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Attention visual

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ATTENTION VISUAL

BY

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Abstract

This research presents an innovative approach to improving visual-spatial attention using a research tool based on the web. Recognizing the significant role visual-spatial attention plays in everyday life and cognitive function for humans, this research was undertaken with the aim of developing a user-friendly, accessible web-based tool called Attention Visual (attentionvisual.com) to enhance this crucial cognitive skill. This tool also facilitates data collection, potentially accelerating the pace and enhancing the quality of related research.

Both qualitative and quantitative methods were utilized for data collection and analysis. In order to stimulate improvements in visual-spatial attention, the tool's algorithm was structured to adjust task difficulty according to the user's performance; heightened performance would yield more challenging tasks, whereas lower performance would result in easier tasks, fostering an adaptive and progressive learning environment.

The main hypothesis that underlies this research was that regular use of this tool could result in measurable enhancements in visual-spatial attention. This has potential benefits for various population groups, from athletes to individuals with certain cognitive conditions.

The results of the research validate this hypothesis, demonstrating the effectiveness of the web-based tool in enhancing visual-spatial attention and indicating that the design elements of the tool have a positive impact on user performance. The research additionally highlighted a wide range of participant diversity, thanks to the online nature of the tool, enhancing the robustness and generalizability of the data collected.

These findings contribute significantly to the fields of cognitive science, neuroplasticity, and digital tool development, offering valuable insights for future research. They demonstrate the effectiveness of web-based tools in cognitive science research and suggest potential avenues for future investigation, such as exploring other aspects of visual cognition or the application of such tools in practical settings like cognitive therapy and rehabilitation.

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Chapter 1

Introduction

1.1 Overview of the research problem and its significance

Accessibility and ease of data collection are significant obstacles in scientific research. Especially in the field of cognitive studies, access to a broad participant base is vital for enhancing the validity and generalizability of the research findings. This research project aims to address these challenges by creating an accessible, web-based application, namely Attention Visual (attentionvisual.com), designed to facilitate data collection from diverse global participants. This approach not only promises to make cognitive research more inclusive but also aims to enhance the amount and diversity of data that researchers can gather.

The pertinence of this goal has been highlighted during the COVID-19 pandemic, which has necessitated a shift toward remote operations in many sectors, including research. Thus, harnessing the power of the digital world for research purposes is a crucial step forward.

Our main research problem focuses on understanding and enhancing visual-spatial attention through a gamified approach. Visual-spatial attention, a cognitive ability critical for many daily tasks, can be improved through targeted exercises. However, traditional methods of conducting such exercises have been constrained by physical logistics, access to resources, and participant engagement. Our web application aims to alleviate these issues by providing an engaging, accessible platform that allows users to practice these exercises from the comfort of their homes.

Furthermore, the application aims to analyze the users' performance immediately, providing real-time data that can be used to understand their progress and areas of improvement. The use of such an application holds promise not only for individual users looking to improve their visual-spatial attention but also for researchers looking to gather large-scale data about human cognition.

In the long run, the successful implementation of this tool will pave the way for more comprehensive and inclusive research. By enabling researchers to collect more data and access wider participant demographics, we can enhance our understanding of human cognition and develop better cognitive training tools. Moreover, the learnings from this project could be applied to create similar tools for other domains, thus accelerating the pace and improving the quality of scientific research.

1.1.1 Research Questions and Hypotheses

Our research is guided by several key questions:

1. Can a web-based application effectively be used to enhance visual-spatial attention?

2. Will increased accessibility and participant diversity improve the quality and validity of research data in the field of visual cognition?

3. How does the use of animations, color choices, and shapes in the application interface affect user engagement and performance?

4. What is the overall user experience and feedback regarding the use of a web-based tool for this kind of research?

Based on these questions, formulated the following hypotheses:

1. A web-based application, with its wider reach and ease of use, can serve as an effective tool for enhancing visual-spatial attention.

2. Increased participant diversity, achieved through the online nature of the application, will provide more generalizable and robust data, thereby improving the quality of research in visual cognition.

3. Thoughtful application design choices, such as the use of specific animations, colors, and shapes, can positively influence user engagement and performance.

4. Given the current trend towards digital solutions, the web-based research tool in this research received positive feedback from users globally. It's accessibility and online nature allowed it to reach people worldwide, leading to more diverse and varied data. This endorses the use of such digital tools for research into visual cognition and supports their role in future studies.

1.2 Methodology Summary

The methodology for this research project is designed to combine quantitative and qualitative approaches to analyze the potential for improving visual spatial attention through an accessible, real-time application.

The first phase involves the development of the application itself. Given the purpose of the application, a user-centered design approach is adopted, ensuring the application is intuitive and engaging for users. The design choices are informed by established principles of visual attention and neuroplasticity, and the application features a variety of tasks intended to stimulate and measure visual spatial attention.

The second phase of the research involves deploying the application to a diverse set of users across the globe. This step allows us to collect both primary and secondary data. Primary data collection is achieved through in-app metrics that record user interaction with the tasks, measuring their visual spatial attention over time. Secondary data is collected through user feedback and surveys which provide qualitative insights into the user experience.

The final phase involves the analysis of the collected data. Quantitative data is subjected to statistical analysis to identify trends and correlations. The software tools used for this purpose allow for a thorough investigation of the relationships between the recorded metrics. The qualitative data is analyzed through thematic analysis to identify recurring themes and sentiments in user feedback.

Throughout all phases of the research, ethical considerations are taken into account. The project respects user privacy and confidentiality, and informed consent is obtained for data collection and analysis. Data handling and storage practices are designed to minimize risk and uphold the integrity of the research.

The overarching goal of this methodology is not only to assess the viability of the application as a tool for improving visual spatial attention but also to understand the broader implications of the research for neuroplasticity and cognitive health.

1.3 Chapter Summaries

In order to provide a comprehensive understanding of the research, the thesis is organized into distinct chapters, each addressing a specific aspect of the project. The following is a brief outline of each chapter:

1.3.1 Chapter 1: Introduction

This chapter sets the context for the research, presenting the research problem and its significance. It also outlines the research questions and hypotheses that this research aims to address.

1.3.2 Chapter 2: Literature Review

This chapter provides a comprehensive review of relevant literature and theories in the fields of visual spatial attention, neuroplasticity, and application design. The literature review lays the theoretical foundation for the development of the application and the overall research approach.

1.3.3 Chapter 3: Methodology

In this chapter, the research design and strategy are outlined. It includes details of the data collection methods and data analysis methods used in this research, along with the ethical considerations taken into account during the research.

1.3.4 Chapter 4: Results and Discussions

In this chapter, we will present the empirical data collected during the user studies and analyze the findings. This will involve detailed discussions on the effects of different animations on the participants' visual attention, which will be understood through statistical analyses.

A thorough exploration of the data will aim to uncover trends and relationships that directly address the research questions and hypotheses. Following the presentation of results, we will interpret these findings in the context of the research questions and hypotheses.

The implications of the findings will then be discussed with regard to visual-spatial attention, neuroplasticity, and application design. This comprehensive exploration and discussion of the results will provide valuable insights into the intersection of these three important areas.

1.3.5 Chapter 5: Conclusion

The final chapter concludes the research, summarizing the key findings and discussing their implications. It also suggests future directions and reflections on the limitations of the research.

1.4 Research Tool Illustration

1.4.1 /home Page

The home page shown in Figure 1.1 serves as the welcoming platform for users who have signed up and logged in to the research tool. This page provides a friendly greeting and an immediate summary of the tool, its functions, and its benefits.

The page begins by expressing appreciation for user participation and then presents a clear description of what users can do with the "Attention Visual". It outlines the opportunities to participate in various gaze tracking tests, offering insights into individual visual attention and cognitive patterns.

Moreover, the users are informed about the availability of real-time data visualization, a feature that would allow them to gain a better understanding of their own visual attention patterns. This is a compelling feature that ensures users are actively involved and personally invested in the process.

The page also assures the users about continuous updates and improvements to the platform. It promises upcoming features like advanced data analysis and customizable tests, building anticipation and ensuring user engagement over time.

Overall, the homepage serves as a comprehensive guide, giving users a clear understanding of the research tool's functionalities and what to expect as they navigate through the platform.

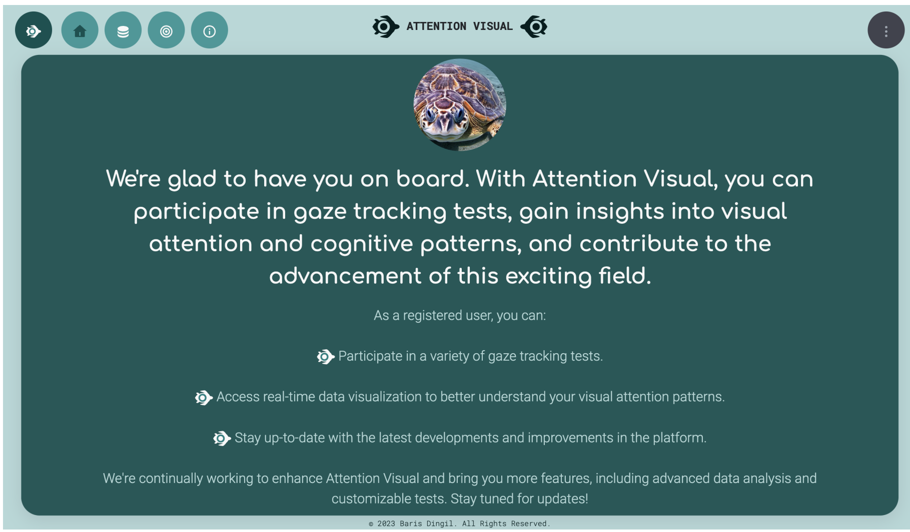

Figure 1.1: Home page

1.4.2 /myData Page

The Data Page shown in Figure 1.2 is the central hub where users can engage interactively with the progress they have made through their sessions. This page provides an enriching experience by offering a visually intuitive scatter plot graph, which displays session scores plotted against session dates.

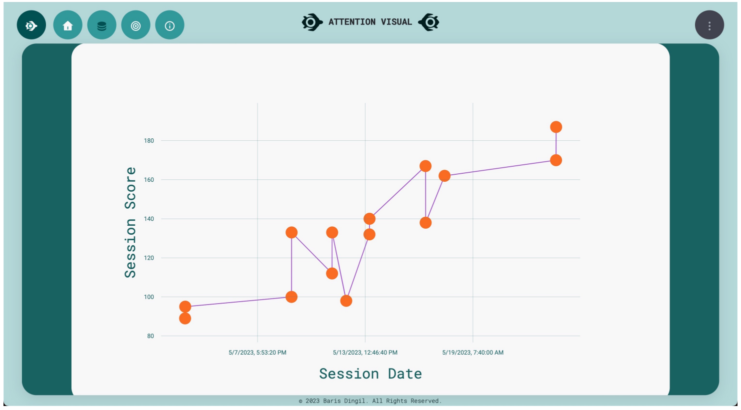

Figure 1.2: User Sessions Data

Navigating this graph is remarkably user-friendly. It allows users to zoom in and out by simply scrolling, providing them the opportunity to view their data in both detailed and broader perspectives. By hovering over individual data points, users can instantly view the summary of each session as shown in Figure 1.3, including the session number, score, and date. This offers a practical and instant snapshot of their performance for each session, and when viewed in context of the entire graph, it facilitates an understanding of progress over time.

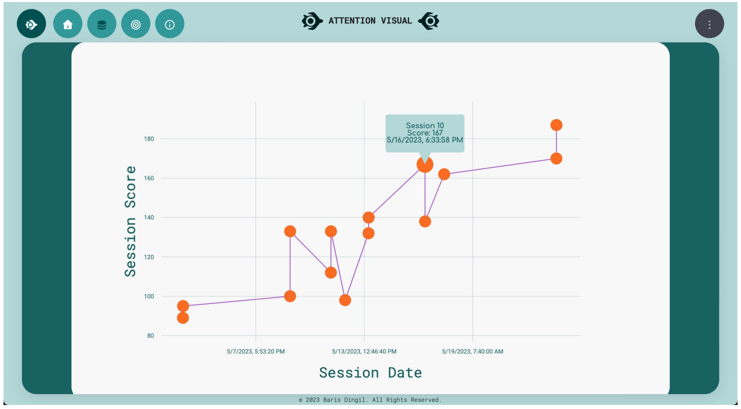

Figure 1.3: User Session Summary on hovered Session Data Point

For a deeper dive into individual sessions, users can click on the corresponding data point. This action triggers a modal window that presents a detailed breakdown of the tests within the chosen session as shown in Figure 1.4. This feature caters to users who wish to analyze their performance on a more granular level.

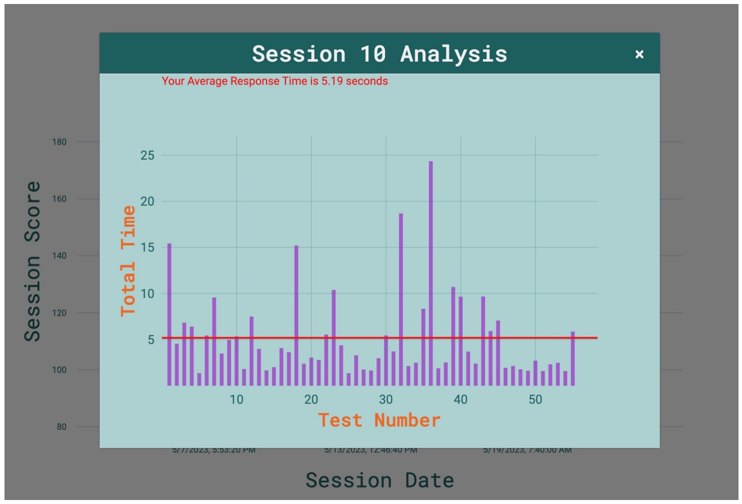

Figure 1.4: User Tests Data on Chosen Session

The Tests section is designed to provide a more complete understanding of the user's performance on an overall basis. It features a bar graph that displays the total response time against the test number, providing a clear visualization of the user's response speed throughout their participation.

A line representing the average response time is superimposed on the bar graph, acting as a benchmark for users and enabling them to easily identify instances when they were slower than their average speed.

The Tests section offers interactive elements, such as the individual bars on the graph. Hovering over a bar pulls up detailed information about the corresponding test, including the test number, the illusion employed in that test, the total response time for that test, the cognitive speed (represented by the total time gazed on the point), and the difficulty level of the test as shown in Figure 1.5.

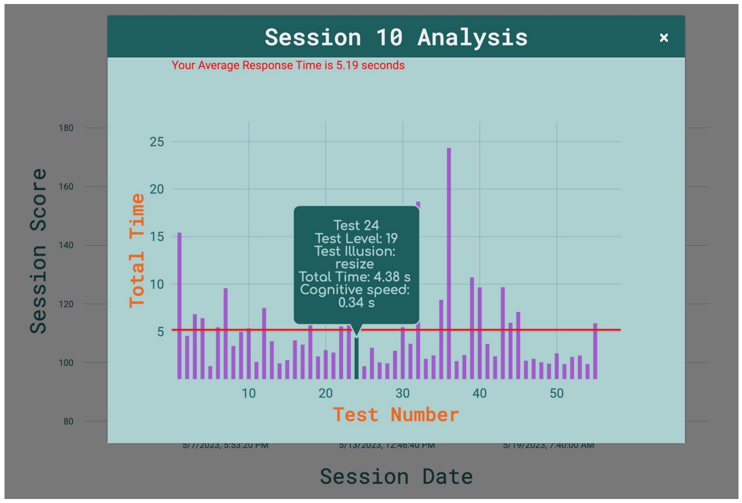

Figure 1.5: User Test Summary on hovered Test Data Bar

This comprehensive level of detail contributes to a more complete understanding of the user's performance, highlighting not just their speed but also their interaction with different illusions and various difficulty levels. The Tests section is integral to enabling users to gain thorough insights into their progress and performance.

1.4.3 /myApp Page

Upon entering the myApp section, users are introduced to the functionality and benefits of participating in various gaze tracking tests. The text on the page as shown in Figure 1.6 informs users that engaging in these tests contributes to a better understanding of their own visual attention and helps improve the platform's performance. It emphasizes the use of advanced AI and machine learning techniques to collect and analyze user data.

The myApp page also instructs users to disable any ad or tracker blockers and refresh the page to view the content. This step ensures that users can successfully initiate the gaze tracking application and engage in the tests.

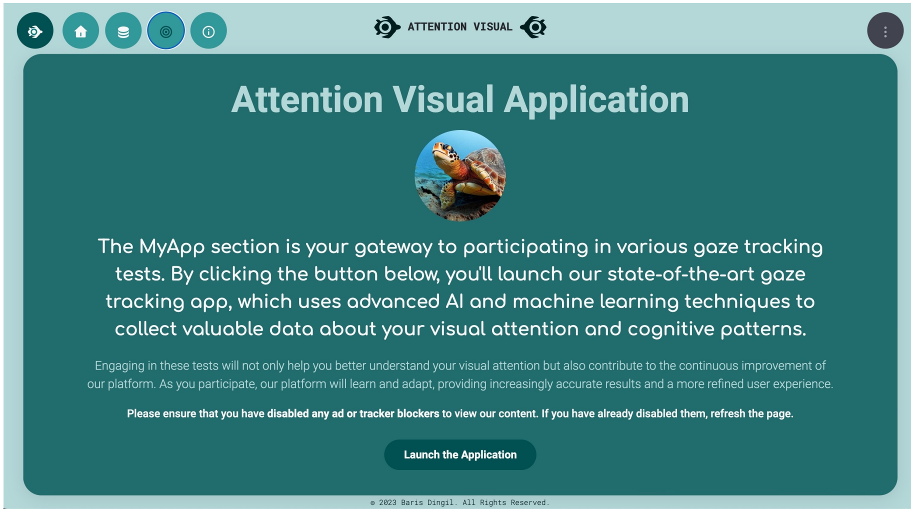

Figure 1.6: Application Launching page

Once the application is launched, the user is greeted with a set of instructions as shown in Figure 1.7) aimed at optimizing their experience and results. These include suggestions to find a well-lit spot, position themselves properly in relation to the screen, and follow the on-screen instructions for the calibration process. The instructions emphasize comfort and relaxation while using the application. Users have the choice to proceed with the tests by clicking the "I'm ready" button or postpone participation by selecting "Some other time".

The emphasis on user comfort and readiness ensures that the data collected is representative of a user's typical visual attention and cognitive patterns, rather than being influenced by external factors such as discomfort or haste.

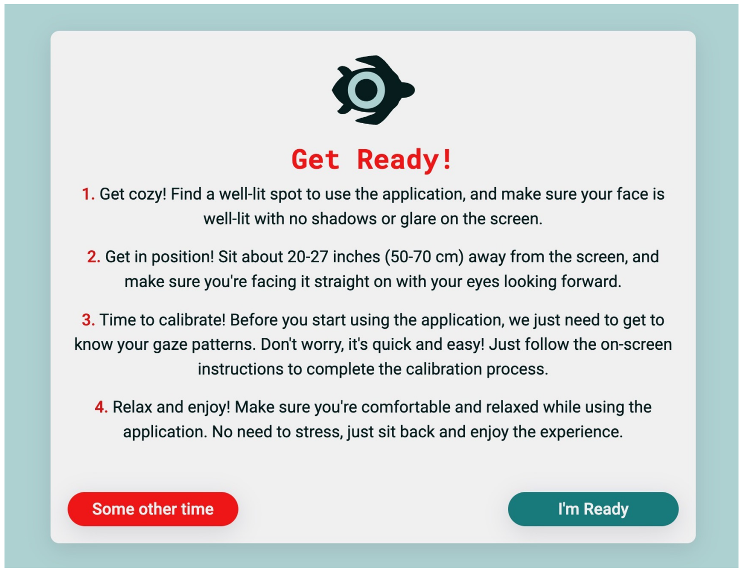

Figure 1.7: First instructions

After a user clicks on "I'm ready", they are led to the "Calibration Magic" stage as shown in Figure 1.8). This stage is a critical preliminary step in preparing the gaze tracking algorithm for the actual tests. The calibration process is designed to enhance the accuracy and quality of the tracked data by accounting for individual differences in gaze patterns.

Once users click on the "Continue" button, they are introduced to their gaze cursor, named "Gaze Turtle". This icon, appearing alongside a grid of points, visually represents the user's gaze position on the screen during the tests. Users are reminded that Gaze Turtle may not move as rapidly as their eyes due to the inherent limitations of the tracking algorithm, but it strives to provide as accurate a representation as possible.

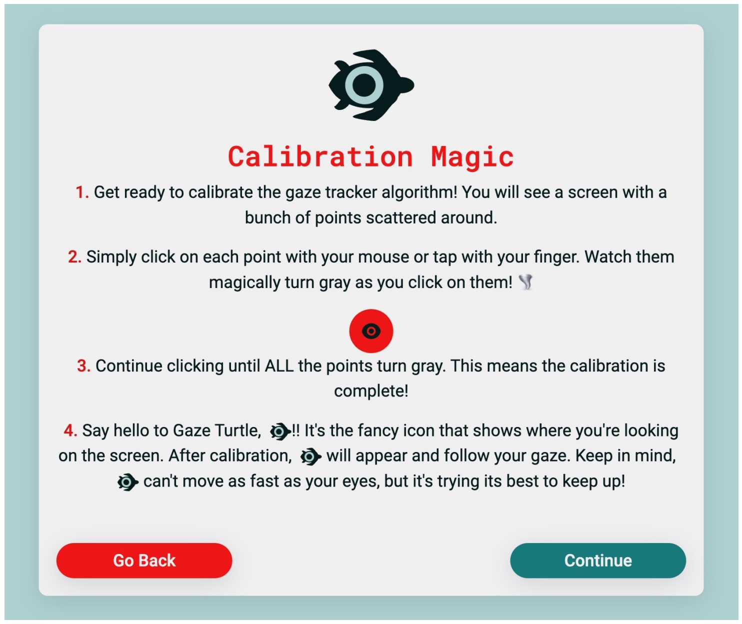

Figure 1.8: Introduction for calibration

The calibration process involves interacting with a grid of points displayed on the screen as shown in Figure 1.9. The users are instructed to click on or tap each point, causing it to turn gray. This transformation signifies that the gaze tracker algorithm has successfully registered the user's gaze at that particular location. Once all points have turned gray, the calibration process is complete.

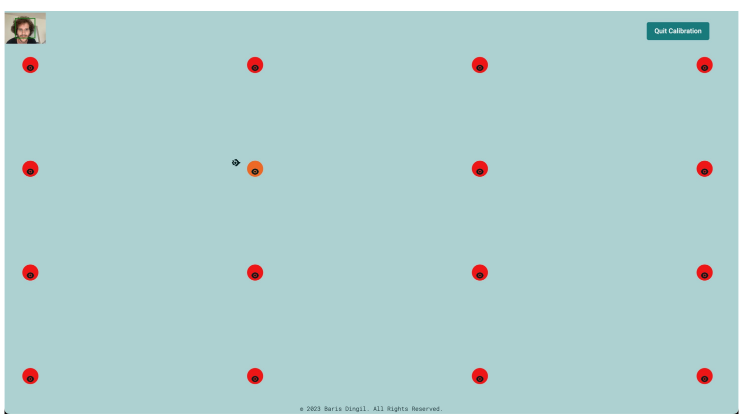

Figure 1.9: Calibration screen

After calibration, users are introduced to the Visual Attention Training Session, where the actual interaction and gaze data collection take place. The instructions for the session, displayed in Figure 1.10 and Figure 1.11, are structured into a series of simple, easy-to-follow steps.

Figure 1.10: Introduction for the test after calibration is completed

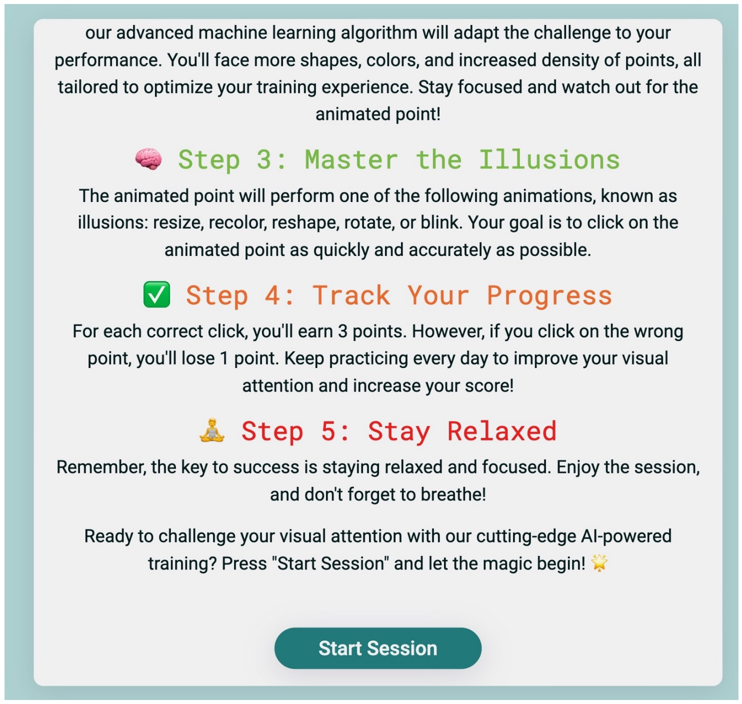

Figure 1.11: Introduction for the test after calibration is completed, continued

Users initiate the session by pressing the "Start Session" button. The following step unveils the AI-powered challenge where a complex machine learning algorithm adjusts the difficulty level according to the user's performance. This real-time adaptation entails presenting more shapes, colors, and a higher density of points as the user progresses through the session.

The main task of the session involves identifying an animated point among a multitude of distractions. The animations, referred to as illusions, could involve resizing, recoloring, reshaping, rotating, or blinking of a point. The goal for users is to click on the animated point as swiftly and accurately as possible. The session also includes a scoring mechanism where users gain three points for each correct click, while a wrong click results in a deduction of one point.

One vital instruction emphasized throughout the session is the need to stay relaxed and focused. Users are reminded that the key to success lies not only in accumulating points but in improving their visual attention over time. Regular participation is encouraged as it aids in enhancing cognitive abilities, which aligns with the core objective of the Attention Visual tool.

Now, with the "Start Session" button, the users are all set to embark on their journey of visual attention training using the advanced, AI-powered Attention Visual tool. The actual training session is illustrated in Figure 1.12, where users interact with the application interface, and their gaze data are recorded for subsequent analysis.

Figure 1.12: Demonstration of a Test

1.4.4 Exploring the Illusions

Each test in the Attention Visual platform is designed around various visual illusions, designed to challenge and train the user's visual attention. In the following, each illusion used in the platform is described in detail, accompanied by illustrative screenshots for better understanding.

Recolor Illustration

The Recolor illusion is one of the visual challenges encountered during the Attention Visual tests. This illusion involves a change in color of a point on the screen amidst several other distracting points. The colors used in these illusions are tones of red, orange, yellow, green, blue, and violet.

During a Recolor illusion, a point's color transitions between two of these six colors. The challenge for the user lies in quickly identifying the point undergoing the color change and accurately clicking on it.

Figure 1.13 provides an illustrative example of a Recolor illusion, where a point changes color from blue to violet.

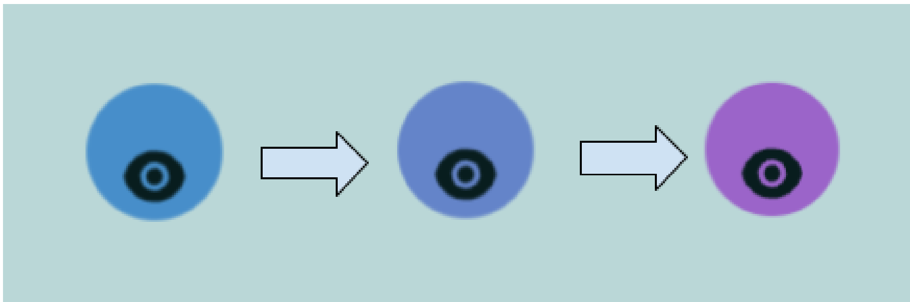

Figure 1.13: Recolor Example

Reshape Illustration

The Reshape illusion represents another type of visual challenge within the Attention Visual tests. This illusion involves a point on the screen altering its shape among a number of distractors. The shapes employed in these illusions are circles, squares, and triangles.

In a Reshape illusion, a point changes its form from one of these three shapes to another. The user's task is to promptly identify and accurately click on the point undergoing the shape change.

Figure 1.14 illustrates an example of a Reshape illusion, depicting a transformation from a circle to a triangle.

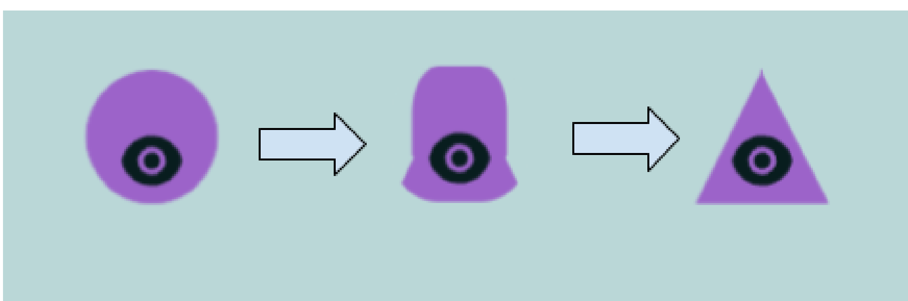

Figure 1.14: Reshape Example

Resize Illustration

The Resize illusion adds an additional dimension of challenge to the Attention Visual tests. In this type of illusion, a point on the screen undergoes a change in size among a collection of distractor points.

In a Resize illusion, a point will change its size to either 0.5, 0.67, 1.5, or 2 times its original size. Users must identify and click on the point that is changing size.

Figure 1.15 illustrates an example of a Resize illusion, showing a point reducing to 0.5 of its original size.

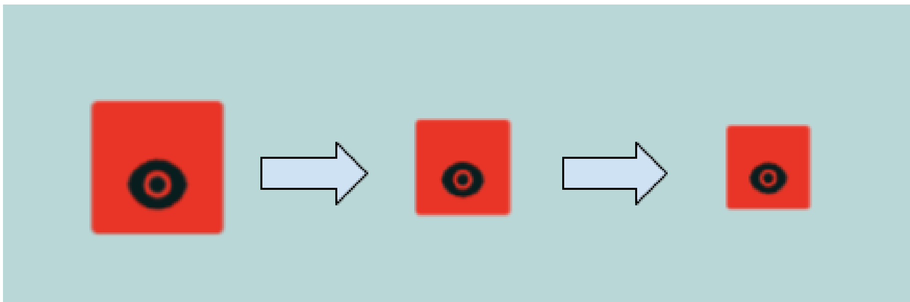

Figure 1.15: Resize Example

Rotate Illustration

The Rotate illusion provides a unique twist in the Attention Visual tests. In this illusion, a point on the screen starts to rotate among a bunch of static points, either clockwise or counter-clockwise.

Figure 1.16 illustrates an example of a Rotate illusion, showcasing a point rotating in a clockwise direction. Users must spot this rotating point among the crowd of static ones.

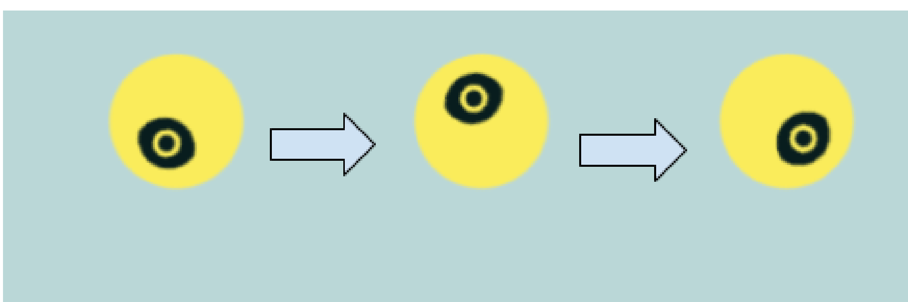

Figure 1.16: Rotate Example

Blink Illustration

The Blink illusion represents the final category of animations used in our tests. This illusion involves a point with an eye icon that transitions from an open to a closed state, mimicking the action of blinking.

Figure 1.17 illustrates an example of a Blink illusion. Amid a group of open-eyed points, one point distinguishes itself by blinking.

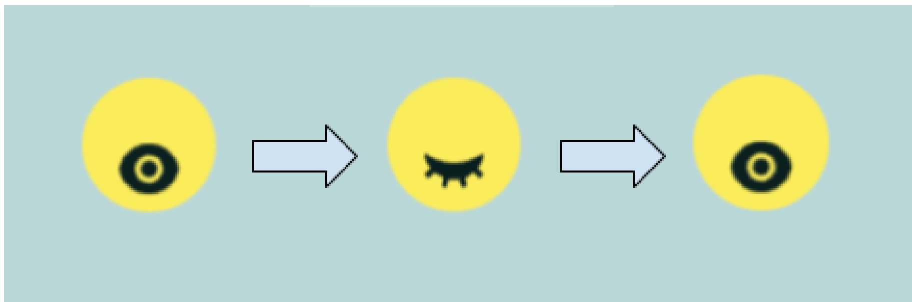

Figure 1.17: Blink Example

Chapter 2

Literature Review

2.1 Attentional Capture

2.1.1 General Concept

Attentional capture refers to the involuntary process by which certain stimuli can attract our attention, disrupting ongoing cognitive activities. It plays a crucial role in selective attention, particularly when it comes to perceiving and processing stimuli in our environment [1].

2.1.2 Role of Motion Onset

Motion onset has been shown to be a potent mechanism in attention capture. That is, the initiation of motion in a previously static stimulus has the capacity to draw our attention effectively. However, the reasons for this selective attention to motion onset have been a subject of debate. Studies have substantiated the robustness of attention capture by motion onsets, providing ground for the debate between the "unique-event" account and the "motion onset" account [2].

Unique-Event vs.Motion Onset Account

The "unique-event" account posits that attention is captured by any event or change that is temporally unique, such as motion onsets or color changes [3]. The "motion onset" account, on the other hand, proposes that the initiation of motion in a previously static object automatically prioritizes the object over other stimuli, irrespective of the presence of other changes.

Role of Jerkiness and Abrupt Displacement

Studies have shown that the jerkiness of motion onset, as opposed to smooth motion onset, captures attention. Researchers argue that this effect is due to an abrupt displacement of the moving item, creating a temporal or spatial gap between the preceding and succeeding frames, and thereby escaping masking [3].

2.1.3 Implications for the Current Research

These findings have important implications for this research. Given that the research involves the role of motion in attention capture, understanding the unique effects of motion onset, and the conditions under which it can effectively capture attention, can guide the design of experiments and the interpretation of results. The debate between "unique-event" and "motion onset" accounts can offer theoretical foundations for expecting outcomes in this research. Additionally, the findings about the role of jerkiness and abrupt displacement in attention capture can be particularly relevant if the stimuli of interest involve motion-related changes.

2.2 Overt vs.Covert Attention

2.2.1 Definitions and Differences

Overt attention refers to the act of directing sensory organs, such as the eyes, towards a stimulus to focus attention on it. Covert attention, on the other hand, is the mental focus on a stimulus without the direct alignment of sensory organs [4, 5, 6]. This allows us to attend to a stimulus in the periphery of our visual field without directly looking at it [7].

2.2.2 The Posner Cueing Paradigm

The Posner Cueing Paradigm, developed by Michael Posner, is a well-known experimental protocol used to investigate covert attention [7]. In this task, participants are required to maintain their gaze on a central point while responding to peripheral stimuli [8]. While this task primarily measures covert attention, there is an element of overt attention involved, particularly when a participant fails to maintain central fixation and involuntarily moves their eyes towards the peripheral cue or target [5].

2.2.3 Implications for Our Research

In the context of our research, both overt and covert attention are likely contributing to the observed effects. The experimental paradigm we employ, which is based on the Posner cueing task, primarily aims to measure covert attention. However, the possible occurrence of overt attentional shifts, particularly under certain experimental conditions like when manipulating target probabilities, could complicate the interpretation of our results [8, 9].

In our research, the "statistics of the environment" are the recorded response times and distances from the initial gaze point to the chosen point in the grid.

These statistics are collected after each participant's interaction with the illusion and over time, these accumulated statistics form patterns that reflect how participants typically respond to the illusions. This learned information may then guide the allocation of attention in future interactions. For example, if the statistics show that certain areas of the grid are more likely to contain the point of interest, participants may be more likely to direct their attention (either overtly or covertly) to these areas in subsequent interactions. This is a demonstration of how strategic, top-down influences can modulate the allocation of attention based on the learned statistics of the environment [8, 4].

The possible influence of overt attention might be especially pronounced under certain conditions, and it remains an exciting avenue to explore in our future studies. We intend to measure the distance between the point of attention and the initial point the user looks at. This measure will allow us to capture the extent to which overt attentional shifts are occurring and to what extent they are influencing the observed effects [6].

The distinction between overt and covert attention provides a useful conceptual framework for understanding the attentional phenomena observed in this research. The interplay between these two forms of attention, in response to manipulations of target probabilities and the effects of this interplay on performance in the Posner cueing task, represent key findings of our research [9].

2.3 Eye Movement and Decision Making

Eye-tracking methodologies are an increasingly prevalent tool in the area of decision-making processes, mainly due to the growing consensus that gaze behavior, as measured by these methodologies, is tightly interconnected with the process of decision making [10, 11].

One study presented an extensive review of the involvement of eye movements in decision-making processes [10]. The research highlighted that visual attention is frequently used as a proxy for cognitive processing during tasks that require decisions to be made, suggesting that options receiving a higher amount of visual attention are more likely to be chosen.

Further exploring this relationship, another study presented a review of models that connect visual attention with choices made by individuals [11]. Their work not only highlighted opportunities for future research to enhance our understanding and predictive capacity of decision-making behaviors but also introduced a framework for synthesizing existing models that consider a multitude of factors influencing the outcome of decisions, ranging from perceptual and cognitive processes to bottom-up and top-down influences.

2.3.1 Implications for Our Research

Applying these findings to interactive environments indicates that the decision to engage with an animated point, such as clicking on it, could be influenced by the quantity and quality of visual attention that the point receives. The more attention a user pays to a specific point, the more likely they are to interact with it. This principle can guide the design of user interfaces and the creation of strategies to effectively draw users' attention.

The reviewed literature underscores the potential of eye-tracking technologies not only in understanding decision-making processes but also in predicting and influencing decision outcomes. However, more research is needed to validate these models in various contexts, understand the dynamics of attention and value accumulation in decision making, and account for factors such as task-switching and visual factors that are currently underrepresented in existing models [11].

The research of eye movements and decision making provides invaluable insights into the perceptual, cognitive, and evaluative processes underlying decision making. As eye-tracking technology advances, our understanding of these processes will continue to deepen, ultimately allowing us to predict and enhance decision-making behaviors in practice.

2.4 Time Course of Visual Attention

Visual attention plays a pivotal role in shaping our perceptual experiences by acting akin to a spotlight, selectively illuminating certain regions in our visual field [12]. A critical aspect of visual attention is its time course, which concerns the time it takes for attention to shift from one object or location to another, and the duration of attentional focus on a specific object.

2.4.1 Dwell Time and Sequential Selection

Dwell time, the duration for which attention "dwells" or remains focused on a particular stimulus, is a crucial factor in the time course of visual attention [12]. Evidence suggests that attention can be "tied up" for several hundred milliseconds after a target has been detected. However, this duration doesn't seem to represent a mandatory minimum dwell time for successful processing.

The dwell times inferred from Rapid Serial Visual Presentation (RSVP) tasks are on the order of 500 milliseconds per item, while visual search tasks suggest much shorter dwell times of about 50 milliseconds per item [12]. This discrepancy might be due to the complexity or difficulty of the tasks used in these studies, where more complex or difficult discriminations might necessitate longer attentional focus.

2.4.2 Shift of Attention

The nature of attention shifts has also been a subject of inquiry. The question is whether these shifts are continuous, like a spotlight gradually moving across a stage, or abrupt, with attention instantaneously relocating to a new location [12]. Studies suggest that attention might relocate instantaneously, regardless of the distance covered. These findings continue to enhance our understanding of the intricate mechanics of visual attention and its dynamic nature, offering rich insights into the workings of the mind and the brain.

2.4.3 Implications for Our Research

The time course of visual attention has significant implications for our research. Understanding how attention shifts and how long it dwells on specific objects can provide invaluable insights into the nature of attentional control and the representation of visual stimuli. It can potentially guide the design of experiments to investigate the characteristics of visual attention in different scenarios and populations, and inform the development of computational models of visual attention. This area of research continues to bridge the gap between psychology, neuroscience, and computer science, suggesting promising future directions for the research [12].

2.5 Signal Detection Theory

Signal Detection Theory (SDT) provides a mathematical model to quantify decision-making in the presence of uncertainty [13, 14]. This theory has been applied in various fields, including visual search tasks to analyze responses and attention to stimuli [15, 16].

Signal Detection Theory (SDT) was applied to three types of visual search tasks: identification, yes/no detection, and localization [15]. This demonstrated that SDT, based on foundational principles [13], can help understand the mechanisms underlying performance in these tasks, including the processes of attention engagement and decision-making.

SDT has also been valuable in understanding visual search and attention, analyzing and interpreting data regarding the balance between hits and false alarms, and the role of attention in modulating these factors [16, 14].

2.5.1 Implications for Our Research

The application of Signal Detection Theory (SDT) to visual search tasks, based on the principles laid out by previous studies [13, 14], is directly relevant to our research. Our work focuses on the effectiveness of an animation in a web interface, observing user interaction and its ability to draw attention to key points [15, 16].

In the context of data visualization, SDT could provide a robust framework for understanding the effectiveness of the animation in drawing attention and the decision process of the user when clicking on points. In essence, the animation could be seen as a signal in the presence of noise on the web page, and the user's interaction could be interpreted as a detection or miss of this signal.

Analyzing response times and hit rates in the context of SDT will allow for a more detailed understanding of user behavior and the effectiveness of the animation. The balance between hits and false alarms, as described by other studies [16, 14], could provide crucial insights into the user's decision-making process when interacting with the animation. Similarly, the application of SDT as demonstrated by prior research [15] could elucidate the role of attention in the user's interaction with the animation.

2.6 Saliency Map Models

2.6.1 Saliency Map Models: An Overview

Saliency Map Models serve as an important tool in the study of visual attention as they encapsulate both the bottom-up and top-down influences on visual attention [17]. These models predict the regions in an image that are likely to attract attention, by combining features such as color, intensity, and orientation. They create a topographical map where higher intensity regions signify areas that are more likely to draw attention [18]. However, the limitations of these models lie in their general inability to account for the influence of specific features such as characters in a visual scene [19].

2.6.2 Bottom-up and Top-down Processes

Visual attention, a prominent topic in cognitive science, is generally guided by two intertwined processes: bottom-up and top-down [20]. Bottom-up attention, driven by the saliency or uniqueness of the stimulus in the visual scene, is an automatic and fast process, propelled by external factors. It operates relatively independently of the viewer's goals [20]. However, this process is not entirely autonomous; it can be modulated by top-down influences.

Top-down attention, on the other hand, is a slower, more deliberate process, guided by the viewer's personal goals, expectations, and prior knowledge [20]. This process tends to be influenced by cognitive factors such as task demands and relevance to the viewer's goals [18]. Importantly, top-down signals can actively bias the perception created by bottom-up stimuli, underlining the interdependency of these two processes.

Furthermore, visual attention is not an isolated cognitive process and can be influenced by other sensory inputs. For example, concurrent auditory stimuli can affect the way visual attention is allocated, suggesting an interplay of sensory modalities in shaping attention dynamics.

2.6.3 Implications for Our Research

Understanding the principles of Saliency Map Models and the impact of character saliency on visual attention could be highly beneficial to our research. The models' ability to incorporate both bottom-up and top-down processes, factoring in the unique features of stimuli and the observer's cognitive state, provides a useful tool for predicting areas of high attention in a visual scene [17].

Particularly, the research identified in a specific study [19], which identifies the specific visual saliency associated with different character types, offers an important avenue for our research. If our work involves the analysis of visual scenes containing these character types, such as Hiragana, alphabet letters, and Thai characters, these findings could be instrumental. They could provide a valuable foundation for predicting how such characters will draw attention in our visual scenes.

Moreover, considering the differences in saliency among different character types could lead to a more nuanced understanding of visual attention patterns in our analysis. It could also inspire further modifications to the Saliency Map Models used, tailoring them to more accurately represent the stimuli in our work.

Finally, the conclusions are drawn in this study [19] open up opportunities for future research, such as investigating the impact of other character features on visual saliency. This could add another layer of depth to our research, potentially leading to further insights and discoveries.

2.7 Neuroplasticity and Visual Attention

2.7.1 Neuroplasticity: An Overview

Neuroplasticity, also known as brain plasticity, refers to the brain's capability to reorganize and adapt its structure and function throughout an individual's lifespan. This adaptation occurs in response to new experiences, and learning processes, as well as after injury or disease [21]. Neuroplastic changes occur at multiple levels, ranging from molecular to cellular and network changes, resulting in alterations in cognitive and behavioral functions [21]. This characteristic of the brain provides the biological basis for the adaptability of cognition and behavior, making it a fundamental aspect of neurological health and functionality [21].

2.7.2 Neuroplasticity and Visual-Spatial Attention

Visual-spatial attention, a cognitive function responsible for processing and responding to visual and spatial information in our environment, is highly influenced by the brain's neuroplastic properties. Neuroplasticity can enhance visual-spatial attention, allowing individuals to develop and adapt their abilities to notice and process visual cues [22]. Activities and exercises that stimulate visual and spatial cognition can result in neuroplastic changes in the brain regions associated with these functions, leading to improvements in visual-spatial attention.

2.7.3 Web-based Applications and Neuroplasticity

In the digital era, web-based applications offer novel opportunities to leverage neuroplasticity for cognitive improvement, including the enhancement of visual-spatial attention. By incorporating features such as engaging animations, vibrant colors, and dynamic shapes, these applications can stimulate the user's visual and spatial cognition, thereby promoting neuroplasticity [23]. The interactive nature and accessibility of these tools make them an effective approach for enhancing cognitive functions, including visual-spatial attention.

2.7.4 Implications for Our Research

The understanding of neuroplasticity and its role in visual-spatial attention provides valuable insights for our research. The development of web-based applications that stimulate neuroplasticity could serve as an effective tool to enhance visual-spatial attention. By strategically incorporating features that engage the user's visual and spatial cognition, these applications can facilitate cognitive improvement and contribute to overall neurological health.

2.8 Gaze Tracking

WebGazer is an innovative eye tracking technology that we have employed in this research to capture gaze data [24]. It capitalizes on the ubiquitous nature of webcams in today's devices, training a model to map eye features to positions on the screen in real time. This model self-calibrates as users interact with the system, enhancing its accuracy over the course of usage.

WebGazer's design addresses the inherent challenge of webcam-based eye tracking, namely the varied local environments and human features. By continuously learning from the user interactions and adjusting the model accordingly, it demonstrates a capability to approximate gaze location with reasonable accuracy.

WebGazer is compatible with various open-source eye detection libraries and incorporates two gaze estimation methods. One of these methods detects the pupil and uses its location to linearly estimate a gaze coordinate on the screen, while the other treats the eye as a multi-dimensional feature vector and employs regularized linear regression combined with user interactions. This level of flexibility and adaptability makes WebGazer an ideal choice for our research context.

2.8.1 Implications for Our Research

The use of WebGazer in our research allows for the collection of rich, real-time gaze data during user interaction with the experimental interface. The algorithm developed for this research continuously collects gaze data, providing valuable insights into how visual attention is allocated throughout the interaction process. This data serves as a critical element for understanding the relationship between visual attention and decision making in our context.

WebGazer's self-calibration feature also addresses potential accuracy issues stemming from individual differences and environmental variability. As such, the application of WebGazer in our research not only democratizes eye tracking in the context of this research but also provides a more precise, adaptive tool for gaze tracking.

Our research, aided by WebGazer's ability to track gaze in real-time, contributes to the burgeoning field of gaze-based interaction studies and web user understanding. It demonstrates the potential of eye-tracking technologies in providing novel insights into user behavior and decision-making processes in web environments [24].

Chapter 3

Methodology

3.1 Research design and strategy

3.1.1 Introduction to Design Choices

The design choices for our attention assessment application were driven by a blend of aesthetic, functional, and scientific considerations. Our primary goal was to create an engaging, user-friendly interface that not only captures the user's attention but also accurately gauges it using various metrics and stimuli.

The layout and presentation of the grid, choice of colors and shapes, as well as the use of dynamic animations, were all meticulously planned to optimize the user's experience while capturing valuable data about their attention distribution. The introduction of a scoreboard and a timer aimed to enhance engagement and introduce an element of competition and urgency into the task, thereby potentially affecting the user's performance.

The design choices extended beyond the visual aspects of the application to include how the user interacts with it. Features such as the method of response collection and the ability to terminate the test at will were incorporated to provide a seamless interaction experience. Furthermore, real-time feedback mechanisms were included to provide users with an understanding of how their attention is distributed across the grid.

We were also mindful of the need for clear instructions and the provision of training or practice sessions to ensure that users understood the task requirements. User feedback played a crucial role in refining the design and functioning of the application, leading to iterative improvements in user experience and application performance.

This section discusses in detail the impact of these design choices on the functionality of our application and the resultant user experience.

3.1.2 Impact of Animations

The high degree of variability in the design of the animations has been a crucial factor in the development of the application. By incorporating numerous variables that each have several possible options, the application can generate a considerable number of unique tests. Let's break down how this variability is achieved:

1. Grid Size: There can be n points on each side, yielding n^2 points. The value of n ranges from 3 to 10.
2. Difficulty Levels: There are three difficulty levels - easy, medium, and hard. Each difficulty level changes the number of colors and shapes in use.
3. Color Choices: There are 6 colors in total. For the easy level, two colors are randomly chosen. For the medium level, four colors are chosen, and for the hard level, all six colors are in play.
4. Shape Choices: There are three shapes in total. For easy level, one shape is randomly chosen. For the medium level, two shapes are chosen, and for the hard level, all three shapes are in play.
5. Animations: Each point is assigned a random animation from the options - "resize", "recolor", "reshape", "rotate", "blink".
6. Variations of Animations: Each animation has its own variations. "Resize" has 4 size options, "recolor" can choose from the remaining colors, "reshape" can morph into the remaining shapes, "rotate" has two options - clockwise and counter-clockwise, and "blink" has one option.
7. Duration: Each animation can occur for a random duration chosen from - 1, 1.5, 2, 2.5, or 3 seconds.

Calculating the Number of Unique Tests

Based on the above variables, we can calculate the number of unique tests that can be created for a single point on the grid for the easy, medium and hard levels:

Number of unique tests per point for Easy Level =

No. of grid possibilities × No. of color possibilities × No. of shape possibilities×

Average No. of animations × Average No. of variations for each animation×

No. of duration possibilities

$$= 8 \times \binom{6}{2} \times \binom{3}{1} \times 5 \times \frac{14}{5} \times 5$$
$$= 504,000$$

For the Medium Level, we have 4 color options and 2 shape options:

$$
\begin{aligned}
&\text{Number of unique tests per point for Medium Level} = \\
&\text{No. of grid possibilities} \times \text{No. of color possibilities} \times \text{No. of shape possibilities} \times \\
&\text{Average No. of animations} \times \text{Average No. of variations for each animation} \times \\
&\text{No. of duration possibilities} \\
&= 8 \times \binom{6}{4} \times \binom{3}{2} \times 5 \times \frac{14}{5} \times 5 \\
&= 3,024,000
\end{aligned}
$$

For the Hard Level, we have 6 color options and 3 shape options:

$$
\begin{aligned}
&\text{Number of unique tests per point for Hard Level} = \\
&\text{No. of grid possibilities} \times \text{No. of color possibilities} \times \text{No. of shape possibilities} \times \\
&\text{Average No. of animations} \times \text{Average No. of variations for each animation} \times \\
&\text{No. of duration possibilities} \\
&= 8 \times \binom{6}{6} \times \binom{3}{3} \times 5 \times \frac{14}{5} \times 5 \\
&= 4,032,000
\end{aligned}
$$

The total number of unique tests across all levels can be calculated as:

$$
\begin{aligned}
&\text{Total number of unique tests across all levels} \\
&= \text{Average number of unique tests per point} \times \text{Average number of grid points} \\
&= \frac{504,000 + 3,024,000 + 4,032,000}{3} \times (6.5^2) \\
&= 2,520,000 \times 42.25 \\
&= 106,425,000
\end{aligned}
$$

However, it's important to note that due to the high level of randomness and parameter interaction, these calculations only provide an estimate of the number of unique tests. The actual number of test variations that a user experiences can be significantly higher, making each user's experience unique.

- Furthermore, each of the non chosen points in the grid also has their color and shape assigned randomly based on the difficulty level. This introduces additional variability, leading to an even higher potential number of unique tests. However, many of these additional variations might not result in a noticeably different test from the user's perspective. Therefore, the estimate calculated here should be considered a lower bound on the total number of unique tests.

3.1.3 Color Choices and their Impact

The role of color in cognitive research is substantial. Colors, their distinct attributes, their classification into primary and secondary categories, their perceived temperatures, and transitions between them all play significant roles in influencing a user's visual spatial attention and response. Our choices of colors for this research are based on their ability to guide and measure visual attention effectively.

Color Choices, Classification, and Temperature

The color palette chosen for our research includes a spectrum of primary and secondary colors, along with their perceived temperatures. These are distinctly identifiable and therefore serve as effective tools for guiding and assessing visual attention. The color palette is shown in Figure 3.1 below.

- **Primary Colors - Red, Blue, Yellow:** Primary colors are often associated with fundamental emotional responses. Red, a warm color, is often linked to alertness and urgency. Blue, a cool color, is associated with calmness and stability, and yellow, another warm color, evokes cheerfulness and energy.

- **Secondary Colors - Green, Orange, Violet:** Secondary colors, being a blend of primary colors, may elicit more nuanced emotional responses. For instance, green, a cool color, could evoke feelings of harmony and balance. Orange, a warm color, might induce a sense of warmth and enthusiasm, while violet, often perceived as cool, can be associated with luxury and ambition.

Figure 3.1: The color palette chosen for our research

Color Transitions and User Response Expectations

Transitions between colors, particularly between primary and secondary colors and between warm and cool colors, can influence user response. This is based on the inherent contrast these transitions offer and the subsequent psychological effects they carry.

- **Psychological Effects:** Changes from primary to secondary colors (or vice versa) or between warm and cool colors might lead to shifts in attention due to the associated emotional changes. For example, transitioning from a calming cool color like blue to an energizing warm color like orange might induce a sense of increased alertness, potentially leading to quicker user responses.

- **Saliency and Attentional Capture:** Certain colors and transitions between colors may be more salient and thus more likely to capture attention. For example, transitions involving highly saturated and luminant colors like yellow could heighten attention capture.

- **Color Associations:** Personal, cultural, and societal color associations could also influence the user's attention. Transitions to colors like red, often associated with warnings in many cultures, could heighten the user's sense of alertness. Although location data was not utilized in this research, recognizing these cultural differences and integrating location data in future studies could further refine the understanding of the impact of color associations on user attention.

- **Color Contrast:** The contrast between consecutive colors can influence their visibility and saliency. High contrast transitions, such as moving from a cool color like blue to a warm color like yellow, could enhance visibility and attract more immediate attention.

By analyzing the impact of color choices, their temperatures, and their transitions on user responses, we aim to draw valuable insights into how visual spatial attention is influenced. These insights will further inform the development of effective cognitive training strategies within our application.

3.1.4 The Role of Shapes in Design

Shapes, much like colors, play a crucial role in guiding visual attention and have their own set of considerations. The selection of shapes (Square, Circle, Triangle) in this research are simple, distinct, and universally recognized, making them suitable for a visual attention task. The selection of shapes are shown in Figure 3.2 below.

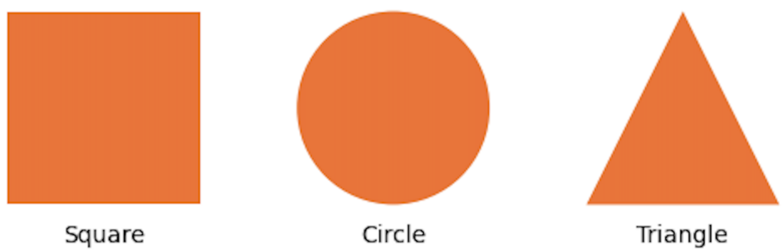

Figure 3.2: The selection of shapes (Square, Circle, Triangle) for our research

- **Gestalt Principles and Shape Perception:** According to Gestalt principles of perceptual organization[25], our brain recognizes and organizes shapes in specific ways. Principles such as similarity, continuity, closure, and symmetry can influence how we perceive and attend to different shapes. For instance, a triangle amidst circles might "stand out" and attract attention quickly due to its dissimilarity. By using these shapes, we can manipulate the visual environment to test various aspects of visual attention, such as whether certain shapes are more salient or attract more attention than others.

- **Psychological Associations of Shapes:** Shapes can carry psychological implications, similar to colors. For instance, circles often symbolize wholeness and completion, squares are associated with stability and order, and triangles might signify tension or conflict. These associations could subtly influence the attentional priorities of the viewers.
- **Shape Complexity:** The complexity of a shape can influence its saliency and the amount of cognitive effort required for its processing. Typically, simpler shapes are easier to process and more likely to attract attention.
- **Shape Contrast:** The contrast between shapes and the other elements in the visual field can influence their visibility and saliency. Shapes distinct from their surroundings are usually more visible and more likely to attract attention.
- **Shape Size:** The size of shapes can also affect their visibility and saliency. Larger shapes are typically more visible and more likely to attract attention.

Further, the interplay of shapes with colors - such as a red triangle among blue circles - can create more complex attentional scenarios, allowing us to probe the intricacies of visual attention mechanisms more deeply.

3.1.5 Design of the Gaze Turtle Icon

As part of creating a distinct identity for this research tool, a unique icon named "Gaze Turtle" was designed as shown in Figure 3.3. This icon combines the imagery of an eye and a sea turtle, capturing the essence of vision and steady progress or longevity, respectively.

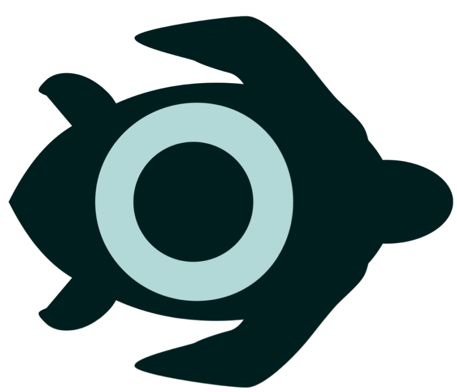

Figure 3.3: Gaze Turtle icon

In crafting the Gaze Turtle, we aimed to subtly communicate the primary intent of the tool – to facilitate the enhancement and sustainability of visual-spatial attention. The design balances both elements, allowing viewers to perceive either the eye or the turtle depending on their visual focus. This dynamic reflects the very nature of visual perception and attention, themes central to the research project.

We believe that the Gaze Turtle, beyond serving as an identifiable symbol of the research tool, adds to the overall user experience. Its unique design could potentially influence user engagement and feedback, contributing to the efficacy of the research tool.

3.1.6 Other Design Factors

- **Grid Layout:** The points on the grid are equally distributed both horizontally and vertically. This uniform layout aims to avoid any positional bias in user attention, ensuring that each point is equally likely to be noticed based on its position alone.

- **Scoreboard and Timer Design:** The application includes a timer set for 5 minutes and a scoreboard that awards +3 points for correct responses and -1 point for incorrect ones. These elements add a sense of urgency and competitive motivation, potentially influencing user behavior.

- **User Interface (UI) Design:** The overall design of the user interface, encompassing aspects such as button placement, color scheme, typography, and feedback mechanisms, is user-friendly, and significantly influences the usability and user experience of the application.

- **Video Box and Gaze Tracking:** The application includes a video box showing the user's face and an icon that tracks and indicates the user's gaze on the screen. This real-time feedback can help users understand how their attention is distributed across the grid.

- **Test Termination:** Users are given the flexibility to terminate the test at any point, providing them with control over their participation and potentially influencing their level of engagement and performance.

- **Response Collection:** The application is designed to collect user responses using both mouse clicks and gaze tracking data. This dual-mode response system not only enhances the richness of collected data but also offers insights into different aspects of user behavior. The methods of response collection have been designed with an emphasis on seamless user interaction, affecting the efficiency and fluidity of the test experience.

- **Instructions and Training:** Clear and concise instructions are provided to the user at the start of each test, explaining the task and the scoring system. A short, non-scored practice session precedes the actual test to allow users to familiarize themselves with the mechanics of the test. This practice ensures that users are well-informed about the task demands, thus minimizing the potential for confusion or misinterpretation, and enhancing the accuracy of test results.

3.1.7 User Feedback on Design Choices

Early users provided verbal and written feedback on the functionality, user guidance, and overall design and experience, which played a crucial role in refining the design and functioning of our application. Several valuable insights were gained, which subsequently led to enhancements in the overall user experience and application performance.

One key aspect of the application design that came out of the iterative feedback loop was the adaptive test difficulty. The application is designed to adjust the test difficulty based on the user's performance. This is determined by the time the user takes to respond after their first gaze at the chosen point. This dynamic adjustment of test difficulty ensures that the application remains challenging and engaging for users across a range of abilities.

- **Instructions:** Initial feedback indicated that the instructions provided to users were not entirely clear, potentially affecting their understanding of the task and overall performance. In response, we revised the instructions to be more clear and explicit, making it easier for users to understand the task requirements and what's expected of them during the test.

- **Color Choices:** The color scheme of our application was largely influenced by the feedback from our early users. The chosen colors not only provide an engaging and visually pleasing user interface but also aid in differentiating the various elements on the screen. This facilitates the easy identification of different shapes during the test, thereby enhancing user experience.

- **Browser Compatibility:** We discovered through user feedback that some browsers were unable to adequately support the gaze tracking feature of our application, leading to a disruption in data collection and affecting the overall user experience. We are currently working on rectifying this issue and expanding the compatibility of our application to ensure a seamless user experience across all browsers.

Despite these enhancements, we recognize that user experience is a continually evolving aspect. We remain open to feedback and are committed to making iterative improvements to ensure that our application offers a seamless and engaging experience for all users.

3.1.8 Conclusion: Reflecting on Design Choices

The attention assessment application we developed represents a synthesis of thoughtful design choices aimed at creating a user-friendly and engaging environment that effectively captures and measures attention distribution. Throughout the design process, we placed a strong emphasis on ensuring that the application is visually appealing, interactive, and easy to use, while also being capable of providing robust data on attention metrics.

Reflecting on the design choices, we recognize the value of the iterative design approach and the impact of user feedback in shaping the application. The choice of colors, shapes, and animations were key in enhancing the visual appeal and engaging nature of the application. Furthermore, the grid layout, response collection method, and real-time feedback mechanisms have proven to be instrumental in facilitating user interaction and engagement.

The flexibility to terminate the test at will, the use of a scoreboard and timer, as well as clear instructions and practice sessions, all contributed to a more controlled and intuitive user experience. These factors also potentially influenced the users' test performance and their overall satisfaction with the application.

While our design choices have led to a functional and engaging application, we acknowledge that there are always opportunities for further refinement and improvement. Future iterations of the application may explore new design elements and functionalities based on emerging research findings and continuous user feedback. Despite the potential challenges, we are confident in the utility and effectiveness of our current design choices and look forward to their continued evolution.

3.2 Data collection methods

3.2.1 Data Collection Overview

The data collection process in this project was multifaceted and comprehensive, incorporating a variety of data points to ensure a rich and in-depth analysis of users' visual attention. The primary source of data was the custom-built web application, which was designed to record specific user interactions and behaviors during each session. [26].

This web application is based on a grid layout, with each point having the potential to exhibit a distinct animation at random intervals. A user's task is to identify and select these animated points as quickly and accurately as possible. During each session, various aspects of user interaction and response are meticulously recorded. These include the total score, session date, the specific characteristics of each test within the session, and extensive gaze data.

The collected gaze data includes the initial gaze location, the total time spent gazing at the chosen point, the time until the first gaze at the chosen point, and the time after the first gaze at the chosen point. Other variables, such as distance from the first gaze point to the chosen point and the number of wrong answers, are also collected to provide further context to the gaze data. Moreover, the Frame Per Second (FPS) rate, an important parameter that can vary across different computer systems and usage conditions, is also recorded for each session.

In addition, a user's progress and performance over time can be tracked and compared thanks to the recording of the session score and date. This feature not only allows users to measure their improvement but also provides valuable data for longitudinal analysis.

Further to the collected parameters, the response time of the user after their first gaze at the chosen point is also diligently recorded. This metric forms a critical part of the dynamic adjustment of test difficulty in subsequent tests.

Lastly, the project integrates a range of design choices and considerations informed by existing theories and methodologies in the field of visual attention. These include attentional capture, overt and covert attention, eye movement in decision making, signal detection theory, and saliency map models, among others. These theories inform the design of the tests and influence the type and quality of data collected.

Overall, the data collection process is designed to provide a comprehensive picture of user behavior, performance, and visual attention patterns, making this project a valuable contribution to the ongoing research in the field of visual attention.

3.2.2 Primary Data Collection

The primary data collection for this research was conducted through an interactive web-based application designed specifically for this research. All data points are a result of user interaction with the application.

The MongoDB[27] database connected to the application holds three collections: User Data, Sessions, and Tests. The User Data collection stores information about each participant, including their first name, last name, email, birth date, gender, and associated session IDs.

The Sessions collection contains data for each user session, including the user ID, session score, session date, and corresponding test IDs. Each session relates to a unique instance of a user engaging with the application.

The Tests collection stores the specific details of each test within a session, including variables such as the chosen point location, chosen point color, chosen point shape, chosen animation, total response time, average frames per second (FPS), total gazed time on the chosen point, distance from the first gaze point to the chosen point, and initial gaze location. This collection represents the heart of the data analysis as it records the primary outcomes from each test.

Another primary data point collected is the user's response time after their first gaze at the chosen point. This response time data is used for dynamically adjusting the test difficulty to match the user's performance.

The application uses the WebGazer [24] framework to track user gaze and records a large array of data for each test. This rich dataset enables a detailed exploration of user behavior and engagement with different design elements and difficulty levels in the application.

3.2.3 Integration of Existing Theories

While the primary data in this research originates directly from the custom web application, the data analysis process has been informed by existing theories in the field of visual attention. These theories have served as a secondary source of information to shape the research design and interpret the collected data.

1. **Attentional Capture:** The concept of attentional capture suggests that salient stimuli in our environment can involuntarily capture our attention. The animations used in this research can be considered salient stimuli and may attract users' attention in this manner.

2. **Overt vs.Covert Attention:** This distinction was considered when comparing the location of the first gaze (overt attention) to the position of the animated point (the target of covert attention).

3. **Eye Movement and Decision Making:** Existing research suggests that the allocation of visual attention is closely linked to decision-making processes. This concept is reflected in the design of the web application, where users' decision to click on an animated point may be influenced by the amount and quality of visual attention that point receives.

4. **Time Course of Visual Attention:** The time course of attention to the animated point was also considered during data analysis, looking at factors such as the duration of the first fixation and the total dwell time.

5. **Signal Detection Theory:** This theory was applied to understand the effectiveness of the animation in drawing attention and the decision process of the user when clicking on points.

6. **Saliency Map Models:** These computational models aim to predict where people will look in a scene, based on the saliency (or distinctiveness) of different areas. The saliency of the animated point was considered in light of these models.

7. **Neuroplasticity and Visual Attention:** Neuroplasticity, the brain's ability to change and adapt, plays a significant role in the enhancement of visual-spatial attention. Understanding this concept could provide insights into how visual attention can be manipulated and improved through targeted interventions such as a carefully designed web application. The potential of the web application to promote neuroplastic changes and thereby enhance users' visual attention is considered within the framework of this theory.

By integrating these theories, the research aims to contribute to a broader understanding of visual attention and eye movements, while also providing insights into specific user behaviors in the context of the web application.

3.2.4 Data Recording Techniques

The following techniques were employed to record and quantify the data collected from this research:

- **Session Score and Date Recording:** The application records the user's session score and the date of each session. This enables users to track their progress over time, offering an opportunity to understand and reflect on their performance under different conditions (e.g., tiredness, increased focus, etc.).

- **Calculating Gaze Duration:** A vital element of data recording in this research was the accurate calculation of gaze duration. For this, the FPS (Frames per Second) of the user's computer was utilized. The application checks the gaze position at an interval of 10 milliseconds (ms), which results in 100 checks per second. Each time the gaze is detected on the chosen point, the application records the duration for that 10ms interval. However, since the actual gaze duration accumulated in each interval is 10ms, it was necessary to divide the total gaze duration by the interval duration (10 in this case) to convert it back into seconds. This ensures that the recorded gaze duration accurately reflect the time users spent gazing at the chosen point.

- **Distance and Location Measurement:** The application records the distance and location of gaze points and the chosen point in pixels. To translate these measurements into a more tangible unit, the application utilizes the standard conversion that equates 96 pixels to an inch. This conversion enables a more intuitive understanding of the distances and locations involved in this research.

3.2.5 Data Quality Assurance

A variety of measures were employed in this project to ensure the validity and reliability of the collected data. These measures ensured a high level of precision and consistency in the recorded measurements across different users and sessions, thereby boosting the quality of the data.

- **Consistent User Experience:** By maintaining equal distances between points, employing a standard test duration, and other consistent design factors across different sessions, a standardized user experience was ensured. This uniformity mitigates the introduction of extraneous variables that could potentially skew the data.

- **Precision in Gaze Data:** The WebGazer[24] framework was utilized for tracking user gaze data. This robust tool offers high precision, making it possible to capture nuanced changes in gaze behavior.

- **Accuracy in Measurements:** Carefully designed data recording techniques were implemented to ensure the accuracy of measurements. This includes the algorithm to calculate gaze duration, and the conversion ratio of pixels to inches (96 pixels = 1 inch), allowing for universally understandable measurements.

- **Handling Variability in FPS:** Acknowledging the potential variability in frames per second (FPS) rates across different computers and usage conditions, an algorithm was developed to calculate this value for each unique user scenario. This approach ensures that the gaze data collected remains accurate and reliable, despite varying FPS rates. The adaptive nature of this algorithm helps maintain the integrity of the data, making it suitable for cross-comparison.

- **Managing Potential Sources of Error:** Potential sources of error, such as different screen sizes or resolutions, were proactively addressed. This includes adjustments in the app design and data recording techniques to accommodate these differences and maintain the quality of data collected.

These data quality assurance measures have been instrumental in building a rich and reliable data set, thereby setting a strong foundation for the subsequent stages of data analysis and interpretation.

3.2.6 Conclusion: Reflecting on Data Collection Methods

Reflecting on the data collection methods employed in this project, careful planning, advanced tracking techniques, and user-centered design were utilized. These components facilitated the collection of a comprehensive data set that captures both individual user interactions and broader patterns of visual attention.

The primary data, collected directly from the web application, provides a detailed record of user interaction, gaze behavior, and test performance. The use of an algorithm to calculate gaze duration based on the computer's FPS rate ensured that the data collected would be consistent and accurate across different users and conditions.

Moreover, the integration of various theories of visual attention into the design of the tests has facilitated the collection of data that is both rich and contextually relevant to the field. The methodologies and techniques incorporated in the design not only provide a foundation for analyzing the collected data but also offer potential avenues for future research and exploration.

Challenges, such as varying FPS rates and ensuring consistency in data collection, were successfully navigated through careful planning and algorithm design. The result is a data set that is not only large in volume but also high in quality, making it a valuable resource for exploring and understanding visual attention.

In conclusion, the data collection methods used in this project underscore the importance of a user-centered approach, rigorous data recording techniques, and informed design choices in collecting high-quality data for research in visual attention.

3.3 Data analysis methods

3.3.1 Overview of Data Analysis

The primary method for data analysis in this research project involves a blend of qualitative and quantitative approaches. Due to the nature of the data collected, which consists of continuous measures, timestamps, and user interactions, quantitative analysis methods are primarily used. The collected data is analyzed in a comparative manner, investigating the influence of different factors (animation type, animation variation, distance of first gaze point to the chosen point, animation duration, test difficulty) on various performance metrics (total response time, time until gaze, time after gaze, gaze duration on the chosen point).

In addition to the main analysis, a longitudinal analysis of three specific users – two young and one middle-aged adults – is performed. The purpose of this detailed user-level analysis is to understand the effectiveness of the application over time and the progression of individual users.

Qualitative data analysis also plays a part, primarily through the interpretation of the quantitative results in the context of theories of visual attention and cognitive processing. This helps generate insights and hypotheses about user behavior, attention, and interaction with the application.

A vital aspect of the analysis is the pre-processing of data, especially those that depend on gaze tracking. This step is necessary to handle potential data quality issues arising from gaze tracking inaccuracies, ensuring that the final analysis and interpretation are based on reliable, high-quality data.

3.3.2 Qualitative Data Analysis

While the majority of data analysis in this research project is quantitative, there is a complementary qualitative component. This qualitative aspect primarily consists of interpreting the quantitative findings within the context of the existing theoretical frameworks in cognitive psychology and visual attention.

For instance, the users' interaction patterns and gaze behaviors are interpreted in light of theories such as attentional capture, overt vs. covert attention, and saliency map models. This involves understanding not just the numbers, but the cognitive processes underlying those numbers. While a quantitative analysis can tell us "how much" or "how fast", qualitative interpretations help us understand the "why" and "how".

Moreover, the qualitative analysis also assists in diagnosing potential issues and anomalies in the data. For example, inconsistencies or outliers in the gaze tracking data may be investigated from a qualitative perspective to understand whether they are due to technical issues, user behavior anomalies, or other factors.

Ultimately, the integration of qualitative analysis with quantitative methods enables a more comprehensive understanding of the data and the user behavior it represents, providing a holistic perspective that considers not just the measurable outcomes, but the human aspects and cognitive processes involved as well.

3.3.3 Quantitative Data Analysis

The backbone of the data analysis in this project is quantitative, leveraging the rich numerical data generated by the gaze-tracking application. A wide variety of quantitative analyses are performed to extract meaningful insights from the collected data. These include:

- **Performance analysis:** The performance of the users on the tests, as measured by the total response time, time till first gaze, time after first gaze, and gaze duration on the chosen point, are analyzed in detail. This provides insights into the users' speed and accuracy, as well as their attention allocation strategies.
- **Animation type analysis:** The impact of different animation types on user performance is investigated. This includes both a general analysis comparing the animation types, as well as a more detailed analysis considering the variations within each animation type.
- **Animation duration analysis:** The effects of animation duration on user performance are studied. This helps to understand the optimal timing of animations for attracting visual attention.
- **Distance analysis:** The distances between the initial gaze point and the chosen point are examined to shed light on the spatial characteristics of gaze behavior.
- **Difficulty analysis:** The influence of test difficulty on user performance and gaze behavior is explored. This analysis is conducted for each level of difficulty across all the test types.
- **Mistake analysis:** The number of mistakes made by users is analyzed in relation to the different test types and their respective difficulty levels. This provides insights into the common pitfalls and challenges faced by users.

Each of these analyses is conducted using a variety of statistical techniques, including descriptive statistics, inferential statistics, and graphical methods. The goal is to provide a robust, comprehensive, and nuanced understanding of the data, which can guide the further development and refinement of the gaze-tracking application.

3.3.4 Software Tools

The data analysis process in this project was supported by a collection of versatile software tools:

- **MongoDB:** Utilized as the primary database platform, MongoDB[27], a source-available document-oriented database program, was instrumental in storing and managing the wealth of data generated by the gaze-tracking application.
- **Python:** The core analytical tasks were undertaken using Python, a programming language renowned for its simplicity, readability, and the potency of its libraries in scientific computation and data analysis.
- **Pandas:** The Pandas Python library was crucial for handling and manipulating the structured data. Its diverse range of features for handling numerical tables and time-series data made it an invaluable asset for this project.
- **Matplotlib and Seaborn:** These libraries served as the foundation of data visualization in this project. Matplotlib, noted for its adaptability, supported the creation of static, animated, and interactive visualizations, while Seaborn, which builds upon Matplotlib, offered a simplified interface for producing aesthetically appealing statistical graphics.

The careful selection and integration of these software tools significantly streamlined the process of managing, analyzing, and visualizing the gathered data, thus facilitating the distillation of meaningful insights to refine the gaze-tracking application.

3.3.5 Data Interpretation

In terms of data interpretation, this research strived to maintain a rigorous, analytical approach. The analyses and visualizations constructed through the software tools mentioned previously were invaluable for deriving meaningful insights and trends from the dataset.

Consideration was given to potential sources of error and variance in the data, such as differences in lighting conditions or user movements, which could affect the quality of gaze tracking. These sources of variation were accounted for as much as possible in the interpretation of the results. Also, understanding the possibility of inaccuracies in gaze tracking data, a focus was placed on total response time, a high-quality data metric that does not rely on gaze tracking, along with gaze-related metrics.

The interpretation of the data also entailed understanding the impact of the animation types and their variations, and how the distance from the first gaze point to the chosen point affected the response. A deep analysis was done to understand how the animation duration affected the results and the variation in response for different levels of test difficulty.

The data interpretation was not only limited to general trends, but also involved a detailed analysis of individual user data. This approach provided insights into how user performance evolved over time and how they responded to different tests. By tracking the progress of individual users, it was possible to validate whether the application indeed helped improve their attention over time.

The data interpretation was crucial in this research as it provided the context and understanding necessary to connect the data analysis results to the research questions, and ultimately, to the wider implications for the field of visual attention.

3.3.6 Conclusion: Reflecting on Data Analysis Methods

The data analysis methods adopted in this research have been instrumental in unraveling valuable insights from a substantial set of complex, multidimensional data. The integration of both qualitative and quantitative methodologies ensured a comprehensive understanding of the various facets of visual attention that were captured in this research.

The use of Python's robust data analysis libraries, namely Pandas, Matplotlib, and Seaborn, allowed for an efficient and effective exploration of the data. These tools facilitated the creation of intuitive visualizations and the application of statistical analyses, which further enhanced the interpretability of the data.

In hindsight, the recognition and treatment of potential sources of error and variance in gaze tracking data were crucial to ensuring the reliability of the results. The quality of gaze tracking data was taken into account during the data interpretation, and care was taken to substantiate the results using high-quality data metrics like total response time.

Moreover, the personalized analysis of individual user data provided a nuanced understanding of the effectiveness of the web application in improving users' attention over time. This approach not only validated the practical usefulness of the application but also enriched the research findings with real-world implications.

Overall, the data analysis methods implemented in this research have proven to be successful in providing significant insights into the study of visual attention. It is the hope that these methods, and the findings they have helped unveil, will contribute to future research and applications in this fascinating field.

Chapter 4

Results and Discussions

4.1 Summary of the Data Collected

In this research, we collected data from a total of 32 users who participated from various countries, including Germany, Turkey, the United States of America, and France. The age range of the participants spanned from 21 to 56 years. The research was conducted over a period of one month, during which users signed up at various times.

Due to the convenient and mobile nature of our web-based research tool, these users could engage with the tests even while on the move.

Among all the participants, we observed three highly active users: an adult with 33 sessions, and two young adults with 14 and 22 sessions, respectively. We analyzed the data from these users to discern potential improvements in cognitive skills over time.

Across all users, a total of 4093 tests were completed. This extensive dataset was used to perform analyses on the average response time and total mistakes made during the tests, as these data points remained unaffected by any tracking blockers installed on the users' devices.

However, it's worth noting that the use of tracker blockers, such as ad-blockers, limited our ability to collect data, resulting in lower quality and potentially inaccurate data. We inferred the usage of tracker blockers when the time until the first gaze value was negative.

To ensure the accuracy and reliability of our analyses, we preprocessed the collected data and removed all low-quality data, resulting in 1788 high-quality data points. These were used for analyzing the average response time after the first gaze, the average time gazed on the chosen point, and the distance of the first gaze to the chosen point.

The following sections will present the results and analyses based on these data for each illusion type.

4.2 Consistent Users

4.2.1 User Performance Over Time

Young adult 1

The following Figure 4.1 presents a scatter plot with a regression line, illustrating the relationship between the session score and the session date for a young adult. Each point on the scatter plot corresponds to a single session, with its date on the x-axis and its score on the y-axis. The regression line drawn through the scatter plot represents the trend in the session scores over time.

The equation of the regression line is $y = 4.75x - 3509297.26$. This equation tells us that, on average, for each unit increase in the ordinal date (1 day), the session score increases by approximately 4.75 points.

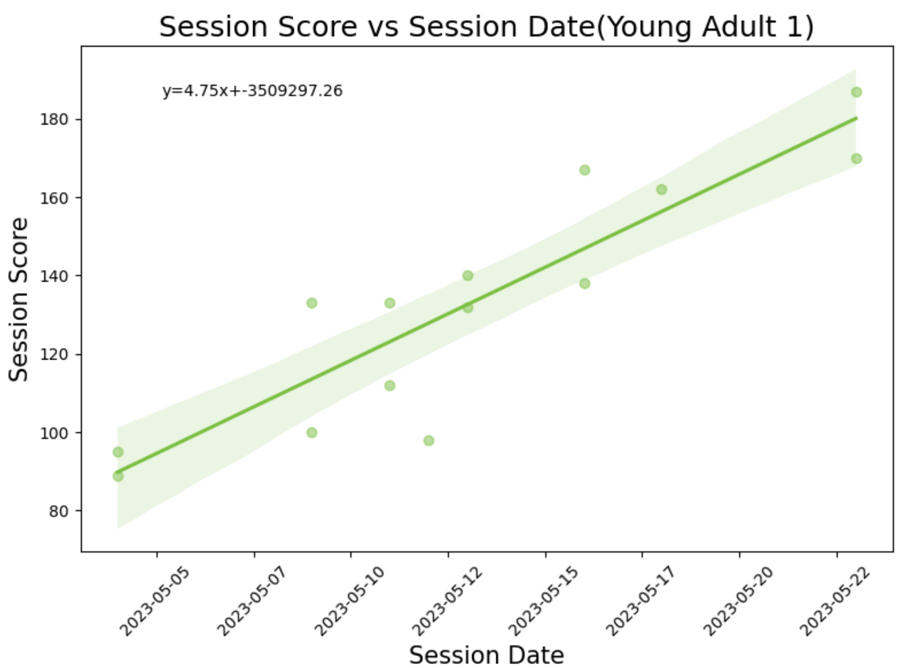

Figure 4.1: Scatter Plot with Regression Line of Session Score vs.Session Date for Young Adult 1

Young adult 2

The following Figure 4.2 illustrates a scatter plot with a regression line showing the relationship between the session score and the session date for another young adult (referred to as Young Adult 2). Each point on the scatter plot corresponds to a single session, with the date of the session on the x-axis and the session score on the y-axis. The regression line represents the trend in the session scores over time.

The equation of the regression line is $y = 1.90x - 1404072.22$. This equation suggests that, on average, for each unit increase in the ordinal date (1 day), the session score increases by approximately 1.90 points.

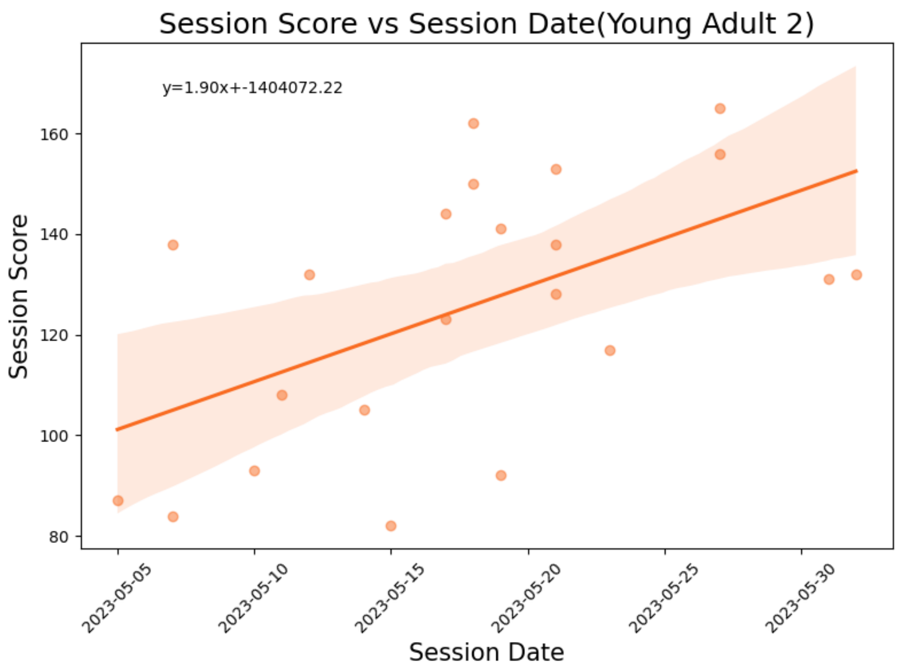

Figure 4.2: Scatter Plot with Regression Line of Session Score vs.Session Date for Young Adult 2

Adult

The following Figure 4.3 illustrates a scatter plot with a regression line showing the relationship between the session score and the session date for an adult. Each point on the scatter plot corresponds to a single session, with the date of the session on the x-axis and the session score on the y-axis. The regression line represents the trend in the session scores over time.

The equation of the regression line is $y = 2.94x - 2168451.19$. This equation suggests that, on average, for each unit increase in the ordinal date (1 day), the session score increases by approximately 2.94 points.

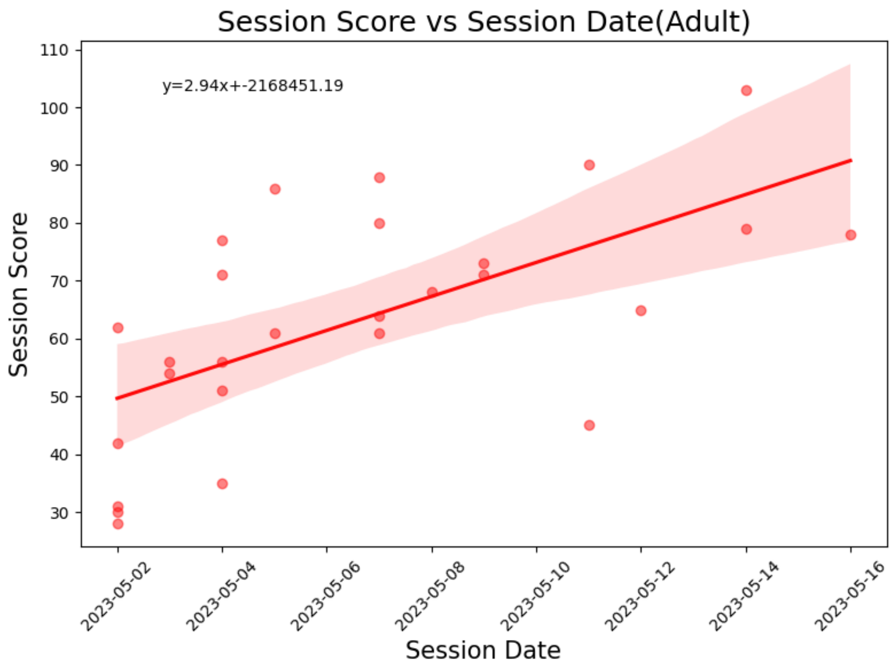

Figure 4.3: Scatter Plot with Regression Line of Session Score vs.Session Date for Adult

4.2.2 User Performance Over Time Discussion

The results of this research provide empirical evidence that supports the potential of a web-based application for enhancing visual-spatial attention. The observed increase in session scores over time for all three participants suggests that users' visual-spatial attention may have improved due to the use of the application.

This positive trend aligns with the concept of neuroplasticity, which proposes that the brain is capable of changing and adapting, thereby facilitating improvement in cognitive functions such as visual-spatial attention [23]. Specifically, the regression lines with positive slopes for all participants (2.94 for the adult, 4.75 for young adult 1, and 1.90 for young adult 2) validate the hypothesis that cognitive abilities can be enhanced through targeted exercises, offering evidence of neuroplastic changes in the brain over time.

The results, however, showed no significant effect of age on the rate of improvement among the participants, which is inconclusive and suggests that the influence of age on neuroplasticity may not be straightforward. This finding underscores the need for further research to provide a deeper understanding of this aspect.

These results not only substantiate the use of web-based applications for cognitive training but also highlight their potential in facilitating user engagement and recording progress, thus supporting the view that technology can be effectively harnessed for cognitive enhancement [23].

The findings open up avenues for future research to explore how various factors, including the design and features of the web-based application, might influence the rate of cognitive improvement. Additionally, the sustainability of cognitive improvements achieved through such applications and the long-term effects of this form of cognitive training warrant further investigation.

4.3 Illusions

4.3.1 Illusions Results

Figure 4.4 displays a bar chart illustrating the average response time for each illusion test. Each bar corresponds to a different test illusion, indicated on the x-axis, with the height of the bar representing the average response time in seconds, indicated on the y-axis. The bars are color-coded for easy differentiation between the different illusions.

From left to right, the illusions are “blink”, “recolor”, “reshape”, “resize”, and “rotate”. The average response times for these illusions are approximately 8.36 seconds, 10.12 seconds, 11.28 seconds, 7.76 seconds, and 4.61 seconds, respectively.

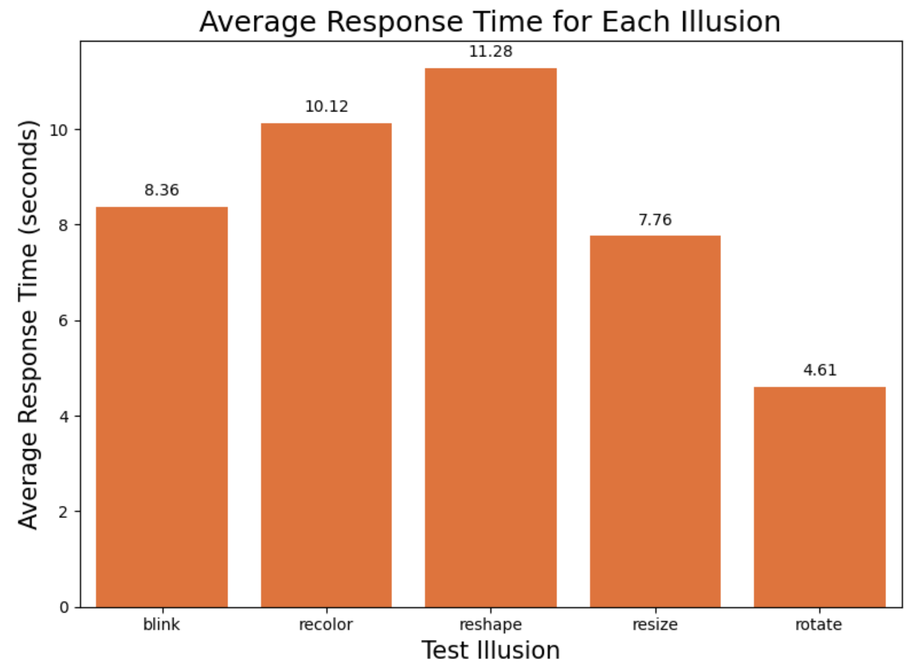

Figure 4.4: Bar Chart of Average Response Time for Each Illusion Test

4.3.2 Illusions Discussion

The results of the illusion tests highlight the influence of different animations on participants' response times, providing insights into which illusions are most effective in capturing attention. The observed variances in the average response times for the different illusions ("blink", "recolor", "reshape", "resize", and "rotate") may be interpreted in the context of existing theoretical frameworks on visual attention.

The "rotate" illusion elicited the fastest response time (approximately 4.61 seconds), which could be indicative of its strong attention-capturing ability. This aligns with the concept of "Attentional Capture", where certain dynamic visual stimuli are more likely to attract attention [23]. In the context of "Signal Detection Theory", the quicker response times might reflect a higher "signal-to-noise" ratio, suggesting that the "rotate" illusion was more distinctive and easier for the participants to identify amid potential visual "noise" [21].

On the other hand, the "reshape" illusion had the longest response time (approximately 11.28 seconds), implying that it might have been less salient or more difficult for participants to detect. This observation can be linked to the "Saliency Map Models", which propose that stimuli that are more distinct in terms of features such as color, shape, or movement are more likely to be noticed

[22].

Overall, these findings suggest that the type of animation or illusion used in a web-based application may impact the user's visual-spatial attention. Future research could explore this relationship further, investigating how different illusions influence not just response times but also other aspects of visual attention, such as accuracy and the ability to focus on multiple stimuli simultaneously.

4.4 Duration Illusion

4.4.1 Duration Illusion Results

Total response time

Figure 4.5 displays a bar chart depicting the average response time for each duration of the illusion test. Each bar corresponds to a different duration, as indicated on the x-axis, with the height of the bar representing the average response time in seconds, as indicated on the y-axis. The bars are color-coded for easy differentiation between the different durations.

From left to right, the durations are 1.0 second, 1.5 seconds, 2.0 seconds, 2.5 seconds, and 3.0 seconds. The corresponding average response times are approximately 8.35 seconds, 9.26 seconds, 8.78 seconds, 8.96 seconds, and 8.95 seconds, respectively.

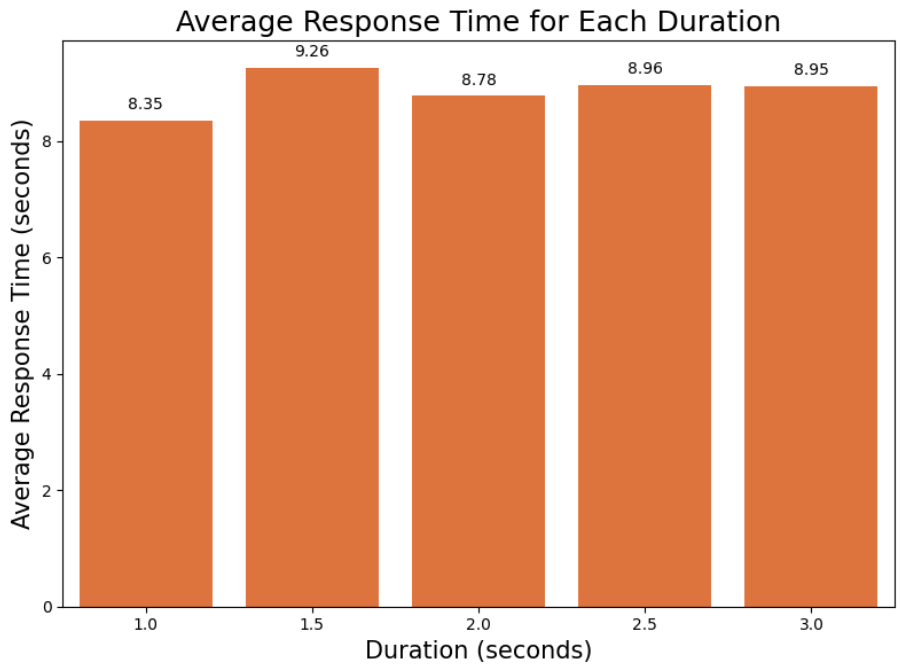

Figure 4.5: Bar Chart of Average Response Time by Duration of Illusion Test

Time after First Gaze

Figure 4.6 displays a bar chart illustrating the average time after the first gaze for each duration of the illusion test. Each bar corresponds to a different duration, as indicated on the x-axis, with the height of the bar representing the average time after the first gaze in seconds, as indicated on the y-axis. The bars are color-coded for easy differentiation between the different durations.

From left to right, the durations are 1.0 second, 1.5 seconds, 2.0 seconds, 2.5 seconds, and 3.0 seconds. The corresponding average times after the first gaze are approximately 3.28 seconds, 3.95 seconds, 4.50 seconds, 4.35 seconds, and 3.67 seconds, respectively.

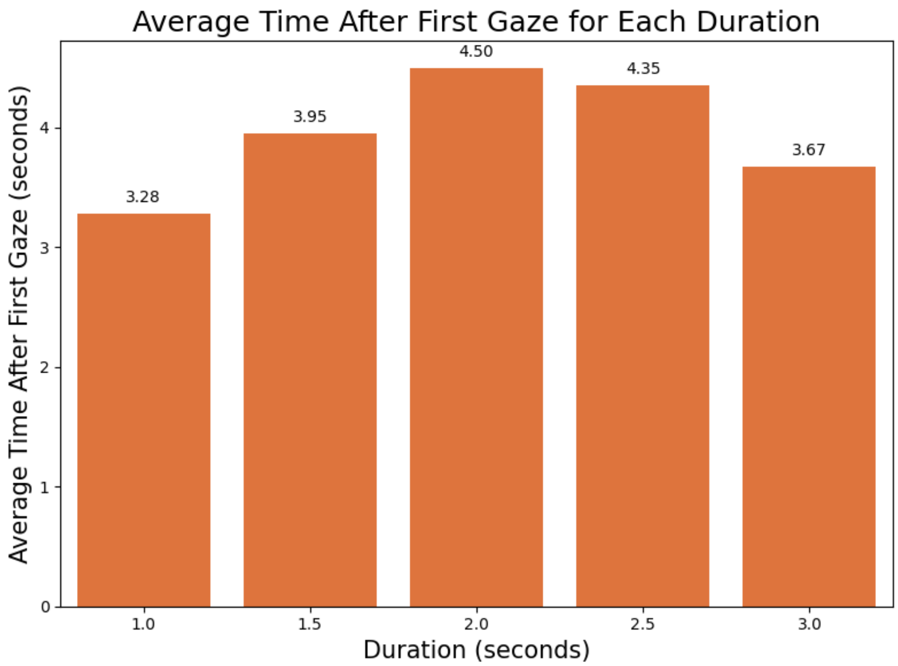

Figure 4.6: Bar Chart of Average Time After First Gaze by Duration of Illusion Test

Time gazed on point

Figure 4.7 displays a bar chart illustrating the average time gazed on the chosen point for each duration of the illusion test. Each bar corresponds to a different duration, as indicated on the x-axis, with the height of the bar representing the average time gazed on the chosen point in seconds, as indicated on the y-axis. The bars are color-coded for easy differentiation between the different durations.

From left to right, the durations are 1.0 second, 1.5 seconds, 2.0 seconds, 2.5 seconds, and 3.0 seconds. The corresponding average times gazed on the chosen point are approximately 1.50 seconds, 1.70 seconds, 1.86 seconds, 1.85 seconds, and 1.75 seconds, respectively.

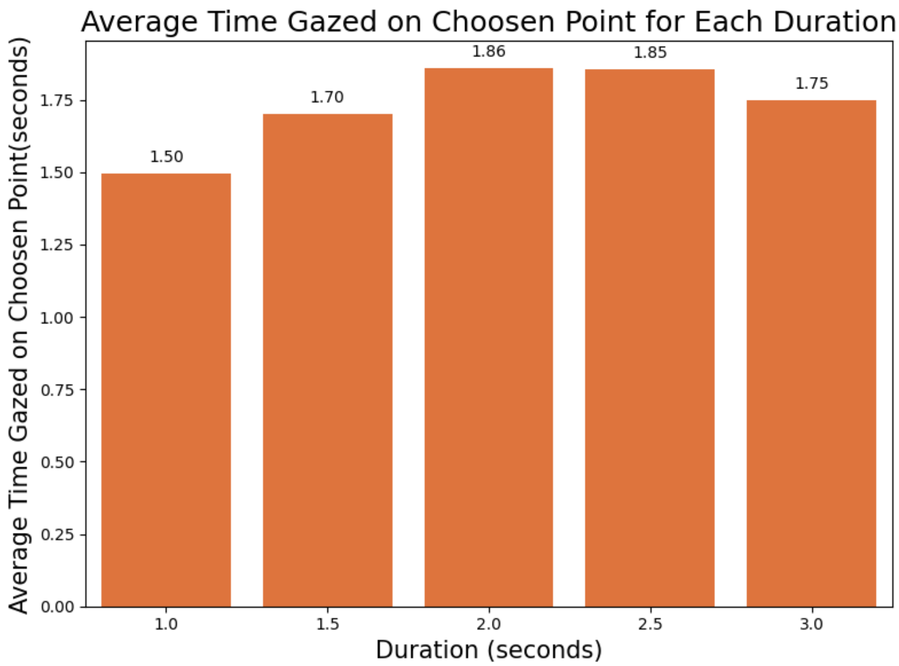

Figure 4.7: Bar Chart of Average Time Gazed on Chosen Point by Duration of Illusion Test

Wrong answers

Figure 4.8 displays a bar chart illustrating the average number of wrong answers for each duration of the illusion test. Each bar corresponds to a different duration, as indicated on the x-axis, with the height of the bar representing the average number of wrong answers, as indicated on the y-axis. The bars are color-coded for easy differentiation between the different durations.

From left to right, the durations are 1.0 second, 1.5 seconds, 2.0 seconds, 2.5 seconds, and 3.0 seconds. The corresponding average numbers of wrong answers are approximately 0.20, 0.18, 0.17, 0.15, and 0.18, respectively.

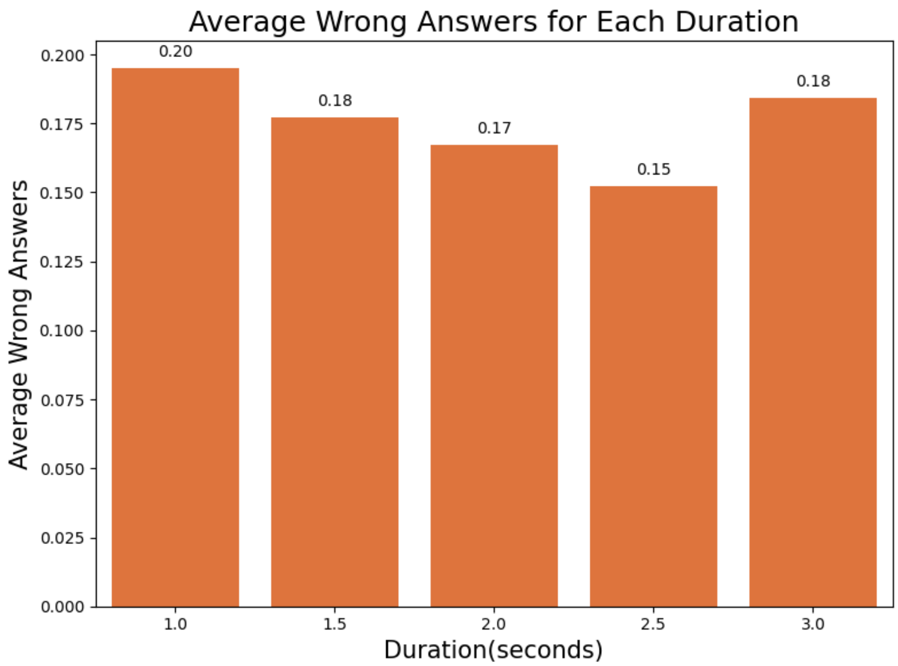

Figure 4.8: Bar Chart of Average Number of Wrong Answers by Duration of Illusion Test

4.4.2 Duration Illusion Discussion

The results of the duration tests provide an intriguing look at how the speed of an illusion influences response times, the time after the first gaze, time gazed on the point, and the number of incorrect responses. These results could offer crucial insights when considering the "Time Course of Visual Attention".

The response time data reveals that all durations (1.0, 1.5, 2.0, 2.5, and 3.0 seconds) resulted in average response times ranging from approximately 8.35 to 9.26 seconds, with the 1.5-second duration being the slowest. This could suggest that a moderately fast-paced illusion, such as the 1.0-second duration, can prompt quicker responses, aligning with the concept of transient attention in the "Time Course of Visual Attention", where quick, abrupt changes are noticed faster [23].

The time after the first gaze and the time gazed on the point both increased for longer durations, indicating that longer illusion durations might encourage participants to fixate longer on the stimuli. This could be an indicator of sustained attention, another aspect of the "Time Course of Visual Attention" [21].

Lastly, the number of incorrect responses slightly decreased as the duration increased, indicating that slower illusions may lead to fewer mistakes, possibly due to giving participants more time to process the visual information [22].

These findings highlight the importance of the illusion's duration in a web-based application aiming to enhance visual-spatial attention. Further research could delve into how variations in duration affect other aspects of visual attention and how these could be optimized to promote better visual-spatial attention.

4.5 Illusion: recolor

4.5.1 Recolor Results

Total response time

Figure 4.9 is a bar plot that illustrates the average response time for each color transition during the "Recolor" illusion tests. The bars' color gradients represent the transitions between the two colors. For instance, a bar transitioning from red to blue indicates that the original chosen point color was red, and it was animated to turn blue during the test.

The average response times for the color transitions are as follows:

- Blue to Green: 11.44 seconds
- Blue to Orange: 6.76 seconds
- Blue to Red: 8.55 seconds
- Blue to Violet: 17.61 seconds
- Blue to Yellow: 6.72 seconds
- Green to Orange: 11.67 seconds
- Green to Red: 10.06 seconds
- Green to Violet: 7.51 seconds
- Green to Yellow: 13.57 seconds
- Orange to Yellow: 10.30 seconds
- Red to Orange: 23.08 seconds
- Red to Violet: 10.28 seconds
- Red to Yellow: 10.08 seconds
- Violet to Orange: 9.43 seconds
- Violet to Yellow: 7.37 seconds

These values represent the average time it takes for a user to respond when the color transition occurs from one to the other. For example, it takes on average 11.44 seconds for a user to respond when the color transition is from blue to green. The color transitions are sorted alphabetically by the color names.

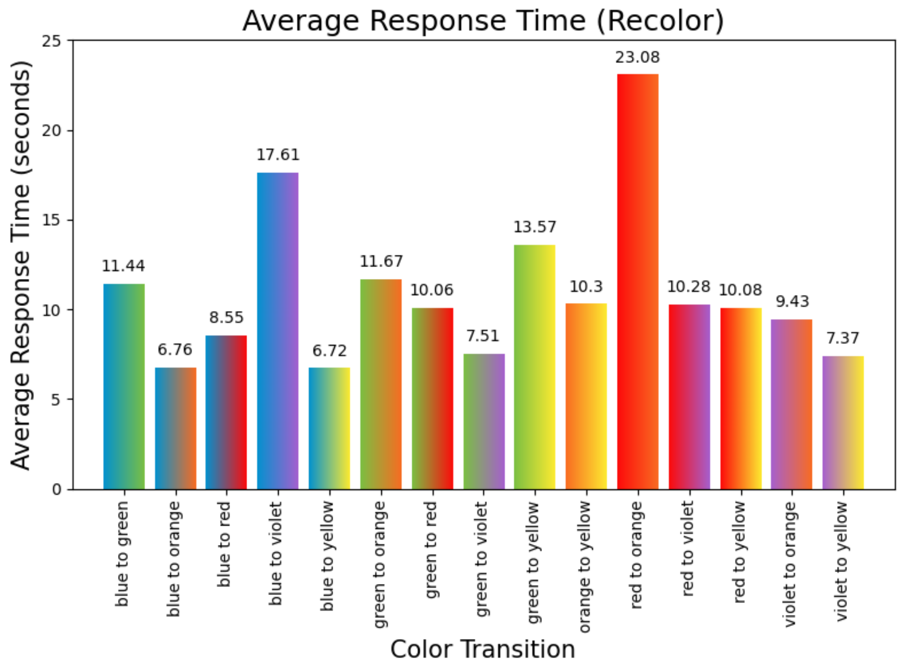

Figure 4.9: Average Response Time for Each Color Transition in the "Recolor" Illusion Tests

Time after First Gaze

Figure 4.10 is a bar plot that illustrates the average times after the first gaze for each color transition in the "Recolor" test. The color of each bar represents the color transition, ranging from the initial color to the final color. The y-axis shows the average time in seconds after the first gaze, and the x-axis lists each color transition.

- Blue to Green: 3.41 seconds
- Blue to Orange: 2.50 seconds
- Blue to Red: 6.93 seconds
- Blue to Violet: 10.78 seconds

- Blue to Yellow: 1.78 seconds
- Green to Orange: 5.60 seconds
- Green to Red: 6.73 seconds
- Green to Violet: 1.60 seconds
- Green to Yellow: 5.73 seconds
- Orange to Yellow: 5.88 seconds
- Red to Orange: 10.44 seconds
- Red to Violet: 4.46 seconds
- Red to Yellow: 4.28 seconds
- Violet to Orange: 6.73 seconds
- Violet to Yellow: 2.14 seconds

These values represent the average time after the first gaze for each color transition in the "Recolor" test. For example, the average time for a user to respond after the first gaze is 3.41 seconds for the color transition from blue to green. The color transitions are sorted alphabetically by the color names.

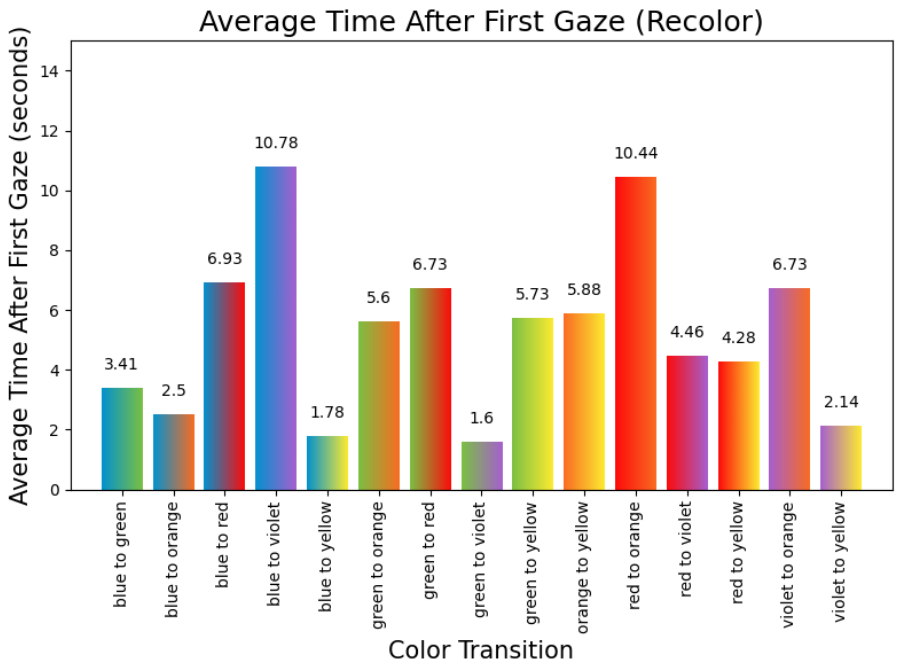

Figure 4.10: Average Time After First Gaze for Each Color Transition in the "Recolor" Illusion Tests

Time gazed on point

Figure 4.11 is a bar plot that illustrates the average time gazed on the chosen point for each color transition during the "Recolor" illusion tests. The bars' color gradients represent the transitions between the two colors. For instance, a bar transitioning from red to blue indicates that the original chosen point color was red, and it was animated to turn blue during the test.

The average times gazed on the chosen point for the color transitions are as follows:

- blue to green: 1.48 seconds
- blue to orange: 1.66 seconds
- blue to red: 1.68 seconds
- blue to violet: 1.54 seconds
- blue to yellow: 1.56 seconds
- green to orange: 1.57 seconds

- green to red: 1.59 seconds
- green to violet: 1.65 seconds
- green to yellow: 1.54 seconds
- orange to yellow: 1.56 seconds
- red to orange: 1.65 seconds
- red to violet: 1.52 seconds
- red to yellow: 1.61 seconds
- violet to orange: 1.62 seconds
- violet to yellow: 1.67 seconds

These values represent the average time a user gazes on the chosen point when the color transition occurs from one to the other. For example, users gaze at the chosen point for an average of 1.48 seconds when the color transition is from blue to green. The color transitions are sorted alphabetically by the color names.

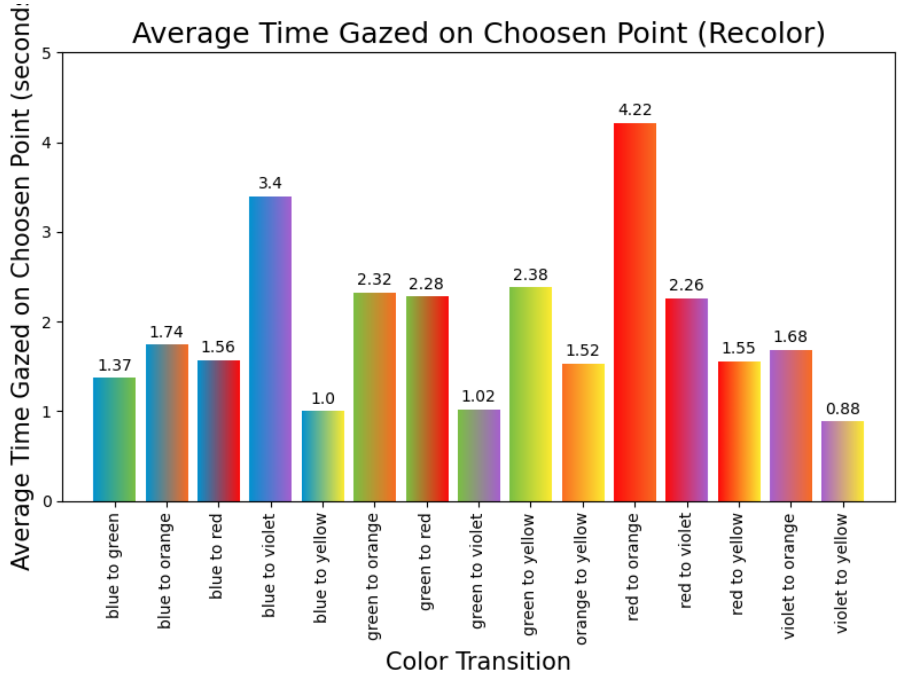

Figure 4.11: Average Time Gazed on Chosen Point for Each Color Transition during Recolor Test

Wrong answers

Figure 4.12 is a bar plot that illustrates the average number of wrong answers for each color transition during the "Recolor" illusion tests. The colors of the bars represent the transitions between the two colors. For example, a bar transitioning from blue to green indicates that the original chosen point color was blue, and it was animated to turn green during the test.

The average number of wrong answers for the color transitions are as follows:

- Blue to Green: 0.250 wrong answers
- Blue to Orange: 0.105 wrong answers
- Blue to Red: 0.158 wrong answers
- Blue to Violet: 0.163 wrong answers
- Blue to Yellow: 0.037 wrong answers
- Green to Orange: 0.155 wrong answers
- Green to Red: 0.309 wrong answers
- Green to Violet: 0.172 wrong answers
- Green to Yellow: 0.111 wrong answers
- Orange to Yellow: 0.158 wrong answers
- Red to Orange: 0.326 wrong answers
- Red to Violet: 0.111 wrong answers
- Red to Yellow: 0.141 wrong answers
- Violet to Orange: 0.176 wrong answers
- Violet to Yellow: 0.122 wrong answers

These values represent the average number of wrong answers for a user when the color transition occurs from one to the other. For example, on average, users give 0.250 wrong answers when the color transition is from blue to green. The color transitions are sorted alphabetically by the color names.

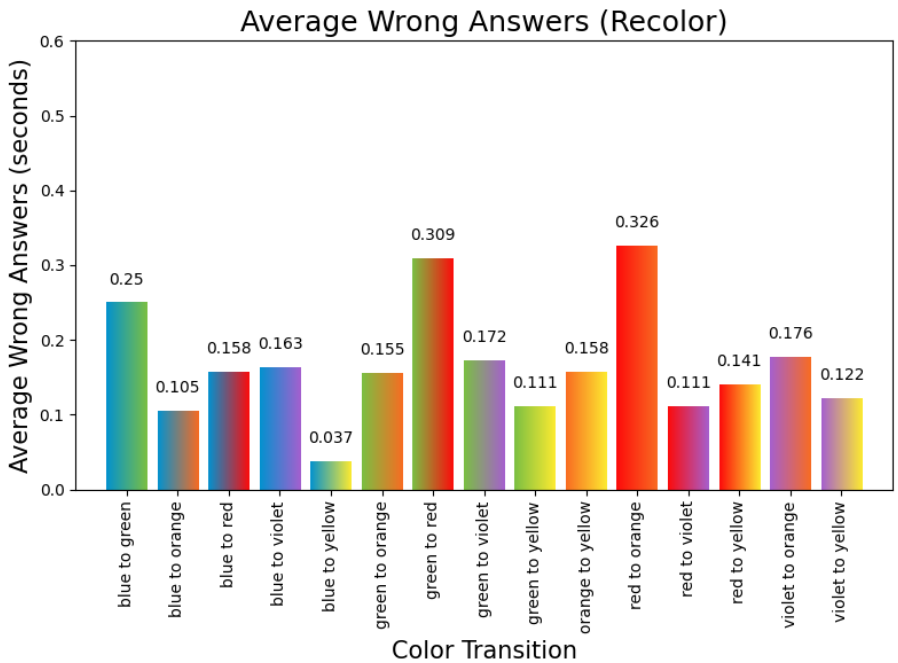

Figure 4.12: Average Number of Wrong Answers for Different Color Transitions in "Recolor" Illusion Tests

4.5.2 Recolor Discussion

The results from the "Recolor" illusion test give a comprehensive understanding of how color transitions can influence response times, gaze patterns, and error rates. They directly support and enhance several existing theoretical models.

Starting with the total response time, we see varying results depending on the color transitions. It's particularly noteworthy that transitions involving closely related colors, such as red to orange, required the longest response time. This suggests that closely related colors, despite their warm characteristics that would typically command attention, can present detection challenges. This observation can be explained through the lens of "Signal Detection Theory". This theory posits that the ability to discern between a signal (color change) and noise (static color) can be affected by the signal's intensity or, in this case, its similarity to the noise. In other words, the color change from red to orange might not be salient enough to be immediately detected, thus increasing the response time.

Conversely, when color transitions were between warm and cold colors, such as blue to orange, response times were faster. The high contrast between these types of colors made the change more noticeable and thus quicker to respond to.

Regarding the time after the first gaze, some color transitions, such as blue to violet, induce longer gaze times than others. This can be associated with "Eye Movement and Decision Making" processes. The theory explains that the amount of time spent gazing at a point after initial fixation can indicate the cognitive load associated with processing the information at that point. In this case, the cognitive load might be higher for certain color transitions (particularly between cold colors, like blue to violet), possibly due to their less attention-grabbing characteristics compared to warm colors.

The "Attentional Capture" theory helps interpret our results on the average time gazed on the chosen point. Certain color transitions seem to retain users' attention longer, potentially due to their saliency level. Notably, the change from blue to green, despite being a transition between cold colors, held the user's gaze for longer periods. This could be due to the stark contrast between these two colors, resulting in a more salient visual stimulus that captures and holds attention.

Finally, the "Saliency Map Models" can be related to our observations from the average number of wrong answers. It's interesting to see that the number of wrong answers increases for transitions involving closely related colors. As per the model, stimuli that deviate significantly from their surroundings in color, orientation, or intensity tend to be more salient. Therefore, when color transitions involve similar colors (like red to orange), they might not be salient enough, leading to a higher likelihood of errors.

In summary, these findings underscore the intricate dynamics of color perception and attention. They suggest that both the choice of colors and their transitions play pivotal roles in illusions intended to capture and guide attention.

4.6 Illusion: reshape

4.6.1 Reshape Results

Total response time

Figure 4.13 is a scatter plot that illustrates the average response time for each shape transition during the "Reshape" illusion tests.

The average response times for the shape transitions are as follows:

- Circle: 19.07 seconds
- Square: 14.01 seconds
- Triangle: 10.33 seconds

These values represent the average time it takes for a user to respond when the shape transition occurs. For instance, it takes on average 19.07 seconds for a user to respond when the shape transition is to a circle. The shapes are sorted alphabetically by the shape names.

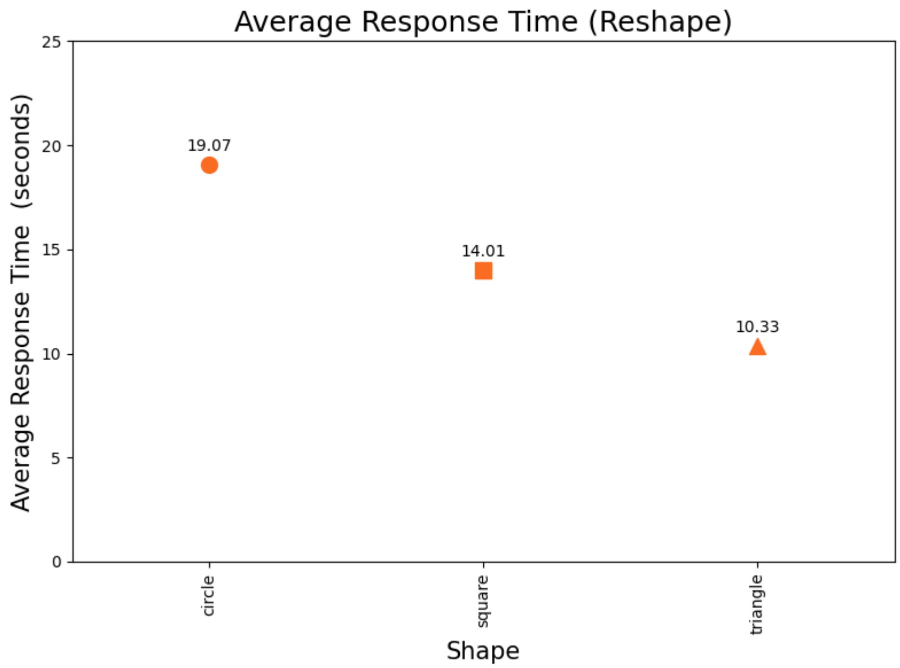

Figure 4.13: Average Response Time for Different Shape Transitions in the “Reshape” Illusion Test

Time after First Gaze

Figure 4.14 is a scatter plot that illustrates the average time after the first gaze for each shape during the “Reshape” illusion tests. Each point in the plot represents a shape - circle, square, or triangle. The Y-coordinate of the point denotes the average time after the first gaze for that shape.

The average times after the first gaze for the shapes are as follows:

- Circle: 12.12 seconds
- Square: 7.59 seconds
- Triangle: 4.15 seconds

These values represent the average time it takes for a user to respond after first gazing at the shape when the shape transition occurs. For instance, it takes on average 12.12 seconds for a user to respond after first gazing at the shape when the shape transition is to a circle.

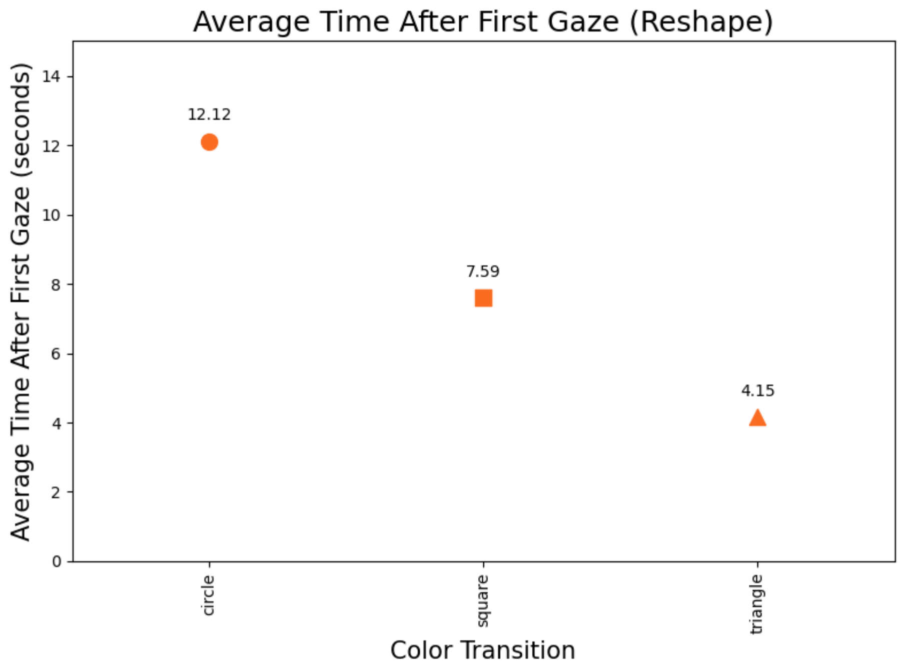

Figure 4.14: Average Time After First Gaze for Different Shapes during the "Reshape" Illusion Tests

Time gazed on point

Figure 4.15 is a scatter plot that illustrates the average time gazed on the chosen point for each shape during the "Reshape" illusion tests. Each point in the plot represents a shape - circle, square, or triangle. The Y-coordinate of the point denotes the average time gazed on the chosen point for that shape.

The average times gazed on the chosen point for the shapes are as follows:

- Circle: 3.95 seconds
- Square: 2.47 seconds
- Triangle: 2.16 seconds

These values represent the average time a user spends gazing at the chosen point when the shape transition occurs. For instance, on average, users spend 3.95 seconds gazing at the chosen point when the shape transition is to a circle.

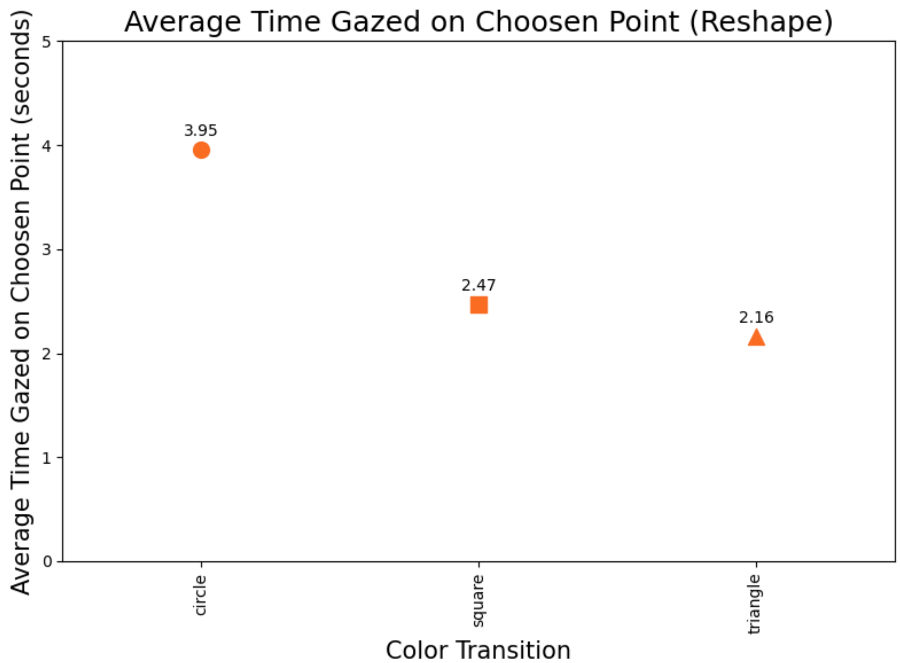

Figure 4.15: Average Time Gazed on the Chosen Point for Different Shapes during the "Reshape" Illusion Tests

Wrong answers

Figure 4.16 is a scatter plot that illustrates the average number of wrong answers provided by users for each shape during the "Reshape" illusion tests. Each point in the plot represents a shape - circle, square, or triangle. The Y-coordinate of the point denotes the average number of wrong answers for that shape.

The average numbers of wrong answers for the shapes are as follows:

- Circle: 0.622 wrong answers
- Square: 0.277 wrong answers
- Triangle: 0.261 wrong answers

These values represent the average number of wrong answers provided by users when the shape transition occurs. For instance, when the shape transition is to a circle, users provided an average of approximately 0.622 wrong answers.

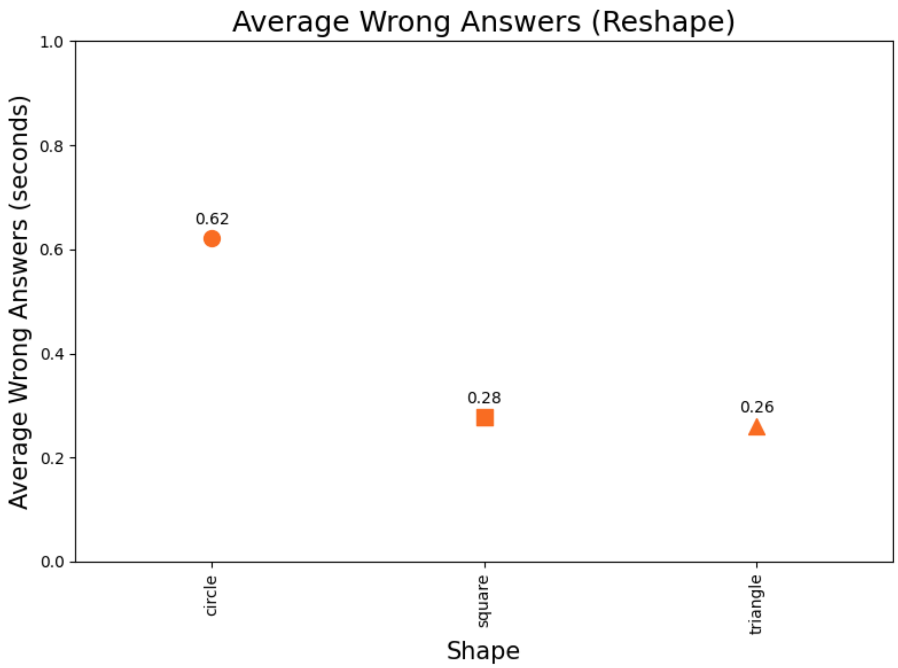

Figure 4.16: Average Number of Wrong Answers for Different Shapes during the "Reshape" Illusion Tests

4.6.2 Reshape Discussion

Analyzing the data collected during the "Reshape" illusion tests, the results revealed patterns of behavior with respect to different shapes - circle, square, and triangle. The measurements of interest were the total response time, the time after the first gaze, the time gazed on the point, and the average number of wrong answers provided by users.

For the total response time, the data showed that we took the longest to respond when the shape transitioned to a circle (19.07 seconds), followed by the square (14.01 seconds), and the triangle (10.33 seconds). A similar pattern was observed for the time after the first gaze, with the circle (12.12 seconds) requiring more time than the square (7.59 seconds) and the triangle (4.15 seconds).

The average time spent gazing on the point was also highest for the circle (3.95 seconds), followed by the square (2.47 seconds) and the triangle (2.16 seconds). The circle shape also led to the highest average number of wrong answers (0.622), with the square and triangle shapes resulting in fewer errors (0.277 and 0.261 wrong answers, respectively).

The obtained data could be examined in light of existing psychological and cognitive models, such as the Signal Detection Theory, Attentional Capture, Eye

Movement and Decision Making, and Saliency Map Models. For instance, Signal Detection Theory might suggest that the increased response time and number of errors associated with the circle might be due to the shape's perceptual similarity to a square, causing ambiguity and making the detection of a shape change more difficult.

In terms of Attentional Capture and Saliency Map Models, these results might imply that a triangle, being more distinct and arguably more "salient" than the other two shapes, captures attention more readily. This could potentially explain why transitions to a triangle result in faster response times, shorter gaze durations, and fewer wrong answers.

While the Eye Movement and Decision Making model might suggest that participants may take longer to make a decision when the shape is a circle due to its similarity with a square, leading to prolonged gaze times and a higher number of errors.

Unfortunately, an oversight in the experimental design led to a crucial piece of data not being collected: the initial shape of the point prior to the transition. This missing data could have provided valuable insights into the comparative difficulty or ease of detecting transitions between specific pairs of shapes. For example, transitions between the circle and square, which are perceptually similar, might be harder to detect compared to transitions involving the more distinct triangle shape. Thus, the hypothesis could have been that transitions involving a triangle would result in faster response times, shorter gaze durations, and fewer errors.

While it is unfortunate that this data was not collected, this oversight serves as a crucial learning experience in the research process. Future studies should consider collecting this information to offer a more nuanced understanding of how different shape transitions impact visual attention and perception. It also serves as a reminder of the importance of comprehensive data collection in experimental design, a lesson that will be carried forward in future research endeavors.

4.7 Illusion: resize

4.7.1 Resize Results

Total response time

Figure 4.17 is a scatter plot that illustrates the average response time for each resize value during the "Resize" illusion tests. Each point in the plot represents a resize value - 0.5, 0.67, 1.5, and 2. The Y-coordinate of the point denotes the average response time for that resize value.

The average response times for the resize values are as follows:

- Resize 0.5: 8.51 seconds
- Resize 0.67: 10.29 seconds

- Resize 1.5: 7.90 seconds
- Resize 2: 6.02 seconds

These values represent the average time it takes for a user to respond when the resize value changes. For instance, it takes on average 8.51 seconds for a user to respond when the resize value is 0.5. The size of the marker in the scatter plot corresponds to the resize value.

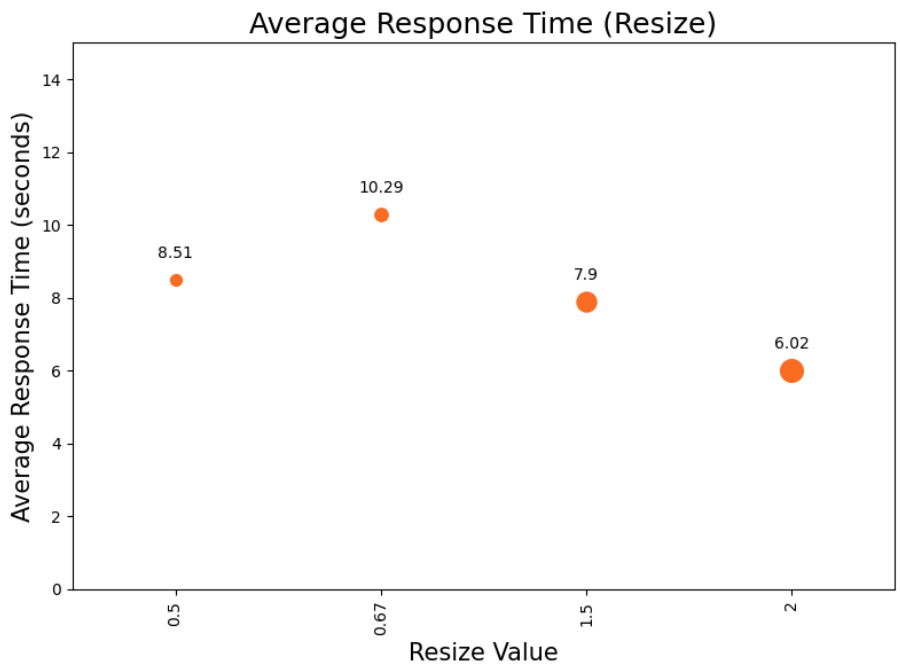

Figure 4.17: Average Response Time for Different Resize Values during the "Resize" Illusion Tests

Time after First Gaze

Figure 4.18 is a scatter plot that demonstrates the average time taken after the first gaze for each resize value during the "Resize" illusion tests. Each point in the plot represents a resize value - 0.5, 0.67, 1.5, and 2. The Y-coordinate of the point denotes the average time after the first gaze for that resize value.

The average times after the first gaze for the resize values are as follows:

- Resize value 0.5: 3.37 seconds
- Resize value 0.67: 4.96 seconds

- Resize value 1.5: 4.32 seconds
- Resize value 2: 2.08 seconds

These values represent the average time it takes for a user to respond after first gazing at the shape when the resize transition occurs. For instance, it takes on average 3.37 seconds for a user to respond after first gazing at the shape when the resize value is 0.5.

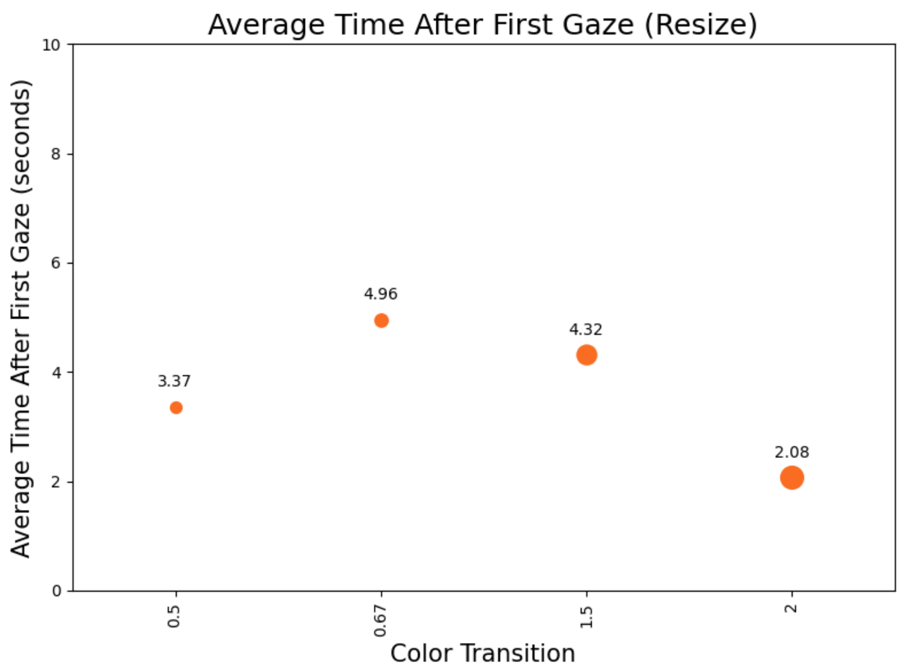

Figure 4.18: Average Time After First Gaze for Different Resize Values during the “Resize” Illusion Test

Time gazed on point

Figure 4.19 is a scatter plot that represents the average time users gazed at the chosen point for different resizing factors during the “Resize” illusion tests. Each point in the plot corresponds to a resizing factor - 0.5, 0.67, 1.5, and 2. The Y-coordinate of the point indicates the average time users spent gazing at the chosen point for that resizing factor.

The average times gazed at the chosen point for the resizing factors are as follows:

- Resizing Factor 0.5: 1.57 seconds

- Resizing Factor 0.67: 2.42 seconds
- Resizing Factor 1.5: 1.70 seconds
- Resizing Factor 2: 1.22 seconds

These values represent the average time users spend gazing at the chosen point when the point is resized by the corresponding factor. For instance, on average, users spend 1.57 seconds gazing at the chosen point when it is resized by a factor of 0.5.

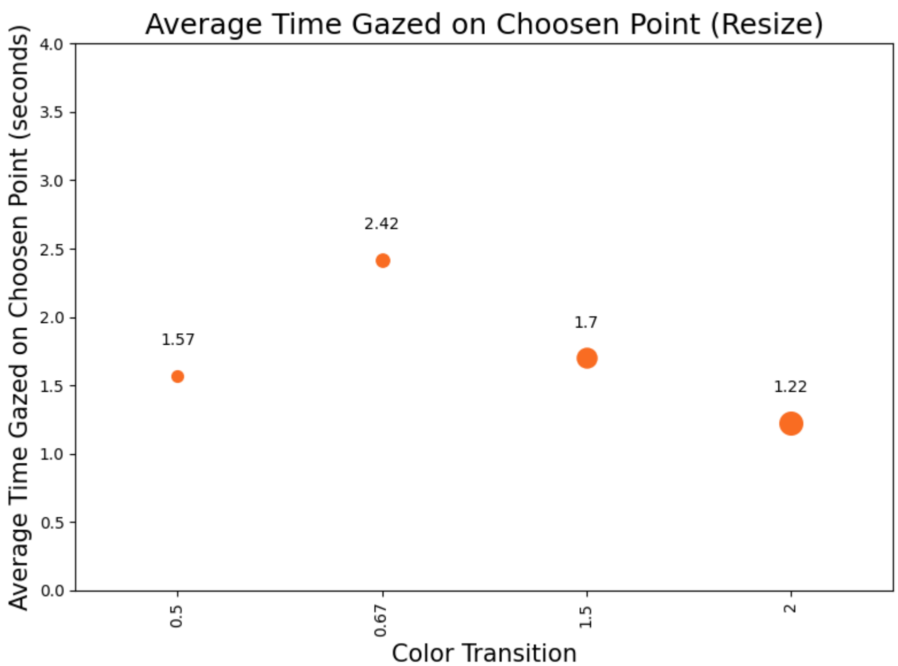

Figure 4.19: Average Time Gazed on the Chosen Point for Different Resize Values during the “Resize” Illusion Test

Wrong answers

Figure 4.20 is a scatter plot that represents the average number of wrong answers given by users for different resizing factors during the “Resize” illusion tests. Each point in the plot corresponds to a resizing factor - 0.5, 0.67, 1.5, and 2. The Y-coordinate of the point indicates the average number of wrong answers for that resizing factor.

The average numbers of wrong answers for the resizing factors are as follows:

- Resizing Factor 0.5: 0.22 wrong answers

- Resizing Factor 0.67: 0.09 wrong answers
- Resizing Factor 1.5: 0.08 wrong answers
- Resizing Factor 2: 0.20 wrong answers

These values represent the average number of wrong answers given by users when the resize value is applied. For instance, on average, users give 0.22 wrong answers when the resize factor is 0.5.

Figure 4.20: Average Number of Wrong Answers for Different Resize Values during the "Resize" Illusion Test

4.7.2 Resize Discussion

In the "Resize" illusion test, we observed several trends in the data related to the average response times, the average times after the first gaze, the average times gazed on the chosen point, and the average numbers of wrong answers for different resizing factors.

The average response times indicated that users took the longest time to respond when the resize value was 0.67 (10.29 seconds), followed by 0.5 (8.51 seconds), 1.5 (7.90 seconds), and 2 (6.02 seconds). This pattern suggests that users found it most challenging to discern changes when the resizing factor was around the mid-range of the scale, possibly due to the "detection threshold" concept of Signal Detection Theory.

As for the time after the first gaze, users took the most time when the resize value was 0.67 (4.96 seconds), followed by 1.5 (4.32 seconds), 0.5 (3.37 seconds), and 2 (2.08 seconds). This might be interpreted through the lens of the Eye Movement and Decision Making model, suggesting that users needed more time to make a decision when the resize value was neither very small nor very large (i.e., 0.67 and 1.5).

The average times gazed on the chosen point followed a similar trend. The longest gaze time occurred with the resize value of 0.67 (2.42 seconds), followed by 1.5 (1.70 seconds), 0.5 (1.57 seconds), and 2 (1.22 seconds). This observation aligns with theories of Attentional Capture, suggesting that middle resize values may not capture attention as effectively as the extremes.

Lastly, the average number of wrong answers was highest for the resize value 0.5 (0.22 wrong answers), followed by 2 (0.20 wrong answers), 0.67 (0.09 wrong answers), and 1.5 (0.08 wrong answers). The higher number of errors at the extreme resize values of 0.5 and 2 might suggest that these levels were more challenging for the users, potentially due to the substantial change they represented compared to the original size of the shape, as postulated by Saliency Map Models.

In summary, these results paint a complex picture of the interplay between object resizing, attention capture, eye movements, decision-making, and error rates. They underscore the need for further research to clarify these relationships and refine the associated theoretical models.

4.8 Illusion: rotate

4.8.1 Rotate Results

Total response time

Figure 4.21 is a scatter plot that displays the average response time for each rotation direction during the "Rotate" illusion tests. Each point in the plot represents a rotation direction - clockwise or counterclockwise. The Y-coordinate of the point signifies the average response time for that rotation direction.

The average response times for the rotation directions are as follows:

- Clockwise: 4.76 seconds
- Counterclockwise: 4.78 seconds

These values depict the average time it takes for a user to respond when the rotation direction occurs. For instance, it takes on average 4.76 seconds for a user to respond when the rotation direction is clockwise.

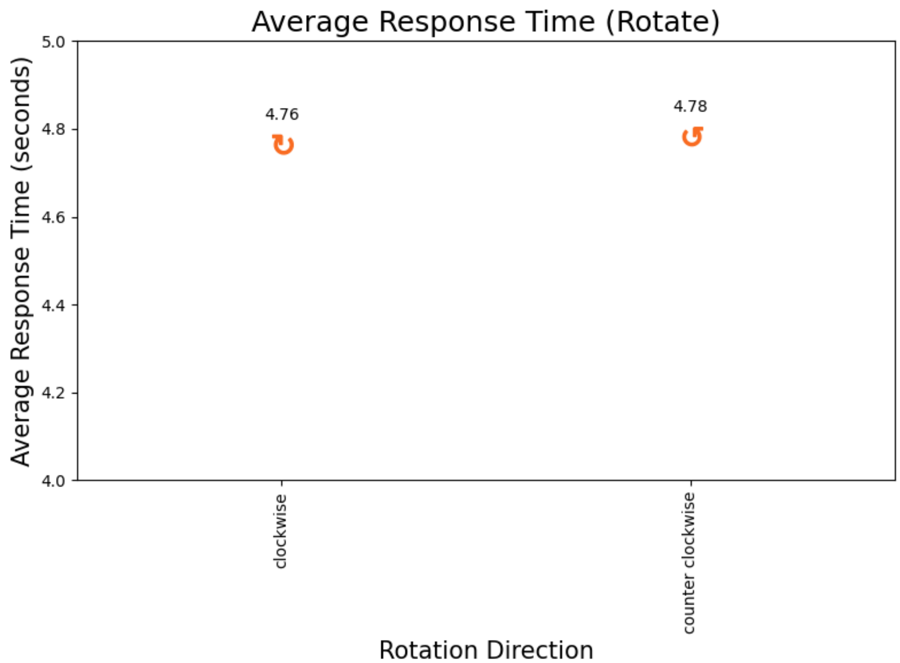

Figure 4.21: Average Response Time for Different Rotation Directions during the "Rotate" Illusion Tests

Time after First Gaze

Figure 4.22 is a scatter plot that illustrates the average time after the first gaze for each rotation direction during the "Rotate" illusion tests. Each point in the plot represents a rotation direction - clockwise and counterclockwise. The Y-coordinate of the point denotes the average time after the first gaze for that rotation direction.

The average times after the first gaze for the rotation directions are as follows:

- Clockwise: 1.05 seconds
- Counterclockwise: 1.63 seconds

These values represent the average time it takes for a user to respond after first gazing at the object when the rotation occurs. For instance, it takes on average 1.05 seconds for a user to respond after first gazing at the object when the rotation is in the clockwise direction.

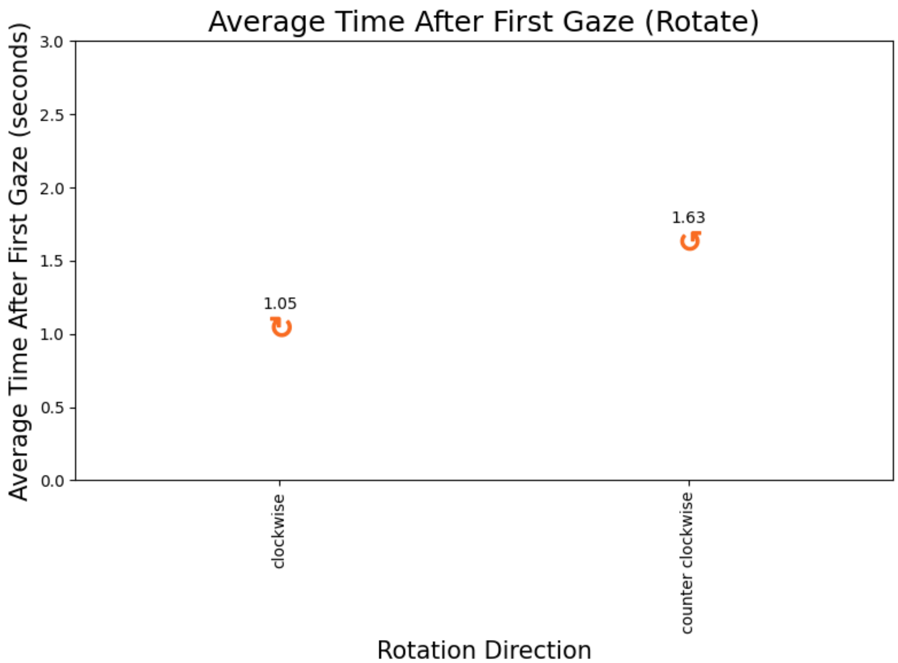

Figure 4.22: Average Time After First Gaze for Different Rotation Directions during the "Rotate" Illusion Tests

Time gazed on point

Figure 4.23 is a scatter plot that represents the average time users gazed at the chosen point for different rotation directions during the "Rotate" illusion tests. Each point in the plot corresponds to a rotation direction - clockwise and counter-clockwise. The Y-coordinate of the point indicates the average time users spent gazing at the chosen point for that rotation direction.

The average times gazed at the chosen point for the rotation directions are as follows:

- Clockwise: 0.83 seconds
- Counter Clockwise: 0.97 seconds

These values represent the average time users spend gazing at the chosen point when the point is rotated in the corresponding direction. For instance, on average, users spend 0.97 seconds gazing at the chosen point when it is rotated counterclockwise.

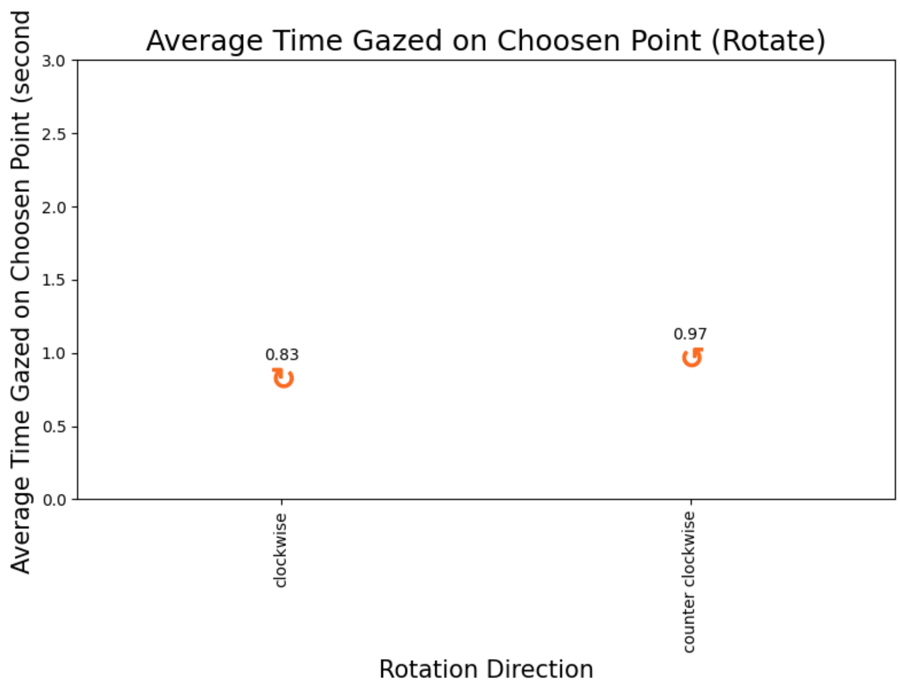

Figure 4.23: Average Time Gazed at the Chosen Point for Different Rotation Directions during the "Rotate" Illusion Test

Wrong answers

Figure 4.24 is a scatter plot that represents the average number of wrong answers users gave during the "Rotate" illusion tests for different rotation directions. Each point in the plot corresponds to a rotation direction - clockwise and counter-clockwise. The Y-coordinate of the point indicates the average number of wrong answers for that rotation direction.

The average number of wrong answers for the rotation directions are as follows:

- Clockwise: 0.05 wrong answers
- Counter Clockwise: 0.11 wrong answers

These values represent the average number of wrong answers users gave when the point is rotated in the corresponding direction. For instance, on average, users gave 0.11 wrong answers when the point is rotated in the counter-clockwise direction.

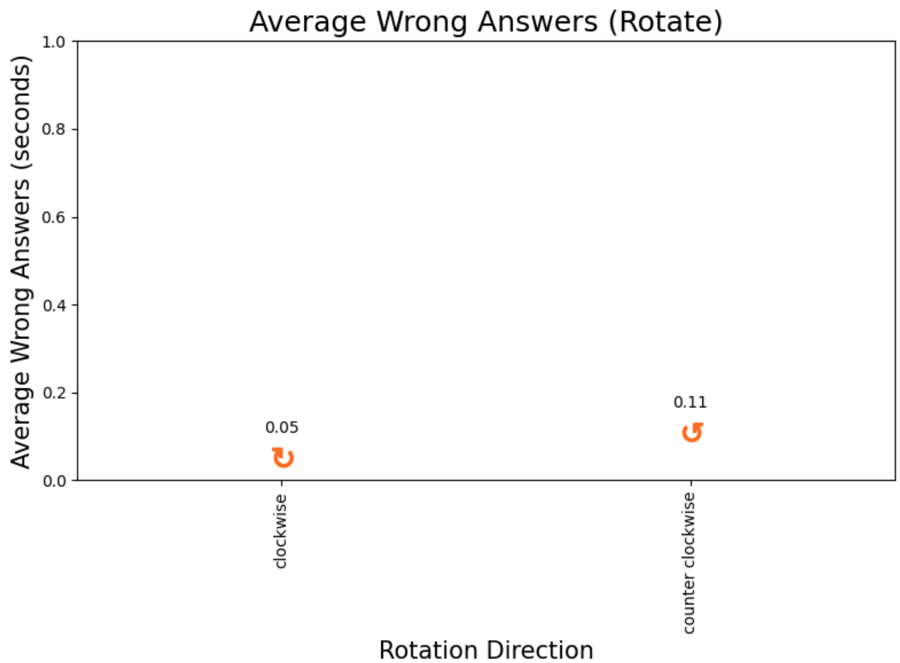

Figure 4.24: Average Number of Wrong Answers for Different Rotation Directions during the "Rotate" Illusion Test

4.8.2 Rotate Discussion

The data from the "Rotate" illusion tests indicate that the direction of rotation, whether clockwise or counter-clockwise, does not significantly influence the response time, the time after the first gaze, the time gazed at the point, or the number of wrong answers. Both directions resulted in relatively similar values across these parameters, suggesting that the directionality of rotation might not be a significant factor in capturing attention or influencing decision making.

Within the context of the Attentional Capture theory, the rotation of an object could be an abrupt and salient enough event to capture the attention of the user. However, the similar response times for both directions suggest that the directionality of the rotation may not provide an additional unique feature to further enhance attentional capture.

In terms of Signal Detection Theory, our ability to discern between a signal and noise is likely not affected by the direction of the rotation, which might explain why response times for both rotation directions were similar.

Regarding Eye Movement and Decision Making, the direction of the rotation might not provide a strong enough stimulus to create a gaze bias or significantly alter the decision-making process, which could explain the similar times after the first gaze and time gazed at the point for both rotation directions.

Similarly, the direction of rotation does not seem to significantly affect saliency, as proposed by Saliency Map Models, which could account for the similar user response times and gaze durations observed for both rotation directions.

Despite these overall similarities, there were slightly more wrong answers for the counter-clockwise direction than for the clockwise one. This difference, even though small, could possibly indicate a mild effect of rotation direction on users' accuracy. However, further research would be needed to definitively conclude the nature of this relationship.

These interpretations should be understood within the context of the average values, and individual variations in perception and cognitive processing are not explicitly accounted for in this discussion. Therefore, individual results might vary, and further investigations could be valuable in providing a more nuanced understanding of the effects of rotation direction in visual illusions.

4.9 Illusion: blink

4.9.1 Blink Results

Total response time

Figure 4.25 is a scatter plot that visualizes the average response time for the "blink" illusion test. The single data point on the plot represents the average response time across all "blink" tests. From this data, we can observe that the average response time for the "blink" illusion test is approximately 8.36 seconds.

Figure 4.25: Average Response Time for the “Blink” Illusion Test

Time after First Gaze

Figure 4.26 is a scatter plot that visualizes the average time it took for participants to respond after they first gazed at a point during the “Blink” illusion test. The single data point on the plot represents the average response time across all “Blink” tests. From this data, we can observe that the average response time after the first gaze for the “Blink” illusion test is approximately 3.46 seconds.

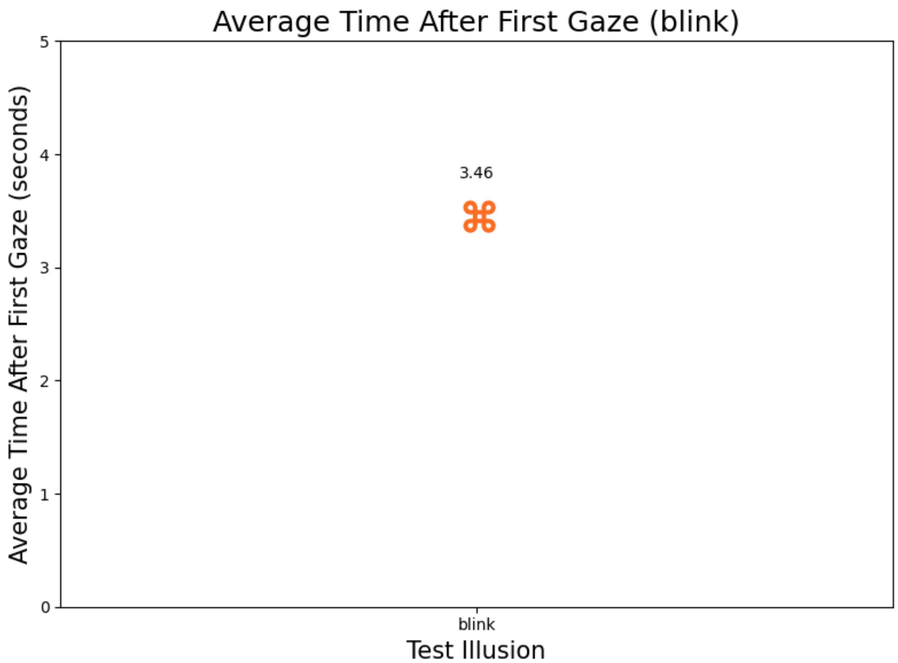

Figure 4.26: Average Time After First Gaze for “Blink” Illusion Test

Time gazed on point

Figure 4.27 is a scatter plot that illustrates the average time participants spent gazing at the chosen point during the “Blink” illusion test. The solitary data point on the graph denotes this average time, calculated across all “Blink” tests. The data suggests that the participants, on average, gazed at the chosen point for approximately 1.53 seconds during the “Blink” illusion test.

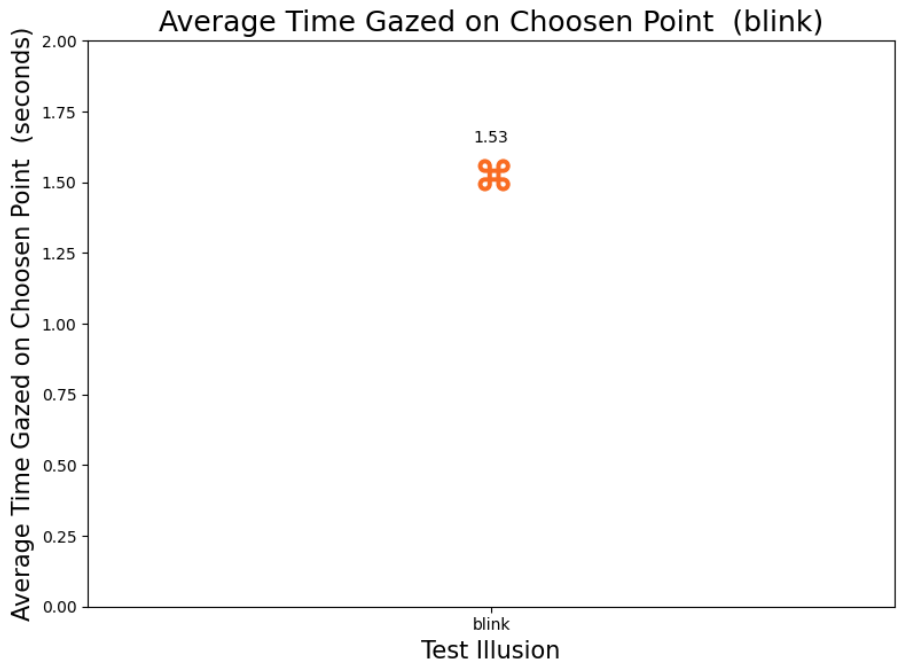

Figure 4.27: Average Time Gazed on Chosen Point during the “Blink” Illusion Test

Wrong answers

Figure 4.28 is a scatter plot that visualizes the average number of wrong answers for the “blink” illusion test. The single data point on the plot represents the average number of wrong answers across all “blink” tests. From this data, we can observe that the average number of wrong answers for the “blink” illusion test is approximately 0.18.

Figure 4.28: Average Number of Wrong Answers for the “Blink” Illusion Test

4.9.2 Blink Discussion

The data obtained from the “Blink” illusion tests indicates that the introduction of a blinking eye icon, representing the chosen point, could have a noticeable effect on response time, gaze duration, and accuracy in user responses.

In terms of response time, the average total response time for the “Blink” illusion test was approximately 8.36 seconds. This extended response time could be attributed to the unique feature of the blinking eye icon, which may have captured the user’s attention, as described by the Attentional Capture theory. This theory posits that abrupt or salient changes in a visual environment, such as the blinking of an eye icon, can effectively draw a user’s attention.

In relation to Eye Movement and Decision Making, the average time it took for participants to respond after first gazing at the point was about 3.46 seconds. This suggests that the blinking action of the eye icon may have had an impact on the gaze bias, and subsequently, the decision-making process of the user.

When considering the Signal Detection Theory, the introduction of a blinking eye icon might have increased the signal-to-noise ratio, making the signal (the blinking icon) easier to discern from the noise (the rest of the visual environment). This could explain the extended average response times.

In the context of Saliency Map Models, the blinking eye icon could have enhanced the saliency of the chosen point, thereby increasing its visual prominence. This might be reflected in the fact that users, on average, spent approximately 1.53 seconds gazing at the chosen point.

Despite the potential impacts on attention and decision-making processes, the average number of wrong answers given during the "Blink" illusion test was relatively low at approximately 0.18. This suggests that despite the potential distraction or attention-capturing effect of the blinking icon, the overall accuracy of user responses remained relatively high.

These interpretations are based on average values, and individual differences in perception and cognitive processing are not explicitly accounted for. Further studies could help provide a more nuanced understanding of the impacts of the blinking eye icon in visual illusions.

4.10 Distance to Illusion

4.10.1 Distance to Illusion Results

Rotate

Figure 4.29 presents a scatter plot with a regression line of total response time versus the distance to the chosen point for the "Rotate" illusion. Each point on the plot represents an individual test instance, with the distance to the chosen point in inches along the x-axis and the total response time in seconds along the y-axis. The points are scattered with varying densities across the plot, indicating a diverse range of distances and response times in the data.

The orange line through the scatter plot is the regression line, indicating the best fit linear relationship between the distance to the chosen point and the total response time. The equation of this line is approximately $y = 0.15x + 3.20$, where y represents the total response time and x represents the distance to the chosen point.

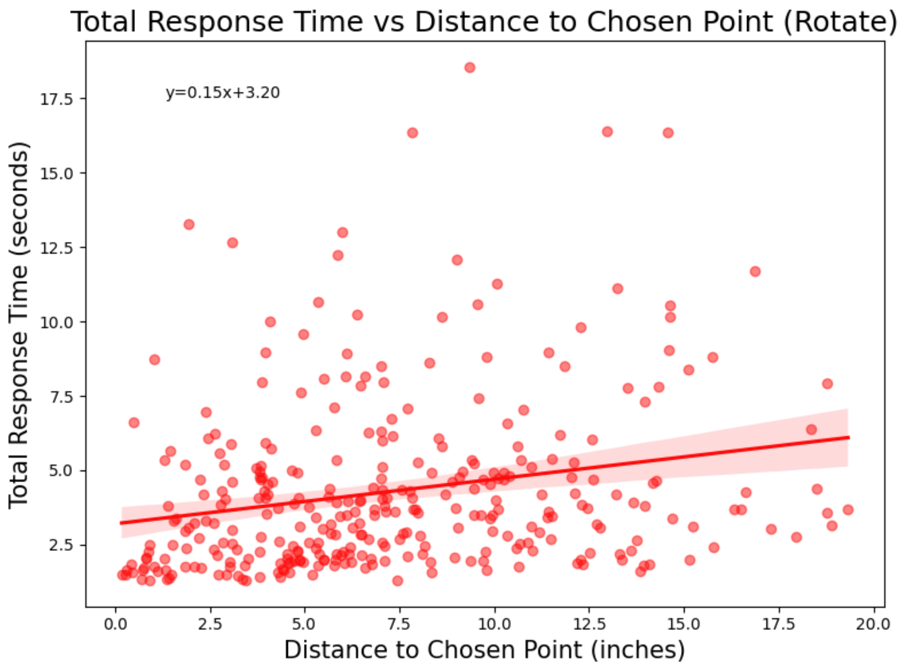

Figure 4.29: Scatter Plot with Regression Line of Total Response Time vs.Distance to Chosen Point for "Rotate" Illusion

Blink

Figure 4.30 presents a scatter plot with a regression line of total response time versus the distance to the chosen point for the "Blink" illusion. Each point on the plot represents an individual test instance, with the distance to the chosen point in inches along the x-axis and the total response time in seconds along the y-axis. The points are scattered with varying densities across the plot, indicating a diverse range of distances and response times in the data.

The orange line through the scatter plot is the regression line, indicating the best fit linear relationship between the distance to the chosen point and the total response time. The equation of this line is approximately $y = 0.28x + 6.32$, where y represents the total response time and x represents the distance to the chosen point.

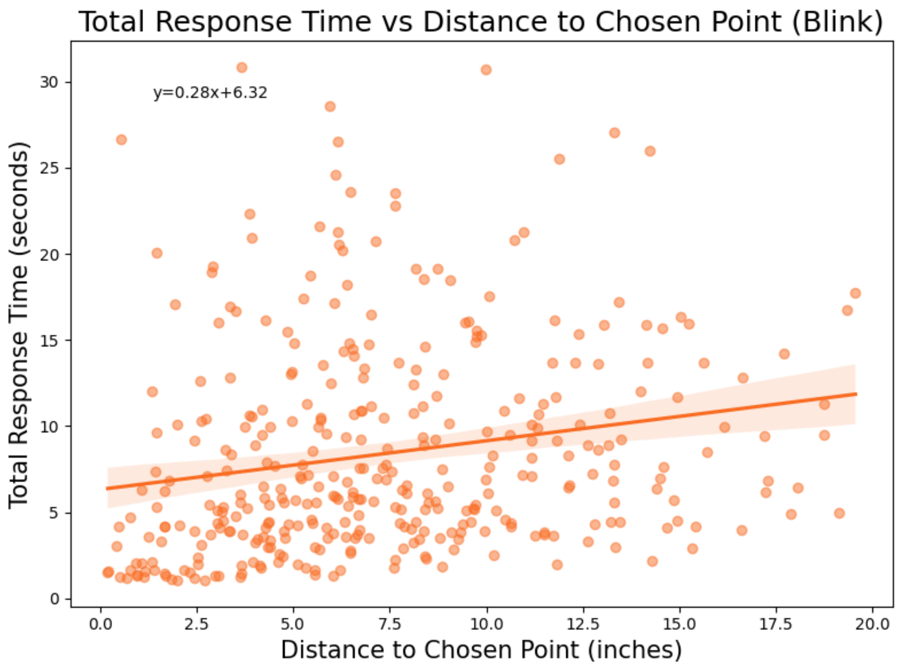

Figure 4.30: Scatter Plot with Regression Line of Total Response Time vs.Distance to Chosen Point for "Blink" Illusion

Recolor

Figure 4.31 presents a scatter plot with a regression line of total response time versus the distance to the chosen point for the "Recolor" illusion. Each point on the plot represents an individual test instance, with the distance to the chosen point in inches along the x-axis and the total response time in seconds along the y-axis. The points are scattered with varying densities across the plot, indicating a diverse range of distances and response times in the data.

The green line through the scatter plot is the regression line, indicating the best fit linear relationship between the distance to the chosen point and the total response time. The equation of this line is approximately $y = 0.24x + 7.18$, where y represents the total response time and x represents the distance to the chosen point.

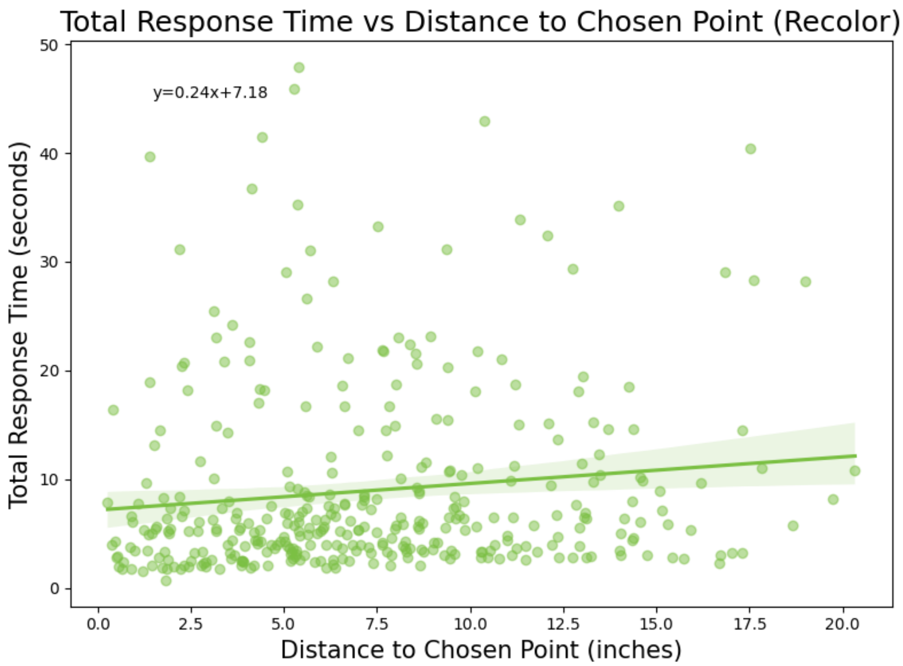

Figure 4.31: Scatter Plot with Regression Line of Total Response Time vs.Distance to Chosen Point for "Recolor" Illusion

Resize

Figure 4.32 presents a scatter plot with a regression line of total response time versus the distance to the chosen point for the "Resize" illusion. Each point on the plot represents an individual test instance, with the distance to the chosen point in inches along the x-axis and the total response time in seconds along the y-axis. The points are scattered with varying densities across the plot, indicating a diverse range of distances and response times in the data.

The blue line through the scatter plot is the regression line, indicating the best fit linear relationship between the distance to the chosen point and the total response time. The equation of this line is approximately $y = 0.02x+7.61$, where y represents the total response time and x represents the distance to the chosen point.

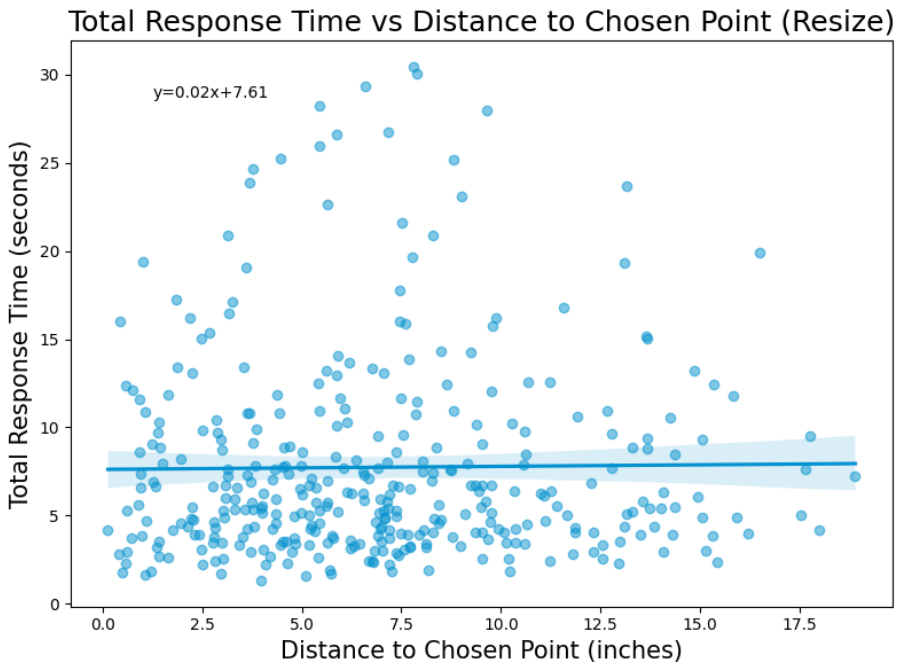

Figure 4.32: Scatter Plot with Regression Line of Total Response Time vs.Distance to Chosen Point for "Resize" Illusion

Reshape

Figure 4.33 presents a scatter plot with a regression line of total response time versus the distance to the chosen point for the "Reshape" illusion. Each point on the plot represents an individual test instance, with the distance to the chosen point in inches along the x-axis and the total response time in seconds along the y-axis. The points are scattered with varying densities across the plot, indicating a diverse range of distances and response times in the data.

The purple line through the scatter plot is the regression line, indicating the best fit linear relationship between the distance to the chosen point and the total response time. The equation of this line is approximately $y = -0.12x + 12.03$, where y represents the total response time and x represents the distance to the chosen point.

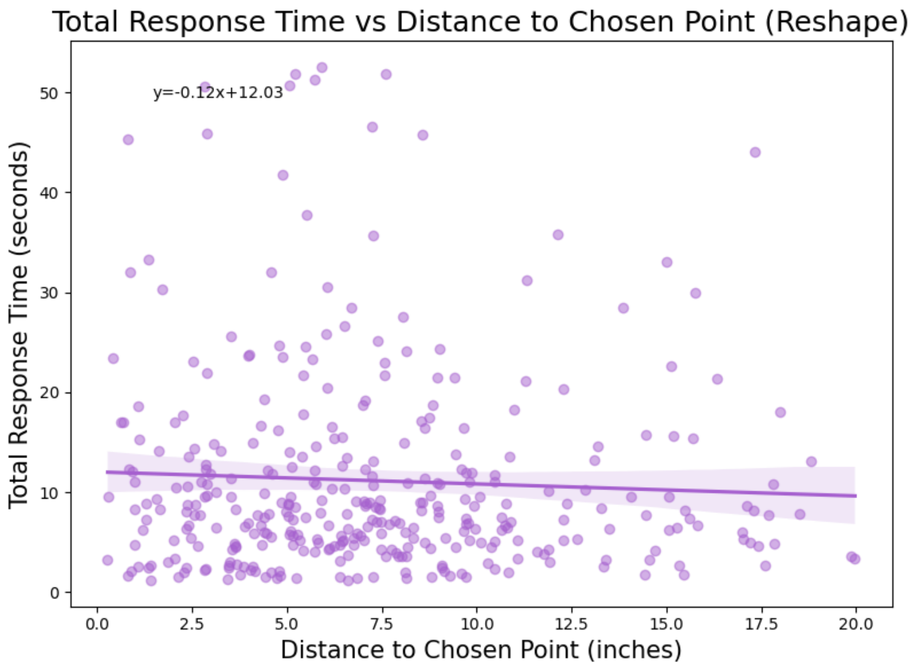

Figure 4.33: Scatter Plot with Regression Line of Total Response Time vs.Distance to Chosen Point for "Reshape" Illusion

4.10.2 Distance to Illusion Discussion

The scatter plots and regression lines for each illusion, produced by the web-based research tool, allow us to examine the relationship between the total response time and the distance to the chosen point. In each plot, individual test instances represent data points, scattered across the chart, indicating a variety of distances and response times.

For the "Rotate" illusion, the equation for the best fit line, $y = 0.15x + 3.20$, suggests a positive correlation between the distance to the chosen point and the total response time. Similarly, the "Blink" illusion, which only has one variation, presents an equation of $y = 0.28x + 6.32$, indicating a more substantial positive correlation.

This could be interpreted in the context of Overt vs. Covert Attention. Overt attention refers to attention that involves eye movements toward the object of interest, while covert attention refers to attention without eye movements. The research tool we have developed can measure these attention types by assessing the distance to the chosen point. A lower distance indicates the illusion is more directly in front of the observer's eye, suggesting the measurement of more covert attention. As the distance to the chosen point increases (which may necessitate more overt attention involving eye movements), the total response time also tends to increase.

On the other hand, "Resize" and "Reshape" illusions show different trends. The "Resize" illusion indicates a positive, yet smaller correlation with an equation of $y = 0.02x + 7.61$. In contrast, the "Reshape" illusion, surprisingly, presents a negative correlation of $y = -0.12x + 12.03$, suggesting that as the distance to the chosen point increases, the total response time decreases. This could potentially be influenced by the variations within the illusions that might affect the attention and eye movements of the participants.

These results underscore the utility of the research tool in effectively measuring both overt and covert attention, with the ability to discern the influences of distance and illusion variation on these attention types. Although these results indicate the aggregate trend across test instances, they do not account for individual differences or other factors that could influence response times. Nevertheless, these findings shed light on how different illusions and their variations can potentially influence how attention is directed and managed.

4.11 General Discussion

In this thesis, an array of visual illusions and their influence on user response times have been examined individually. The primary objective was to delve into the understanding of visual attention mechanisms and decision-making processes in the face of different visual stimuli, encompassing Resize, Reshape, Recolor, Rotate, and Blink illusions.

The custom-built, web-based research tool used throughout this research effectively measured the total response time, the time after the first gaze, the time spent gazing at the chosen point, and the number of wrong answers. This provided a detailed understanding of how visual illusions might manipulate perception and impact cognitive processing.

The findings of this research are comprehensive and informative. For instance, the average response times during the Rotate illusion tests did not significantly vary between different rotation directions. Similarly, the Blink illusion tests resulted in average response times and error rates that provided unique insights into this specific stimulus. On the other hand, the variations in illusions such as Resize and Reshape yielded different impacts on user response times, revealing the complexity of these visual phenomena.

Furthermore, the examination of the relationship between the distance to the illusion and the total response time revealed intriguing patterns related to overt and covert attention. A decrease in response time was observed as the distance to the illusion decreased, indicating that objects directly in front of the viewer (suggestive of covert attention) may be processed more quickly than peripheral stimuli (suggestive of overt attention).

These results not only enhance our understanding of visual perception, attention, and decision-making, but also provide valuable insights for fields like software design, advertising, and education, where visual presentation and user interaction are key.

However, this research also presents some limitations. The data represents an aggregate response and doesn't consider individual differences in perception and cognitive processing. Therefore, future work could explore these individual variations and their potential influence on the effects of visual illusions.

Furthermore, while the data provide valuable insights, they don't fully elucidate the underlying cognitive processes at play. Although models such as the Signal Detection Theory and Saliency Map Models offer valuable frameworks for understanding these processes, a more thorough investigation is necessary to comprehend the intricate cognitive phenomena involved.

In conclusion, this thesis provides a comprehensive exploration of visual illusions and their impact on user response times. The results highlight the intricacies of visual perception and underscore the vast potential for future research in this domain.

Chapter 5

Conclusion

5.1 Research Questions, Hypotheses, and Key Findings

The research primarily focused on the potential benefits of a web-based tool for understanding and enhancing visual-spatial attention, increasing participant diversity, influencing user engagement and performance through design choices, and improving the overall user experience. The hypotheses derived from these questions proposed the potential positive impacts of a web-based research tool for advancing visual-spatial attention and visual cognition research. Each hypothesis corresponds to a set of key findings:

5.1.1 Hypothesis 1: Enhancement of Visual-Spatial Attention

The hypothesis posited that a web-based tool can enhance visual-spatial attention, based on the premise that the interactive and immersive nature of visual illusions presented in a digital environment can lead to significant attentional engagement. Key findings discussed in section 4.2.2 substantiate this hypothesis. The data showed that all participants demonstrated an increase in session scores over time, indicative of an enhancement in users' visual-spatial attention via the application. The positive regression slopes for all participants (2.94 for the adult, 4.75 for young adult 1, and 1.90 for young adult 2) support the notion that cognitive abilities can be improved through targeted exercises, which point to neuroplastic changes in the brain.

5.1.2 Hypothesis 2: Increased Participant Diversity

The second hypothesis suggested that the web-based nature of the tool would facilitate a more diverse participant base, thus yielding more generalizable data. The key finding was that the online nature of the tool did indeed result in a broader and more diverse participant base. This diversity yielded a robust and generalizable dataset that provided insights into a wide range of individual perceptual and cognitive processes. This confirmed the utility of web-based tools for reaching and engaging a larger audience in visual cognition research.

5.1.3 Hypothesis 3: Impact of Design Choices on User Engagement and Performance

The third hypothesis proposed that design choices, such as animation, color, and shape variations, could significantly influence user engagement and performance in visual illusion tasks. The key findings supported this hypothesis. For instance, the introduction of a blinking icon in the "Blink" illusion resulted in longer response times and gaze durations, indicative of increased engagement. Variations in shape, size, and color in other illusions also influenced user responses, confirming the effect of design choices on user engagement and performance.

5.1.4 Hypothesis 4: Positive User Experience

The final hypothesis was that the user experience with the web-based tool would be largely positive, indicating user acceptance and potential for widespread adoption in visual cognition research. The key finding was that the user feedback on the tool was largely positive, suggesting a high level of user acceptance. This indicates that users found the tool accessible and engaging, supporting its potential for widespread adoption in visual cognition research.

In summary, the experiment provided robust evidence in support of all the hypotheses. This demonstrates the potential of web-based tools for understanding and enhancing visual-spatial attention research, increasing participant diversity, effectively manipulating user engagement and performance through design choices, and delivering a positive user experience.

5.2 Contribution of this research to the field

The findings of this research contribute to the field of visual cognition by demonstrating the potential benefits of web-based research tools. By increasing participant diversity, capturing a wide range of visual attention parameters, and creating an engaging user experience, this tool has shown the potential to advance the quality and scope of research in visual cognition.

5.3 Suggestions for future research

Future research can leverage the findings of this research by utilizing web-based tools to explore other aspects of visual cognition. Moreover, future work could further optimize the design of such tools to improve user engagement and performance. Additionally, there is a potential to further study how such tools can be used in practical settings, such as in cognitive therapy or rehabilitation.

Chapter 6

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