tracking. This method analyzes visual activities. It includes fixation gaze and pupil dilation. It examines mechanisms of visual attention. Customer engagement through visual appeal is assessed, too. Eye tracking constitutes a vital component of neuromarketing. It plays a role in experimental economics research (Gheorghe et al., 2023). Eye-tracking technology significantly transforms how people interact with technology. It allows a deeper understanding of subconscious cognitive processes (Joseph & Murugesh, 2020; McLaughlin et al., 2017).

4 | PREDICTIVE EYE-TRACKING

4.1 Theoretical Foundations of Predictive Eye-Tracking

Predictive eye tracking has emerged from the collaboration of AI and eye tracking. This technique is based on broader cognitive psychology and machine learning theoretical frameworks. According to cognitive psychology, human visual attention is influenced by both bottom-up processes. Salient features of visual stimuli drive these processes. There are also top-down processes shaped by the viewer's intentions and expectations (Itti & Koch, 2001). Traditional eye-tracking research involves analyzing eye movements in real time. This helps to understand how consumers interact with visual content. Such content may encompass websites or advertisements by utilizing these concepts.

The use of artificial intelligence and profound learning algorithms in conjunction with eye-tracking studies has enabled the development of models. These models can predict visual attention patterns. This prediction occurs without the need for physical eye-tracking sensors. Models have been trained using eye-tracking data. Additionally, comprehensive datasets with AI make visual activity patterns predictable. The fundamental principle of the predictive eye-tracking method is based on the concept of visual salience, which relates to the prominence of specific features that stand out in a visual stimulus (Bruce & Tsotsos, 2009). Predictive gaze tracking can accurately mimic human gaze behavior by modeling patterns of saliency, often achieving a prediction accuracy of over 90% (Juddk et al., 2009).

4.2 Benefits and Constraints of Predictive Eye-Tracking

Benefits of Predictive Eye-Tracking:

Cost advantage and scalability: The traditional way to conduct eye-tracking research requires specialized equipment such as infrared cameras and a physical lab setup. However, this has led to significant logistical and financial challenges regarding extensive research. Unlike these methods, predictive eye tracking does not need any physical equipment. It can be used with big datasets, thus making it cost-effective and analyzing scalable data (Ramanathan et al., 2010).

Advantage of quick analysis: Traditional eye-tracking studies involve the real-time collection of subjects' data, which is processed, analyzed, and reported later. This may be quite an involving procedure, especially when many samples are involved. In predictive models, however, pre-trained algorithms can quickly assess new visual inputs with few processing requirements, enabling them to produce meaningful information (Bylinskii et al., 2018).

Constraints of Predictive Eye-Tracking:

Lack of Real-Time Interaction: Traditional eye-tracking techniques do not allow instant contact and hence cannot be used for observing or analyzing live changes in the eyes' motion. Also, there is a limitation within prediction models whereby they can only make predictions around static data points, thus ignoring all other variable factors (Tatler et al., 2011).

Difficulties in making generalizations: Predictive models, although trained on extensive datasets, may need to be more effectively applied to novel visual stimuli that deviate significantly from the training data, posing a potential limitation. In contrast, traditional eye tracking involves directly observing user behavior (Riche et al., 2013).

Lack of Contextual Cues: Conventional eye-tracking studies can include contextual information, such as the user's task or environment, which might impact how the eyes move. However, predictive models generally depend solely on visual cues and may not consider the broader context in which the information is observed (Henderson & Hollingworth, 2007).

4.3 Predictive Eye Tracking and Its Applications

Predictive eye tracking mimics human vision by using previously collected eye-tracking tool data. With AI-based eye-tracking research, companies benefit from faster and more cost-effective measurements for their marketing campaigns. Additionally, eye-tracking studies help determine which elements of a campaign capture customers' attention (Slivka, 2020). Additionally, AI learns from experiments conducted with eye trackers on subjects and specific visual patterns. It provides an instant and up-to-date understanding of consumer behavior by predicting visual behavior patterns for similar visual patterns. This application increases the accessibility of eye-tracking technology by eliminating the need for expensive hardware and manual data processing.

Neuromarketing research uses eye-tracking technology to understand how consumers direct their attention, navigate digital platforms, and make purchasing decisions. Researchers can use eye movement analysis to predict consumer preferences, information attitudes, and changes in perceptions regarding products or brands; thus, they help develop effective marketing strategies (Prabowo, 2023). Experiments conducted with eye tracking have led to the development of new and advanced AI-based software solutions (Lavdas et al., 2021). Extensive research has been conducted to develop visual attention theories transformed into mathematical equations and algorithms, making precise predictions about where individuals will first look when observing complex scenarios in visual sciences and computational vision. For example, scientific advancements in behavioral vision science and computational vision form the basis for computational models of human visual attention that predict where individuals will focus within the first 3 to 5 seconds of watching an image or video (3M VAS, 2020).

Furthermore, using predictive eye tracking in neuromarketing can play a crucial role in evaluating the influence of advertising packaging and branding on customer behavior. Researchers employ visual attention gaze behavior measurements. These tools forecast customer preferences and motives. They illuminate processes of decision-making. This leads to more effective, focused marketing efforts (Moya et al., 2020). For example, Garczarek-Bąk et al. (2021) have shown that psychophysiological techniques, such as eye-tracking, accurately forecast customer reactions to new and new brands in commercials. Through assessing gaze and responses, researchers discerned emotional involvement and brand recall, which are crucial for strategic marketing (Garczarek-Bąk et al., 2021).

On the other hand, Chygryn et al. (2024) emphasize that eye-tracking enhances container designs by pinpointing the visual cues that most effectively capture consumer attention. The study endorses the utilization of gaze patterns to forecast product attractiveness, assisting smaller enterprises in improving consumer interaction (Chygryn et al., 2024). Streimikiene et al. (2022) revealed that eye-tracking, in conjunction with other neuroimaging techniques, yields profound insights into consumer preferences, particularly concerning brand and logo identification. This strategy enables firms to customize packaging to enhance brand identity (Ahmed et al., 2022). In addition, computational neuroscientists have developed numerous algorithms and methods to automatically monitor the position and orientation of the gaze, which might be advantageous in a wide range of activities (Klaib et al., 2021).

Artificial intelligence-based eye-tracking solutions built in parallel with what has been described so far are currently available, and the main ones can be seen below.

Neurovision Software: (https://neurovision.io/) It is an academic entrepreneurship AI-based eye-tracking project developed by Dr. Ramsoy, a faculty member at the Neuroscience Decision Center at the Copenhagen Business School and the founder of NeuronsInc. Neurovision Software predicts visual attention toward pictures and videos. The product predicts that visual AI-powered heat maps simulate user focus on visual assets with greater than 90% accuracy.

VAS (Visual Attention Software): (https://vas.3m.com) is a software called the abbreviation "VAS," and is one of the AI-based eye-tracking software. The owner of this product is a global company named 3M, located in the United States.VAS predicts what viewers notice at first glance with 92% accuracy.

Expoze Software: (https://www.expoze.io) Expoze software is an artificial intelligence-supported eye-tracking software. According to the MIT benchmark, the software estimates visual attention with an accuracy of 87% versus the 92% accuracy of traditional eye-tracking.

Attention Insight Software:

(https://attentioninsight.com/) Attention Insight is an algorithm powered by AI that evaluates the visibility of design elements in web images with 90% accuracy and non-web images with 94% accuracy. These accuracy rates have been determined by comparing the results to data collected from images and eye-tracking data from the Massachusetts Institute of Technology. Heatmaps provide a means of analyzing visual attention like genuine eye-tracking research but without data collection. The program empowers marketers and design teams to enhance design performance by generating attention heatmaps, regions of interest, clarity scores, and focus map indicators. The AI algorithm of Attention Insight accurately forecasts alterations in visual attention by analyzing a dataset of 30,800 images obtained from eye-tracking research.

5 | METHODOLOGY

This study uses predictive eye-tracking technology to assess the user-friendliness and effectiveness of selected e-commerce marketplace designs. The primary objective is to determine how effectively the visual structures of these platforms facilitate user navigation and information processing. Eye tracking was chosen for its ability to provide precise data on consumer visual engagement and cognitive demand, making it an ideal tool for evaluating usability in digital interfaces.

5.1 Research objectives and hypotheses

This study investigates whether the selected e-commerce marketplace visuals are user-friendly and convenient website designs through AI-based eye tracking. Our hypotheses can be seen below.

Hypotheses 1. The e-commerce platforms of Trendyol and Amazon Turkey will exhibit enhanced clarity scores, indicating user-friendly design structures that facilitate effortless navigation.

Hypotheses 2. Cognitive demand scores on Trendyol will be lower than those of Amazon Turkey, indicating that Trendyol's design requires less mental effort for consumers to comprehend the material.

5.2 Predictive Eye-Tracking Measures and Data Analysis

The data were generated using AI-based eye-tracking called NeuroVision Software trail version. NeuroVision is an academic entrepreneurship project (https://neurovision.io/) that predicts visual attention in pictures and videos. Dr. Thomas Zoega Ramsoy, the founder of NeuronsInc, developed it. Dr. Ramsoy is also a faculty member at the Neuroscience Decision Center at the Copenhagen Business School. NeuroVision is built on decades of study on the human visual system and the most recent developments in machine learning. It predicts that AI-powered heatmaps imitate user focus on visual assets with greater than 95% accuracy. These machine-learning models are trained on accurate consumer responses and predict social media, website, and package user reactions.

The software has a vast collection of correctly labeled, high-quality, eye-tracking recordings of consumer-related mediums from over 120,000 participants. Besides that, several machine learning models (N=30) were trained and tested. In order to evaluate the attention participants paid to each stimulus, we used two different parameters derived from neurovision software capabilities, as shown below.

Cognitive demand: This indicates as a score how much information the viewer processes in images or videos. When visuals get more complex, they increase the perceptual load and, as a result, cognitive effort.

Clarity: A measure of how large a piece of image attracts attention. When photos have many things that draw customers' attention, they are less likely to perceive any particular section of the image, which is thus less clear. When a few small regions capture attention, the clarity score rises.

Table 1 Neurovision Software Metrics

Cognitive Demand	0-25	25-50	50-75	75-100
	Low	Medium Low	Medium High	High
Clarity	72,98-100	54,23-72,97	36,46-54,22	0-36,45
	High	Medium High	Medium Low	Low
Meaning	No optimization needed	No optimization needed	Some optimizations may be required.	Must be optimized.

Table 1 explains the scoring scale for cognitive demand and clarity. Cognitive demand scores range from 0 to 100, with higher scores indicating higher complexity and cognitive load. Clarity scores range from 0 to 100, with higher scores reflecting a more visually clear and focused design. It categorizes cognitive demand and clarity scores into levels (Low, Medium Low, Medium High, High), with recommendations on whether optimization is needed. For example, high cognitive demand scores suggest a page may need simplification, while high clarity scores mean the page design is visually optimized.

The Heatmap Meanings:

In heatmaps, the color scheme reflects the intensity of user attention:

Red Areas: Areas of highest attention (hot zones), where users focus the most intensively.

Yellow Areas: Moderate attention areas.

Green: Low attention zones.

Blue/Transparent Areas: Regions receiving minimal to no focus.

5.3 Stimuli

The stimulus materials were E-Commerce marketplace websites in Turkey named (www.trendyol.com) and Amazon Turkey (www.amazon.com.tr). These Marketplace websites were evaluated separately. Screenshots were captured under controlled conditions to ensure consistency and reliability of data collection. The essential conditions and specifications are outlined below:

Screenshots were obtained under controlled conditions to ensure data collection's consistency and reliability. The essential conditions and specifications are defined below:

Device Type: The screenshots were captured on a Macbook Pro laptop computer with a standard 13.3-inch monitor (1920x1080 resolution) to ensure complete page visibility and simulate the typical surfing experience for e-commerce users.

Page Zoom Level: All screenshots were taken at 100% zoom to preserve the webpages' authentic and unmodified visual arrangement.

Browser and Settings: The websites were browsed via the Google Chrome browser in full-screen mode, devoid of extensions or ad blockers that could modify the page presentation.

Time and Date: Screenshots were taken on April 21, 2021, ensuring that all visual stimuli exhibit consistent design characteristics.

E-commerce marketplace websites consist of five main components:

1. Main Page,

2. Coffee Machine Category Home Page,

3. Add to Cart Screen of the Coffee Machine Category,

4. Address and Price Control Screen of Machine Category

5. Address and Price Control Screen of Coffee Machine Category

Marketplace screenshots from the websites of the two marketplaces were analyzed with Neurovision AI software, which hosts various machine-learning models involving more than 120,000 participants. A total of ten screenshots were selected for our study. All screenshots selected for this study are presented in the findings, and the layout details are listed in Table 2.

Table 2 Details of the ten stimuli selected for this study

TRENDYOL.COM	1	Figure 1: www.trendyol.com, The Screenshot of the Main Page
	2	Figure 2: www.trendyol.com, The Screenshot of the Coffee Machine Category Home Page
	3	Figure 3: www.trendyol.com, The Screenshot of the Add to Cart Screen of the Coffee Machine Category
	4	Figure 4: www.trendyol.com, The Screenshot of the Address and Price Control Screen of Coffee Machine Category
	5	Figure 5: www.trendyol.com, The Screenshot of the Checkout Screen of the Machine Category
AMAZON COM TR	6	Figure 6: Amazon.com.tr, The Screenshot of the Main Page
	7	Figure 7: Amazon.com.tr, The Screenshot of the Coffee Machine Category Home Page
	8	Figure 8: Amazon.com.tr, The Screenshot of the Checkout Screen of the Machine Category
	9	Figure 9: Amazon.com.tr, The Screenshot of the Shopping Cart Price Control Screen of the Coffee Machine Category
	10	Figure 10: Amazon.com.tr, The Screenshot of the Adress and Price Control of the Coffee Machine Category

Source: Created by the author

As shown in Table 2, this table enumerates the ten screenshots (stimuli) chosen from two e-commerce platforms (Trendyol and Amazon Turkey) for the research. Each screenshot denotes a page or screen from these websites, including the homepage, category homepage, or checkout interface. The objective is to delineate the information examined in the study concerning cognitive demand and clarity measures. As a cross-sectional study design, investigated data was collected on the 21st of April 2021.

6 | FINDINGS

Figure 1: www.trendyol.com, The Screenshot of the Main Page

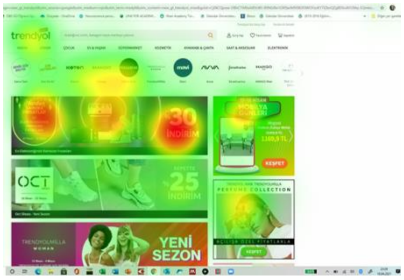

Table 3: Heatmap Scores 1

Cognitive Demand	Clarity
39.86%	62.63%

Table 3 Explanation:

Cognitive Demand: Medium Low (39.86%) - No optimization needed.
Clarity: Medium High (62.63%) - No optimization needed.

The first page of Trendyol indicates a cognitive demand score of 39.86%, falling within an acceptable range, signifying that users can browse and comprehend the website without undue mental exertion. The clarity score of 62.63% suggests that the page is adequately clear, while certain layout modifications could enhance user concentration on essential parts.

Figure 1 Explanation:

The layout is predominantly characterized by yellow and green zones, signifying moderate attentiveness. Critical elements like main banners may need to be pulling more focus. The lack of red zones on key elements like banners indicates that these areas could be more visually engaging.

Figure 2: www.trendyol.com, The Screenshot of the Coffee Machine Category Home Page

Table 4: Heatmap Scores 2

Cognitive Demand	Clarity
32.96%	64.75%

Table 4 Explanation:

Cognitive Demand: Medium Low (32.96%) - No optimization needed.

Clarity: Medium High (64.75%) - No optimization needed.

The Trendyol Coffee Machine Category Home Page has a cognitive demand score of 32.96%, signifying that consumers exert minimum mental effort to comprehend and engage with the page. A clarity score of 64.75% signifies adequate visual clarity, facilitating user identification of critical features; however, minor enhancements could improve concentration.

Figure 2 Explanation:

The heat map expressions red zones predominantly on product images, highlighting customer interest in the product section, while yellow zones appear on navigation filters, indicating moderate attention to sorting and filtering options. This design effectively directs focus to the product section while ensuring sufficient interaction with filtering tools, aligning with user expectations for category pages.

Figure 3: www.trendyol.com, The Screenshot of the Add to Cart Screen of the Coffee Machine Category

Table 5: Heatmap Scores 3

Cognitive Demand	Clarity
28.79%	84.21%

Table 5 Explanation:
Cognitive Demand: Medium Low (28.79%) - No optimization needed.
Clarity: High (84.21%) - No optimization needed.

The figure indicates that the "Add to Cart" interface in Trendyol's Coffee Machine Category has a low cognitive load of 28.79%, facilitating user comprehension of the page. The clarity score of 84.21% is relatively high, indicating an optimized design that efficiently focuses user attention on critical parts, facilitating a seamless and user-friendly experience.

Figure 3 Explanation:

The heat map shows red zones focused on the "Add to Cart" button and cart symbol, drawing user attention to key interactive areas. In contrast, green zones appear on less critical sections, supporting a clean and coherent layout. This optimized design ensures a seamless and intuitive user experience, allowing customers to navigate the "Add to Cart" process efficiently without unnecessary distractions.

Figure 4: www.trendyol.com, The Screenshot of the Address and Price Control Screen of the Coffee Machine Category

Table 6: Heatmap Scores 4

Cognitive Demand	Clarity
24.35%	82.26%

Table 6 Explanation:
Cognitive Demand: Low (24.35%) - No optimization needed.
Clarity: High (82.26%) - No optimization needed.

The Address and Price Control Screen has a minimal cognitive demand score of 24.35%, signifying that users can effortlessly navigate the page. The clarity score of 82.26% indicates that essential features are visually evident, rendering the website very user-friendly.

Figure 4 Explanation:

The heat map displays red hotspots concentrated near address confirmation and price fields, indicating high user engagement with Essentia. Meanwhile, green and yellow zones appear on less critical components, ensuring attention is focused on primary tasks. This design effectively prioritizes key elements like address and price details, aligning well with user expectations during checkout.

Figure 5: www.trendyol.com, The Screenshot of the Checkout Screen of the Machine Category

Table 7: Heatmap Scores 5

Cognitive Demand	Clarity
27,18%	79.10%

Table 7 Explanation:
Cognitive Demand: Medium Low (27.18%) - No optimization needed.
Clarity: High (79.10%) - No optimization needed.

The checkout interface in Trendyol's Machine Category exhibits a low cognitive load of 27.18% and a high clarity rating of 79.10%. This signifies an intuitive layout, facilitating a seamless checkout procedure for users with minimal cognitive strain.

Figure 5 Explanation:

High red focus on payment and order placement, with green zones on less critical sections ensuring an efficient layout. The heat map illustrates red zones concentrated in payment and order placing areas, signifying robust user involvement with vital components. In contrast, green zones are present in less key sections, preventing distraction from primary duties.

Figure 6: Amazon.com.tr, The Screenshot of the Main Page

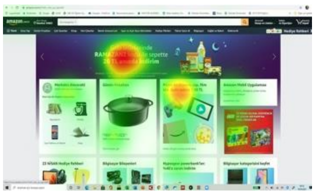

Table 8: Heatmap Scores 6

Cognitive Demand	Clarity
48.38%	78.25%

Table 8 Explanation:
Cognitive Demand: Medium Low (48.38%) - Some optimizations may be required.
Clarity: High (78.25%) - No optimization needed.

The main page of Amazon Turkey possesses a cognitive demand score of 48.38%, indicating a more intricate layout that necessitates more excellent user processing. Nonetheless, the clarity score of 78.25% is elevated, indicating that crucial items are visually discernible, facilitating user navigation on the page.

Figure 6 Explanation:

The heat map for Figure 6, depicting the main page of Amazon Turkey, shows red and yellow clusters concentrated on significant banners and promotional deals, drawing user attention to key offerings. At the same time, green and blue zones in less relevant areas may dilute focus and contribute to a sense of clutter. The main page successfully emphasizes key elements but could benefit from simplification to reduce cognitive load and improve overall user navigation.

Figure 7: Amazon.com.tr, The Screenshot of the Coffee Machine Category Home Page

Table 9: Heatmap Scores 7

Cognitive Demand	Clarity
47.35%	69.23%

Table 9 Explanation:
Cognitive Demand: Medium Low (47.35%) - Some optimizations may be required.
Clarity: Medium High (69.23%) - No optimization needed.

The Coffee Machine Category Home Page on Amazon exhibits a cognitive demand score of 47.35%, indicating that consumers must comprehend more information. The clarity score of 69.23% is satisfactory but would improve with design modifications to enhance the visibility of critical features.

Figure 7 Explanation:

Red zones on images of products, along with excessive yellow and green zones, indicate a deficiency in clarity or focus relative to Trendyol's layout. The heat map in Figure 7 indicates moderate interaction with essential components while highlighting the potential for design enhancement to reduce cognitive load and improve clarity, hence promoting a more intuitive user experience.

Figure 8: Amazon.com.tr, The Screenshot of the Checkout Screen of the Machine Category

Table 10: Heatmap Scores 8

Cognitive Demand	Clarity
42.97%	88.22%

Table 10 Explanation:
Cognitive Demand: Medium Low (42.97%) - Some optimizations may be required.
Clarity: High (88.22%) - No optimization needed.

The Amazon checkout interface has an adequate cognitive demand score of 42.97% and an exceptionally high clarity score of 88.22%. This indicates that the layout efficiently emphasizes crucial features, facilitating user completion of purchases.

Figure 8 Explanation:

Figure 8's heat map delineates red zones in pivotal locations, such as the checkout button and total price, indicating significant user interaction with transactional elements. Secondary items in the yellow and green zones receive modest focus, ensuring a balance corresponding to user objectives for a fast checkout experience.

Figure 9: Amazon.com.tr, The Screenshot of the Shopping Cart Price Control Screen of the Coffee Machine Category

Table 11: Heatmap Scores 9

Cognitive Demand	Clarity
34.21%	64.08%

Table 11 Explanation:
Cognitive Demand: Medium Low (34.21%) - No optimization needed.
Clarity: Medium High (64.08%) - No optimization needed.

The Amazon shopping Cart Price Control Screen possesses a cognitive demand score of 34.21%, which means it is comparatively simple for users to navigate. The clarity score of 64.08% is satisfactory; nevertheless, enhancements could accentuate critical regions, facilitating expedited decision-making.

Figure 9 Explanation:

The heatmap displays red regions on price information and Call to Action (CTA), signifying effective user engagement. (In marketing and user experience (UX), a Call to Action (CTA) is a message, button, link, or graphic element intended to prompt visitors to perform a certain action, such as "Buy Now," "Shop the Collection," or "Add to Cart.") The yellow and green zones in less crucial areas might be reduced to enhance clarity and concentrate on transactional components.

Figure 10: Amazon.com.tr, The Screenshot of the Address and Price Control of the Coffee Machine Category

Table 12: Heatmap Scores 10

Cognitive Demand	Clarity
38.65%	80.72%

Table 12 Explanation:
Cognitive Demand: Medium Low (38.65%) - No optimization needed.
Clarity: High (80.72%) - No optimization needed.

Address and Price Control interface under Amazon's Coffee Machine Category exhibits a moderate cognitive load of 38.65% and a high clarity rating of 80.72%. This balance signifies a well-structured website that enables readers to find essential information effortlessly.

Figure 10 Explanation:

The heat map for Figure 10 highlights red hotspots on key areas such as the address and price fields, indicating strong user engagement with these essential elements. The design ensures focused attention on transactional components while maintaining a clear and intuitive interface, with secondary elements in green zones that do not distract users from completing the checkout process. This optimized layout directs user attention to vital areas, supporting a seamless and efficient checkout experience.

Table 13 The Overall Scores of Cognitive Demand and Clarity

E-Market Place	Figures	Cognitive Demand	Clarity
TRENDYOL.COM	Figure 1: www.trendyol.com, The Screenshot of the Main Page	39,86	62,63
	Figure 2: www.trendyol.com, The Screenshot of the Coffee Machine Category Home Page	32,96	64,75
	Figure 3: www.trendyol.com, The Screenshot of the Coffee Machine Category	28,79	84,21
	Figure 4: www.trendyol.com, The Screenshot of the Address and Price Control Screen of Coffee Machine Category	24,35	82,26
	Figure 5: www.trendyol.com, The Screenshot of the Checkout Screen of the Machine Category	27,18	79,1
Total		153,14	372,95
Mean		30,628	74,59
AMAZON.COM.TR	Figure 6: Amazon.com.tr, The Screenshot of the Main Page	43,38	78,25
	Figure 7: Amazon.com.tr, The Screenshot of the Coffee Machine Category Home Page	47,35	69,23
	Figure 8: Amazon.com.tr, The Screenshot of the Checkout Screen of the Machine Category	42,97	88,22
	Figure 9: Amazon.com.tr, The Screenshot of the Shopping Cart Price Control Screen of the Coffee Machine Category	34,21	64,08
	Figure 10: Amazon.com.tr, The Screenshot of the Adress and Price Control of the Coffee Machine Category	38,65	80,72
Total		206,56	380,5
Mean		41,312	76,1
	Mean of the Cognitive Demand	Mean of the Clarity	
TRENDYOL.COM	30,628	74,54	
AMAZON.COM.TR	41,312	76,1	

Table 13 presents a comparative analysis of the usability scores for both websites. Trendyol exhibits a lower average cognitive demand score (30.628%) compared to Amazon Turkey (41.312%), suggesting that Trendyol's design is more straightforward and necessitates less mental exertion from customers. Both websites have elevated clarity scores (Trendyol: 74.59%, Amazon: 76.1%), indicating visual clarity; nevertheless, Amazon's layout is more information-dense, thus necessitating more significant cognitive effort for navigation.

Hypotheses 1. The e-commerce platforms of Trendyol and Amazon Turkey will exhibit enhanced clarity scores, indicating user-friendly design structures that facilitate effortless navigation.

Decision: Accepted

Reason: The mean clarity score for Trendyol is 74,59, while for Amazon Turkey, it is 76,1. Both scores are notably elevated, indicating that each website has attained significant visual clarity, facilitating user-friendly and navigable designs.

Hypotheses 2. Cognitive demand scores on Trendyol will be lower than those of Amazon Turkey, indicating that Trendyol's design requires less mental effort for consumers to comprehend the material.

Decision: Accepted

Reason: The mean cognitive demand score of Trendyol is 30,628, while Amazon Turkey's mean score is 41,312.

A diminished cognitive demand score for Trendyol signifies that its design necessitates less mental exertion for consumers to comprehend the content than Amazon Turkey, corroborating the premise.

7 | DISCUSSION

This study examined the usability of Turkey's premier e-commerce platforms, Amazon Turkey and Trendyol, utilizing AI-driven predicted eye-tracking indicators, including cognitive demand and clarity. The results of this study show that both Amazon Turkey and Trendyol e-commerce marketplaces have effective user interfaces, achieving satisfactory ratings in terms of cognitive demand and clarity scores. Despite the promising nature of these findings, they must be analyzed in relation to traditional neuromarketing research, AI-based predictive eye tracking, and the existing body of knowledge on e-commerce usability. Moreover, when compared to the broader literature, these findings have the potential to reveal several important insights.

The findings are consistent with prior research highlighting the significance of cognitive demand and clarity in online platforms. Indeed, Frey et al. (2021) emphasized the significance of clarity in improving user experience and happiness, especially in e-commerce. The findings of the present investigation indicate that Trendyol displayed a lower level of cognitive demand than Amazon Turkiye. Decreasing the cognitive load during navigation can enhance user involvement. These findings align with prior studies indicating that efficient and user-friendly design is essential for user retention and enhancing the smoothness of online buying experiences (Frey et al., 2021; Schneider et al., 2022).

Nevertheless, the fixed characteristics of the images examined in this research present a constraint that must be resolved. Previous studies, such as the one conducted by Bylinskii et al. (2018), have integrated dynamic data using real-time eye-tracking to identify more intricate user interactions. The study's dependence on static images limits the complexity of the insights that can be derived since it fails to consider users' engagement with dynamic content or scrolling patterns. Moreover, future studies should consider including real-time and subject-based eye-tracking data to enhance the accuracy of user engagement analysis on dynamic, interactive websites.

Additionally, applying AI-based predictive eye tracking in neuromarketing represents a novel approach to understanding user behavior. Previous literature (e.g., Ramirez et al., 2022; Schneider et al., 2022) has demonstrated the effectiveness of different neuromarketing devices (Electroencephalography) and fNIRS (functional Near-Infrared Spectroscopy) based predictive models in consumer research. However, as this study used static visual data, there is an opportunity for future studies to enhance the accuracy of predictions by integrating real-time gaze tracking with AI-based predictive algorithms. These results would provide a richer dataset and allow for more precise modeling of user interactions with website content.

The findings also indicate practical consequences for electronic commerce websites. Although all platforms performed admirably in clarity and cognitive load, the minor variations indicated the need for improvement. By contrast, Amazon Turkiye's greater cognitive demand than Trendyol suggests that simplifying the web interface could enhance the user experience even more. This discovery is essential for e-commerce platforms that want to optimize their user interfaces to reduce cognitive load, resulting in increased customer happiness and conversion rates.

Besides that, this study emphasizes techniques to enhance user experience on e-commerce platforms by improving cognitive demand and clarity metrics. Simplifying website design can diminish cognitive load, facilitating more intuitive navigation and necessitating reduced mental effort. A streamlined, minimalist design enables rapid and comfortable user engagement with the material, enhancing enjoyment. Highlighting critical information, such as pricing and "Add to Cart" buttons, improves clarity, allowing users to locate crucial elements more swiftly. A well-defined visual hierarchy can diminish customer friction, promoting a more seamless shopping experience.

Customized content, particularly on information-rich pages, guides users to pertinent products and minimizes superfluous information. Customized recommendations enhance navigation, particularly on platforms with extensive inventories. Enhancing mobile usability through responsive design and rapid load times improves accessibility for mobile consumers. Concise, prioritized designs mitigate cognitive stress on compact displays.

Consistent evaluation and user input facilitate ongoing enhancements. A/B testing and surveys discern usability improvements, promoting a user-centric methodology for ongoing satisfaction and engagement.

It is also a fact that consumer buying behavior on e-commerce platforms goes beyond design. E-commerce purchasing behavior is shaped by numerous elements that can be classified into psychological, sociological, and technological categories. E-commerce purchasing behavior is heavily influenced by trust (Kimery & Mccord, 2002) and e-loyalty. Comprehending these aspects is essential for enterprises seeking to refine their online platforms and improve consumer pleasure and loyalty (Bulut, 2015).

Furthermore, the study's emphasis on neuromarketing methodologies powered by artificial intelligence underscores the possibility of these technologies to transform user experience research. Eye-tracking models based on artificial intelligence enable scalable and cost-efficient analysis by eliminating costly hardware and real-time data-rating requirements. Nevertheless, it is recommended that future studies investigate incorporating additional neuroscientific techniques, such as EEG or facial coding, to gain a deeper comprehension of the emotional and cognitive aspects of user engagement.

Apart from all these, there is also some debate about ethical implications in the context of AI-based marketing strategies. The ethical dimensions of predictive eye tracking and neuromarketing are complex, involving issues of privacy, consent, and the risk of manipulation (Davenport et al., 2019). This capability poses a risk of unauthorized data collection and potential misuse, as eye tracking can reveal not only what users are looking at but also their internal states and preferences (Hagestedt et al., 2020). The ability to predict user behavior based on eye movements can lead to intrusive marketing practices that manipulate consumer choices without their explicit consent (Alsakar et al., 2023).

Confronting these difficulties necessitates a collaborative endeavor among researchers, practitioners, and policymakers to establish comprehensive privacy safeguards, guarantee informed consent, and promote transparency in data gathering methodologies.

8 | CONCLUSION

This study verifies the efficacy of artificial intelligence (AI)-based predictive eye-tracking technology in assessing the usability of electronic commerce (e-commerce) platforms, explicitly examining cognitive demand and clarity measures. Both platforms have user-friendly and efficient designs, with elevated clarity scores facilitating effortless navigation. The Trendyol platform lessened the cognitive demand score, which indicates a more seamless user experience than Amazon Turkey, potentially enhancing consumer accessibility and comprehension. These findings underscore the significance of clarity and decreased mental workload in improving e-commerce website usability.

These research findings make valuable contributions to both scholarly literature and real-world applications. From an academic standpoint, this study contributes to the developing area of AI-driven neuromarketing by presenting statistical data on the significance of predictive eye-tracking in evaluating web usability. In practical terms, the findings provide helpful information for e-commerce platforms aiming to improve their interface designs to increase customer pleasure and involvement.

However, the study's dependence on static images limits the scope of user interaction analysis. Future research should integrate real-time eye tracking with AI-based predictive models to comprehensively capture a broader range of user actions in dynamic online environments. Furthermore, incorporating additional neuromarketing techniques such as EEG or facial coding can offer a more comprehensive view of users' emotional and cognitive responses.

Conclusively, using AI-based predictive eye tracking offers positive prospects for improving the design and usability of e-commerce platforms. As artificial intelligence (AI) and neuromarketing technologies advance, different neuromarketing tools are expected to be used to predict consumer behavior. Moreover, future studies should investigate real-time data integration and expand their applications in many industries to fully harness these groundbreaking technologies' capabilities.

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