

ARCHITECTURAL VISUAL DESIGN – EYE TRACKING ANALYSIS OF CHURCH INTERIORS CREATED USING ARTIFICIAL INTELLIGENCE

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Abstract

The integration of artificial intelligence in scientific research offers novel opportunities and directions for exploration. In this context, an experiment was conducted to examine the application of eye-tracking technology and the indirect insights obtained through OpenAI. This study extends previous research on the design of altars in Catholic churches and their interior architecture. The interior of a church plays a crucial role in fostering the concentration and prayerful engagement of the faithful. Findings from the initial phase of the research were leveraged to design a subsequent experiment. In this phase, visualizations generated using OpenAI's ChatGPT-4.0 were introduced based on predefined guidelines derived from design expertise and prior research outcomes. These guidelines encompassed aspects such as color schemes, architectural styles, and visualization parameters. This article presents the results of the eye-tracking study in this domain as well as providing a comprehensive description of the methodology and the role of artificial intelligence in the research process.

Keywords: Architecture; Visual design; Eye tracking; Altar; Visual analysis; OpenAI; ChatGPT; Artificial Intelligence; AI

Introduction

To explore the potential applications of artificial intelligence (AI) in scientific research, an experiment was conducted that indirectly utilized this technology. AI has demonstrated a positive impact across various fields, including scientific disciplines, by enhancing the quality of products, services, and research processes. However, it is essential to acknowledge that AI should not be employed to generate research results, compose scientific articles, interpret findings, or formulate research methodologies [1]. AI-based tools operate on pre-existing databases, meaning that their outputs and insights are derived from these sources. Given the continuous emergence of new information and research findings, it is crucial to ensure the timely updating of AI source databases to maintain the accuracy and relevance of generated data.

However, this process does not occur instantaneously; therefore, any research findings generated with the assistance of artificial intelligence must be rigorously verified and cross-referenced with traditionally established and reliable sources of knowledge [2]. Nonetheless,

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certain specific aspects of scientific research can benefit from AI support, potentially enhancing both experimental procedures and the reliability of obtained results. At its current level of advancement, artificial intelligence should be regarded as a supplementary research tool, applicable within clearly defined parameters [3]. Importantly, every scientific study represents an original and independent outcome of research efforts, rather than a mere AI-generated response. The experiment discussed in this article was conducted in accordance with this approach, utilizing AI in an indirect and controlled manner.

The foundation of this study was the findings from the initial phase of research, previously published in an article analyzing eye-tracking data from photographs of existing Catholic churches [4]. These results provided insights into which colors could be perceived as neutral by viewers and which elements might divert visual attention. As a continuation of this research, a subsequent experiment was conducted utilizing eye-tracking technology [5]. However, unlike the previous study, this phase did not involve photographs of actual church interiors but instead employed AI-generated visualizations, specifically created using ChatGPT-4.0.

It is important to clarify that throughout the entire study, the only element influenced by artificial intelligence was the generation of 12 visualizations. All other aspects of the research, as well as the entirety of this article, are the product of the author's independent work, ensuring originality and the absence of plagiarism. Furthermore, the AI-generated visualizations used in the experiment are also free from any form of plagiarism [6]. This study exemplifies a hybrid approach, integrating traditional scientific methodologies with a limited yet controlled application of AI-generated content.

Experimental part

The primary objective of this research is to examine how interior design influences visual focus and to identify potential modifications that could enhance this effect. Architectural and design solutions typically stem from the knowledge, experience, and aesthetic sensibility of the architect. Often, these solutions are unique, conceived solely by their creator, and difficult for others to replicate.

However, architecture developed over centuries has been systematically categorized into distinct styles. An architectural style encompasses a collection of recurring elements, details, and design principles that characterize buildings constructed within a specific historical period [1]. This raises a fundamental question: how will contemporary architectural works be classified in the future? Can we already establish categories for them? Additionally, to what extent can architectural solutions from past periods still be applied in modern design? [7].

The conducted research primarily aimed to address two key research hypotheses:

Does the color scheme of an interior influence the level of concentration of individuals in religious spaces? Or is form a more significant factor?

Can AI-assisted architectural design contribute to improved designs and more effective solutions?

Both the research process and the discussion of results were structured to provide the most comprehensive answers to these hypotheses. In contemporary scientific research, it is essential to explore and evaluate all available technologies, including artificial intelligence. Within this broad and evolving field, any tool that enhances efficiency, optimizes workflows, or improves the precision of research outcomes warrants serious consideration.

Materials

The materials utilized in this research included findings from the initial phase of the study, AI-generated visualizations, an eye-tracking experiment involving several dozen participants, and data analysis through statistical summaries, tables, and charts.

Generating 12 visualizations using ChatGPT-4.0 required the formulation of highly specific guidelines to achieve the intended graphical representations. Similar visualizations could have been manually created using CAD architectural design software and graphic visualization tools. However, the integration of artificial intelligence introduces entirely new possibilities for exploring architectural interior design.

One of AI's most significant advantages over traditional design methods is the exceptionally rapid generation of visualizations, often within seconds. In contrast, producing a comparable visualization using conventional graphic software would require at least one to two days of manual work. However, a major limitation of current AI-based design tools is the lack of precise control over visualization parameters [8]. The user is unable to make even minor adjustments, as requesting modifications in ChatGPT often results in the generation of an entirely new and different visualization. Consequently, users seeking greater control over the final output must rely on graphic software to manually refine and modify the generated images.

Below is an example demonstrating the generation of three distinct visualizations despite using identical input parameters in ChatGPT-4.0:

Text input used to generate the visualizations in ChatGPT-4.0:

"Create a visualization of the interior of a church and an altar in a modernist architectural style. The altar of a Catholic church seen from the perspective of a person standing just outside the entrance to the church and looking towards the altar. Create a color scheme for the church interior and altar based on RGB (46, 43, 42), RGB (60, 52, 45), RGB (63, 54, 42), RGB (62, 63, 63), RGB (77, 87, 91), RGB (61, 58, 53), RGB (100, 100, 100), RGB (78, 76, 72), RGB (78, 73, 63), RGB (78, 73, 63), RGB (96, 54, 42), RGB (66, 63, 57), RGB (72, 36, 11), RGB (50, 50, 45), RGB (54, 51, 45), RGB (76, 83, 89), RGB (30, 25, 15), RGB (82, 78, 73), RGB (88, 83, 76), RGB (89, 85, 76), RGB (20, 11, 2), RGB (76, 73, 62), RGB (76, 71, 66), RGB (58, 49, 37), RGB (55, 46, 33), choose the proportions of each color at your own discretion. Horizontal visualization format with dimensions of 1920 pixels x 1080 pixels."

Below, in Fig. 1, three visualizations are shown as a response to the same descriptive guideline. As can be seen, artificial intelligence creates quite similar graphic visualizations, but in form and architecture the interiors of the churches differ quite significantly.

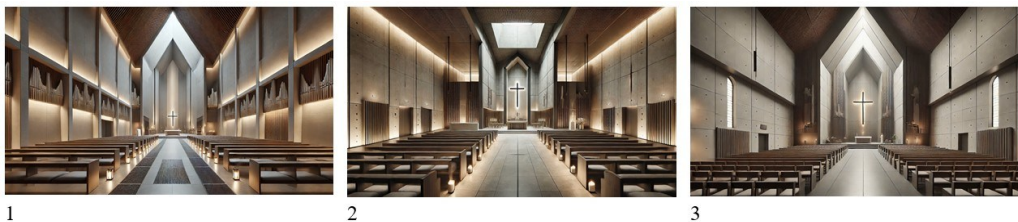


Fig. 1. Three (1, 2, 3) visualizations generated by ChatGPT 4.0, obtained on the basis of the same descriptive guideline, show significant differences in terms of interior architecture and perspective.

First and foremost, the observed differences stem from variations in the design of the church interior. The arrangement of the altar and the walls of the main nave differ, the perspectives and angles of view vary, and the lighting conditions are depicted inconsistently [9]. Additionally, the size of the nave and the viewer's perceived distance from the centrally positioned altar are rendered differently. Although these differences are not necessarily critical or highly pronounced, they nonetheless influence the perception of the interior and its architectural composition.

These variations highlight a key limitation: ChatGPT generates a distinct visualization with each iteration, even when provided with identical guidelines. This suggests that AI offers an effectively infinite number of possible design solutions in response to the same prompt. A particularly intriguing avenue for further research would be the refinement and expansion of input guidelines to progressively reduce the number of variable elements and details across different visualizations. This could provide insight into the extent to which AI-generated architectural designs can be standardized or controlled.

Another notable issue observed in the generated visualizations is the presence of geometric and color inconsistencies. While the overall composition may appear correct at first glance, closer examination reveals distortions that create only an illusion of accuracy. These imperfections further illustrate the current limitations of AI-assisted architectural visualization and highlight areas for potential improvement in future iterations of such technology.

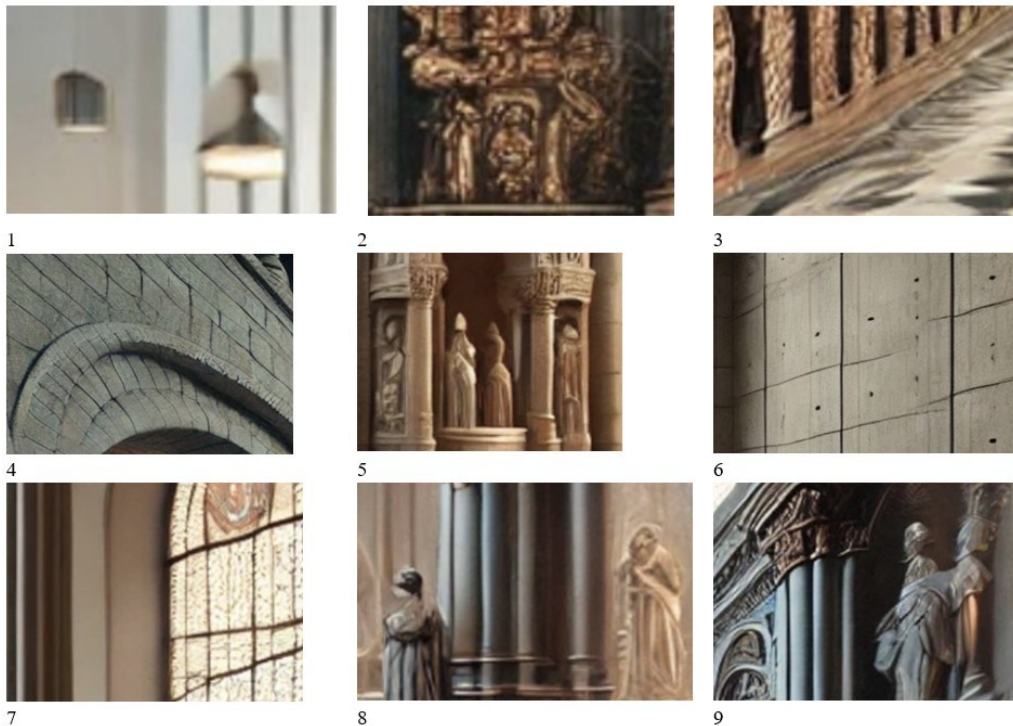


Fig. 2. Deformed elements visible approximately on the obtained visualizations used in the experiment. 1-deformation of the lighting lamp, 2-indistinct ornaments, 3-deformation of the floor and pews, 4-deformation of the arrangement of the wall stonework, 5-indistinct figures, 6-incorrect and distorted division of wall panels, 7-deformation of the stained glass muntin bars, 8-illegible statues of saints, 9-distorted statue and architectural elements.

The deformed details visible upon closer inspection have been highlighted above. These distortions primarily affect elements related to statues, ornaments, architectural structures, and construction details. In the case of figures, only general outlines are discernible, while facial features, hands, and clothing lack accurate definition. Additionally, numerous sections of windows and walls exhibit deformation. The ornaments depicted in the visualizations do not maintain coherent geometry when examined closely. Their appearance often resembles an arbitrary collection of shapes and colors, superficially mimicking architectural elements such as column capitals [10]. Upon closer inspection, these details take on an abstract, undefined form, leading to the assertion that the generated visualizations exhibit characteristics akin to impressionist abstraction.

Despite these errors and deformations in detail, the overall integrity of the experiment remains unaffected, as these imperfections are only noticeable upon close examination. When viewing the entire visualization holistically, these inconsistencies are not readily apparent. Moreover, each study participant was exposed to a visualization for only five seconds, a duration determined based on prior research [11]. This time frame was deemed appropriate for architectural visualizations, as it allows for an adequate number of fixations without causing excessive dispersion of attention or compromising the validity of the results.

Building upon findings from the initial phase of the research, as presented in the article *Architectural Visual Design—Eye-Tracking Analysis of Church Altars: A Case Study* [30], specific neutral colors were identified. The selection of these colors was based on areas in the images that participants did not fixate on during the experiment. These colors were recorded using the RGB (Red, Green, Blue) format and were incorporated into the initial parameters for the AI-generated visualizations created by OpenAI.

(46,43,42)	(60,52,45)	(63,54,42)	(62,63,63)	(77,87,91)	(61,58,53)	(100,100,100)
(78,76,72)	(78,73,63)	(78,73,63)	(96,54,42)	(66,63,57)	(72,36,11)	(50,50,45)
(54,51,45)	(76,83,89)	(30,25,15)	(82,78,73)	(88,83,76)	(89,85,76)	(20,11,2)
(76,73,62)	(76,73,62)	(76,71,66)	(58,49,37)	(55,46,33)		

Fig. 3. Based on preliminary research and the previously conducted eye-tracking experiment, a set of colors was identified in the results that were not in the field of interest of the people participating in the study (Red, Green, Blue), and based on these colors, a guideline was introduced for the color palette of the visualization.

In order to obtain 12 visualizations of the interiors of Catholic churches using artificial intelligence technology (ChatGPT), it was necessary to define descriptive guidelines. The introduced descriptive parameters were divided into several elements.

The first was to introduce a general task and specify the style of the church architecture expected to be in it.

“Create a visualization of the interior of the church and the altar in the architectural style of classicism.”

Next, a guideline was introduced specifying how the shot should be generated, i.e., from what perspective.

“The altar of the Catholic church seen from the perspective of a person standing right at the entrance to the church and looking towards the altar.”

The next scope was to introduce the expected color palette of colors specified by the RGB color system. In order to obtain freedom in using colors, a description was added specifying the proportions of using each color at the discretion of AI.

“Create a church interior and altar color scheme based on RGB (46, 43, 42), RGB (60, 52, 45), RGB (63, 54, 42), RGB (62, 63, 63), RGB (77, 87, 91), RGB (61, 58, 53), RGB (100, 100, 100), RGB (78, 76, 72), RGB (78, 73, 63), RGB (78, 73, 63), RGB (96, 54, 42), RGB (66, 63, 57), RGB (72, 36, 11), RGB (50, 50, 45), RGB (54, 51, 45), RGB (76, 83, 89), RGB (30, 25, 15), RGB (82, 78, 73), RGB (88, 83, 76), RGB (89, 85, 76), RGB (20, 11, 2), RGB (76, 73, 62), RGB (76, 71, 66), RGB (58, 49, 37), RGB (55, 46, 33) choose the proportions of each color according to your own discretion.”

The last guideline was to indicate the proportions and resolution of the visualization. These are guidelines resulting from the parameters of the equipment in the eye-tracking laboratory.

“Horizontal visualization format with dimensions of 1920 pixels x 1080 pixels.”

Different descriptions were introduced in place of the style. In order to verify the presentation of different interiors and architecture, 12 visualizations were planned. The rest of the text was unchanged for each visualization. The styles indicated for creating the visualization are 1-modernist, 2-baroque, 3-classicist, 4-eclectic, 5-romanesque, 6-contemporary, 7-parametric architecture, 8-romantic, 9-art nouveau, 10-expressionist, 11-minimalist Japanese architecture with reinforced concrete elements, and 12-surrealist.

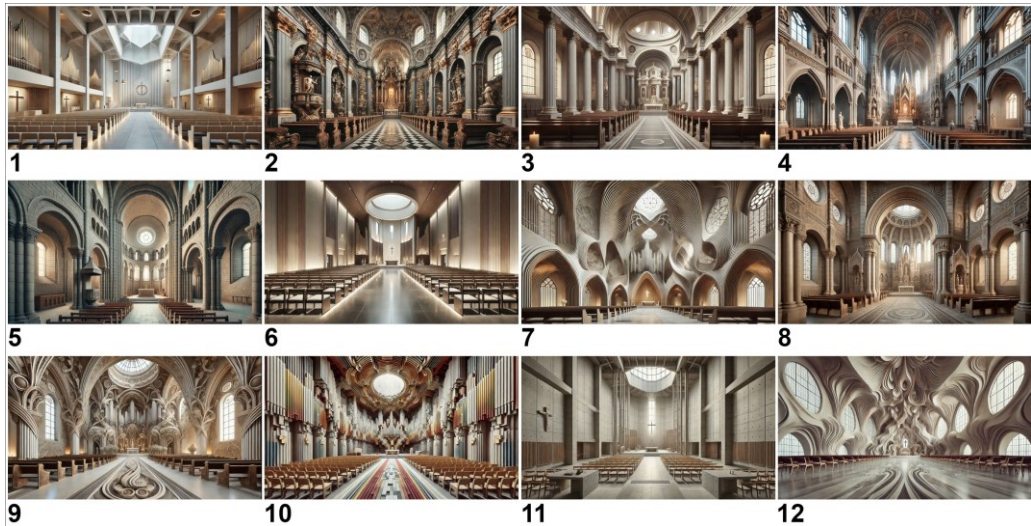


Fig. 4. Visualizations obtained on the basis of the descriptive guidelines introduced in ChatGPT 4.0.

An important challenge worth addressing is the relative difficulty in obtaining AI-generated visualizations that align precisely with the intended design requirements. ChatGPT occasionally produces extraneous or incomprehensible elements that were not specified in the input guidelines. As a result, the visualization generation process often needs to be repeated multiple times until a suitable version is achieved [12]. This necessity complicates the workflow, as even when a visualization meets the general research criteria, the presence of unwanted elements may render it unusable. Furthermore, the inability to make minor modifications directly within the AI-generated image necessitates regenerating the visualization, leading to unintended variations in interior design, architectural style, and overall composition [6].

Among the most common unwanted elements in AI-generated visualizations, the following can be distinguished:

A. Unnecessary color palettes. In some cases, ChatGPT includes a color palette overlay within the visualization, indicating the colors used in the generated image. While this might be useful in other contexts, it is redundant for this study and the eye-tracking experiment. If such elements were retained, they would interfere with the results by drawing attention away from the architectural features under investigation.

B. Human silhouettes. Previous research findings indicate that human figures attract disproportionate visual attention, significantly influencing fixation points [7]. This phenomenon is likely rooted in human cognitive processing, as the brain is naturally inclined to detect and focus on human faces and silhouettes [8]. Consequently, the inclusion of such elements in AI-generated visualizations introduces an unintended bias in the experiment and must be avoided.

C. Incorrect visualization format. Despite explicitly defined guidelines regarding image proportions, ChatGPT occasionally produces visualizations in unintended formats. Adhering to the specified dimensions is crucial, as the research equipment used for the eye-tracking

experiment is calibrated for particular aspect ratios. Any deviation from these standards could compromise the accuracy and comparability of the results.

These challenges illustrate the inherent unpredictability of working with ChatGPT-4.0. Despite the provision of detailed input parameters, achieving the desired visualization format and style remains inconsistent, highlighting a key limitation in the use of AI-generated imagery for scientific research.

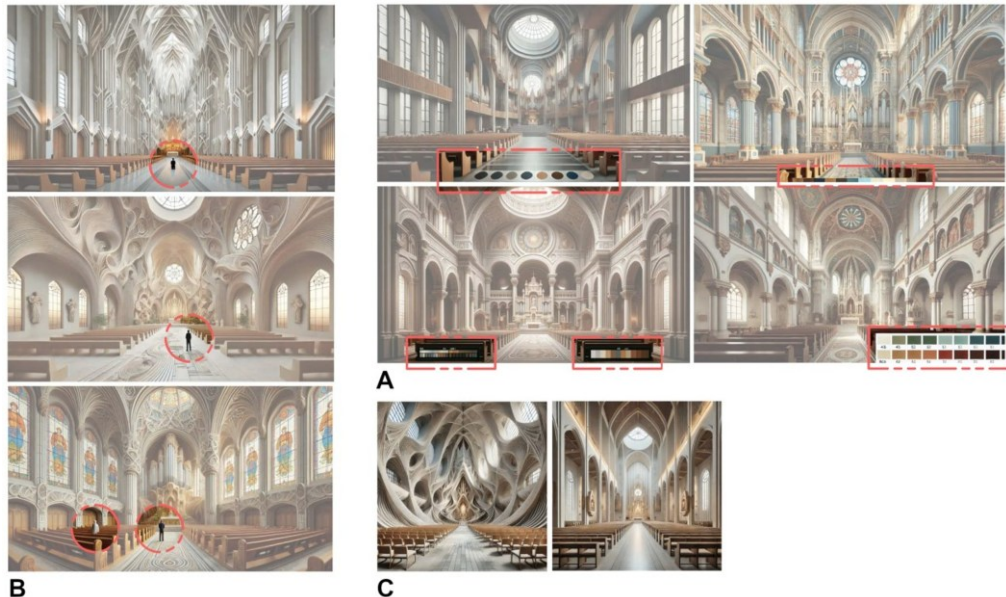


Fig. 5. Visualizations obtained with unwanted elements A-graphic representation of the color palette, B-silhouettes of people, C-incorrect visualization format.

Methods

The conducted research used eye-tracking techniques to record and analyze where and how long respondents looked when stimuli in the form of visualizations of church interiors were displayed to them. An experiment was prepared and carried out on an eye-tracking stand equipped with the Tobii TX300 eye tracker (Tobii AB, Sweden, <http://www.tobii.com>). It is a stationary, binocular, video-based device that operates in the near infrared and uses a dark pupil and corneal reflection to calculate gaze position. This device tracks and records the movements and resting states of both eyes 300 times per second, i.e., every 3ms. The Tobii TX300 operates with an accuracy of $0.4\text{--}0.9^\circ$ and precision of $0.04\text{--}0.15^\circ$ depending on lighting conditions, gaze angle, and other factors. During this type of study, there is no need to immobilize the subject's head; the participant can move his head freely within the same range (width $\times$ height: 37×17 cm, at a distance of 65cm from the eye tracker to the eyes) [9].

Stimuli were displayed on a 23-inch, 1920×1080 widescreen TFT monitor integrated with the eye tracker unit. The eye tracker and monitor were connected to the Asus G750JX-T4191H laptop (Intel Core i7-4700HQ, 8GB RAM) with the Windows 10 operating system running the Tobii Studio version 3.3.2 software (Tobii AB, Sweden, www.tobii.com). Participants' eyes were positioned between 65 and 75cm from the eye tracker.

The experiment was conducted in the laboratory of the Department of Computer Science located at the Centre for Innovation and Advanced Technologies at the Lublin University of Technology. The room where the research took place was soundproofed and lit by artificial light. During the research there were two people in it: the participant and the moderator, who supervised the experiment. Each participant, after giving their consent to participate in the study, was informed about the purpose and conduct of the experiment and was instructed not to

move but to look at the screen during the study. After the subject took the appropriate position on the chair and the moderator collected sociodemographic data, a 9-point automated calibration was performed to accurately calculate the gaze point. Then the actual experiment began, during which the participants were shown 12 boards showing the interiors of churches. Each visualization was displayed for 5 seconds. During this time subjects freely viewed the slides, and they did not have any specific task to perform. Each slide was followed by a 2-second break during which a blackboard was displayed. Subsequent slides were displayed automatically.

As a result, 65 video recordings were obtained, showing a sequence of sequentially displayed church interiors along with a pointer changing its position over time, showing the current position of the subject's gaze point. Eye gaze data from multiple subjects superimposed on the visual stimulus enabled the generation of heat maps, opacity maps, and scan path maps. These three types of result visualization, which involve displaying data directly over the elements to which they refer, reduce cognitive effort and therefore allow for quick and easy understanding of data [10]. Heat maps are a way of presenting results in which colors are used to indicate where and how long subjects focus their visual attention on the presented stimuli. They are generated on the basis of the cumulative number of fixations or fixation durations for all participants. This type of imaging is useful when the goal of the study is to determine the amount of interest in stimulus elements during free browsing, i.e., in tasks without specific instructions to do, which was the case in this experiment [11]. Whereas scan paths are created as a result of making a series of eye movements and consist of fixations (circles) and saccades (lines). The numbers in the circles show the order in time of fixations, and the saccades illustrate the direction of the respondent's visual attention moves. The visualization of all scan paths of participants who took part in the experiment on a specific stimulus takes the form of a multicolored cloud of circles connected by lines, i.e., fixations connected with saccades. On the other hand, the gaze opacity maps, being an inverse of the heat maps using black and white shades, only reveal those areas that were noticed by the subjects, hiding the others not explored by them.

Figures 7.A-18.A show heat maps for the 12 stimuli displayed to participants during the experiment. In order to enable reliable comparison of the level of attention between different visualizations (stimuli), a global scaling of the data was performed, i.e., normalization, after which the amount of "heat" would be proportional to the level of the represented variable, in this case the number of fixations on the captured unit area. The upper threshold of the number of fixations was determined experimentally so that the heat map would correctly reflect the range of values from the perspective of the study conducted and thus allow easier visual assessment of the acquired data [10].

For the purpose of analyzing the results, the so-called intensity of attention (IA) metric was used on the hot area, which means the concentration of fixations per unit area of the stimulus. For the 12 stimuli used, the maximum number of fixations ranged from 9 to 24 fixations per unit area (fpa) of the stimulus. In the analyses, an area of 50px square was used to count the number of fixations, which was placed in the hot areas defined by heat maps. The average intensity calculated for all visualizations was taken as 22fpa based on the results provided by the software Tobii Studio.

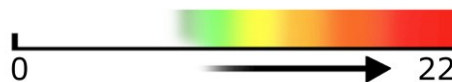


Fig. 6. The legend for all heat maps after normalization, number of fixations.

Based on the hot spots identified in the heat maps, that is, the places where attention is focused on elements of the analyzed stimulus, regions of interest (AOIs) were created. For these areas, descriptive statistical measures were calculated and used for further qualitative analyses. AOI analysis involves assigning eye-tracking data to specific areas of interest or elements of the

visual scene [15-13]. These regions of interest enable researchers to analyze and compare various visual indicators within them [6]. In this study, the following indicators were considered: time to first fixation (TTFF) in a specific AOI, mean fixation duration (FD) within the AOI, and the percentage of participants (PF) who fixated at least once within an AOI.

Based on the average time to first fixation expressed in seconds, it is possible to identify the most important or most attractive object or scene area for observers. In turn, the average fixation duration can indicate the depth of perceptual and cognitive processing [15, 21]. Generally, the longer the fixation duration, the deeper the processing. When multiple areas of interest are present, average fixation durations can be calculated and compared, allowing researchers to determine which areas were viewed longer than others. In this way, it is possible to determine which areas or objects in a visual scene are of greatest interest to observers or contain complex and difficult visual content [12]. The last parameter indicates the percentage of participants whose gaze fell within the AOI at least once.

Figures 7.B-18.B present scan path maps generated for all subjects in the experiment across successive static stimuli. The circles represent fixations, with their size indicating fixation duration and the number showing the fixation order. Scanpaths can illustrate the gaze patterns of an individual subject, multiple subjects, or even an entire group, either for a single stimulus or throughout an entire eye-tracking session [9]. Users' paths are distinguished by different colors. Scanpath analysis is particularly useful for exploratory tasks that do not have a specific goal [13].

In addition to the eye-tracking study, an additional research method was employed, which involved comparing the color and contrast in areas with an increased level of fixation. For this purpose, appropriate graphic processing of the images was performed to highlight the differences in color and contrast levels [14]. The purpose of comparing these parameters is to determine whether warm or cool colors and low or high contrast levels influence the selection of areas with increased fixation [7].

Results and discussion

Based on the results of the conducted eye-tracking experiment, the findings outlined below were obtained. Figures 7 through 18 present the heat maps generated for all 65 participants. Each illustration represents a negative result, indicating the areas of greatest visual interest observed by the participants [15]. From these areas, two regions exhibiting the highest levels of interest were selected for each visualization. For each of these areas, the parameters listed in Table 1 were subsequently determined.

Given the nature of the visualization, which depicts a church interior with the altar, the central area of the view was expected to be the primary focus of attention. This is the region that naturally attracts the participants' gaze and is further emphasized by the perspective in the shot. In addition to the central focus, other areas of interest also emerged, corresponding to places where participants directed their attention. The primary observation from the heat maps is that participants tended to focus their gaze on the central element of the visualization—the altar—along with two or three additional objects. 30 The remaining areas were only briefly scanned, likely as part of a search for more engaging elements [9].

An analysis of the collective heat maps from all participants reveals a high degree of similarity in the regions of greatest visual interest. The dominant elements of attention were architectural and religious in nature. A noteworthy observation is the relatively high level of visual focus on the central element, namely the altar and other religious features.

Additionally, the colors identified in Figure 3 as neutral for vision appear to be confirmed as such in the experiment. Interiors rendered in this neutral color palette do not induce excessive eye movement or a high degree of visual dynamics, suggesting that these colors contribute to a more stable and focused viewing experience.

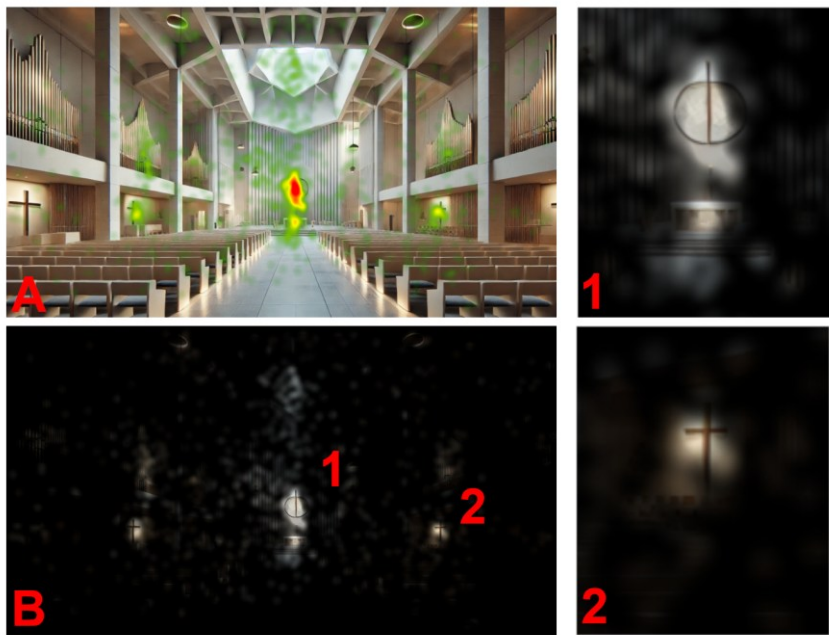


Fig. 7. Image number 1-modernist, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.



Fig. 8. Image number 2-baroque, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

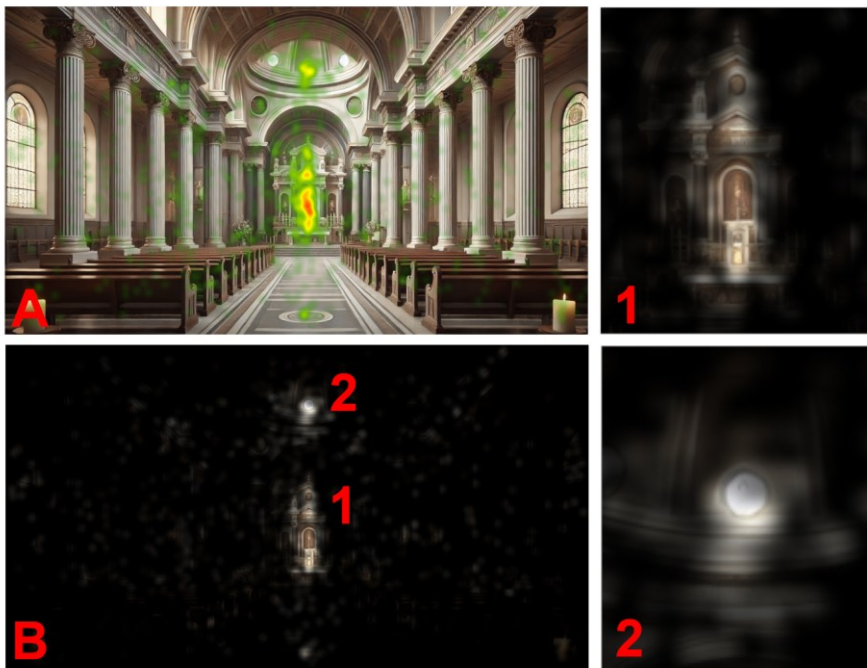


Fig. 9. Image number 3-classicist, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

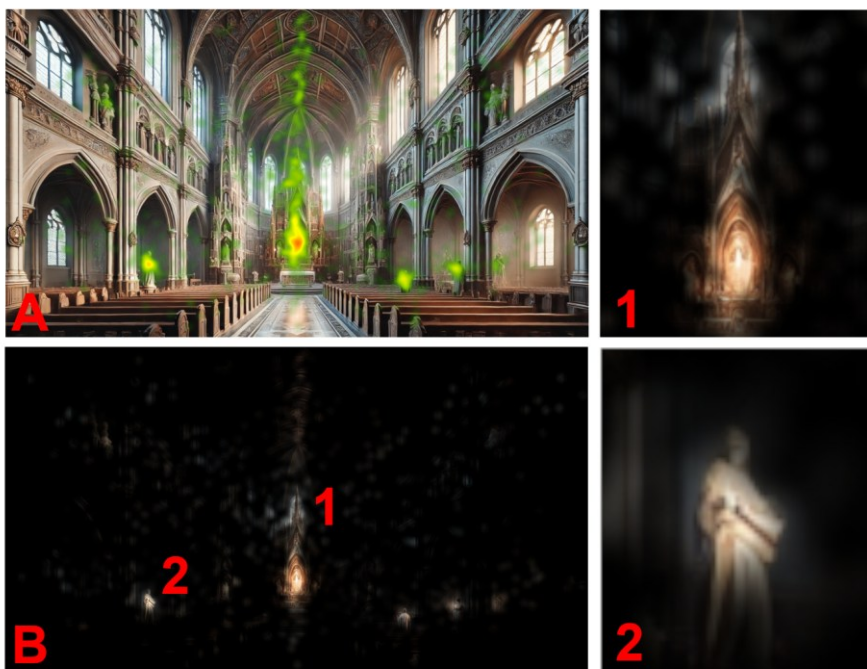


Fig. 10. Image number 4-eclectic, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

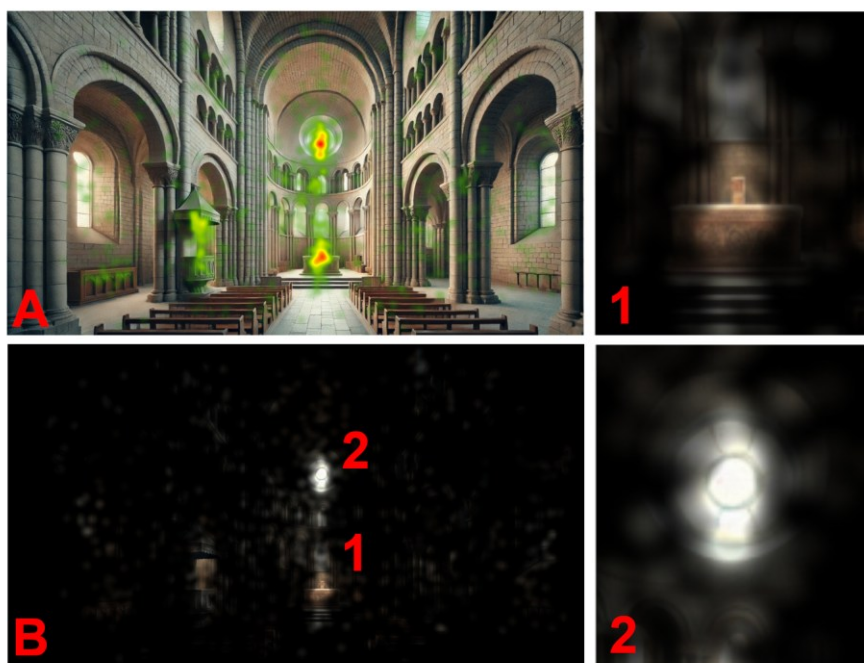


Fig. 11. Image number 5-romanesque, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

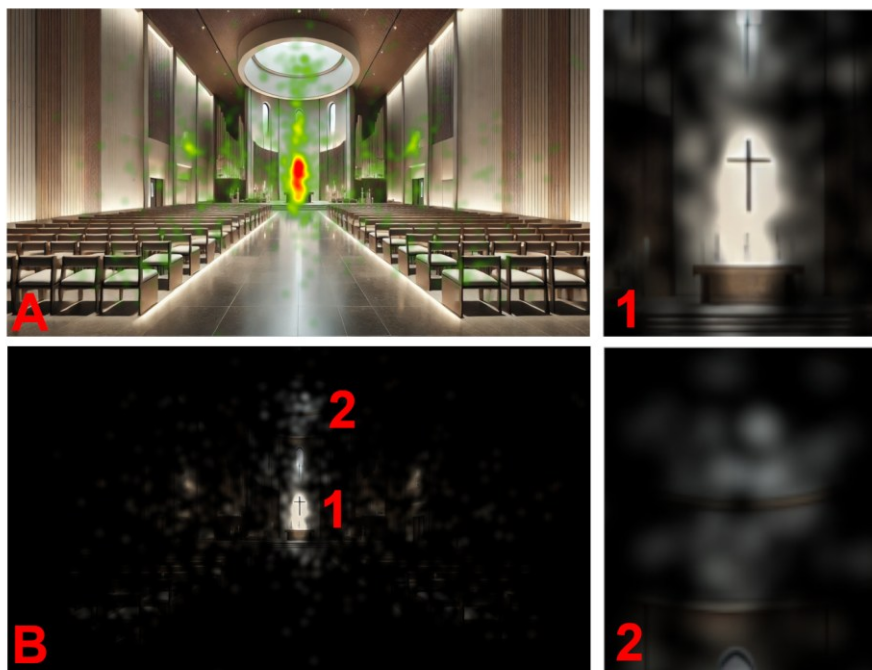


Fig. 12. Image number 6-contemporary, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.



Fig. 13. Image number 7-parametric architecture, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.



Fig. 14. Image number 8-romantic, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

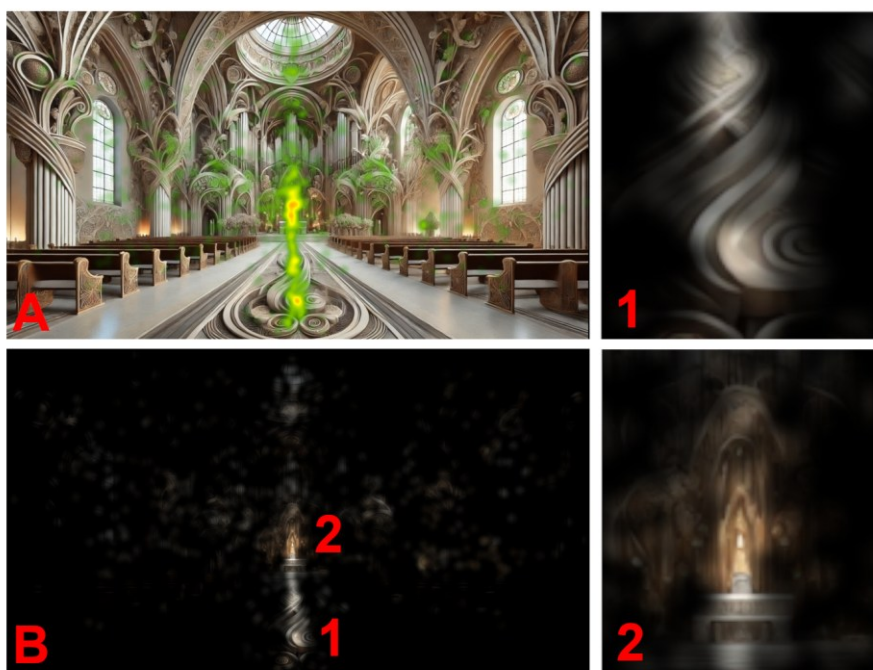


Fig. 15. Image number 9-secessionist, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

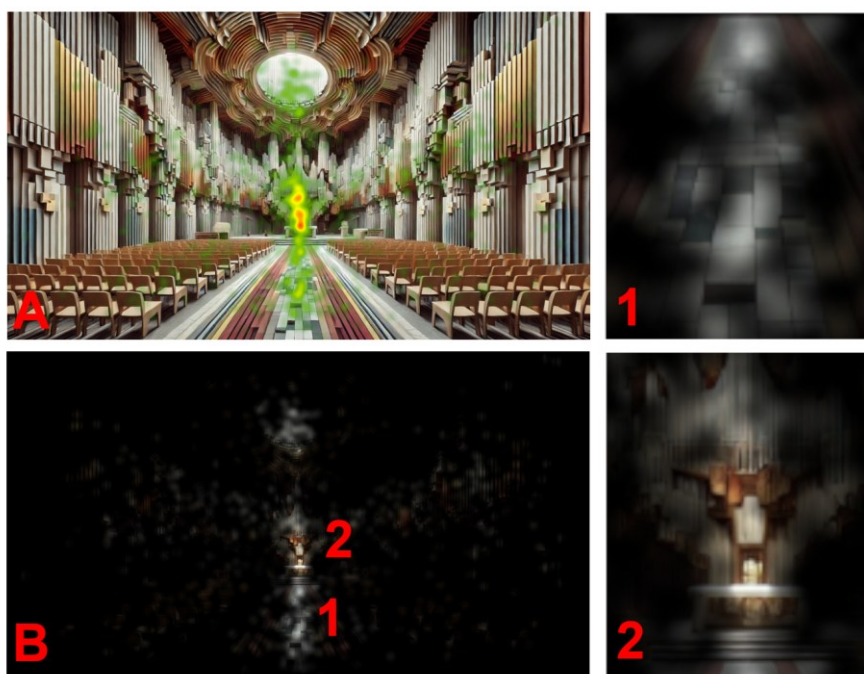


Fig. 16. Image number 10-expressionist, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

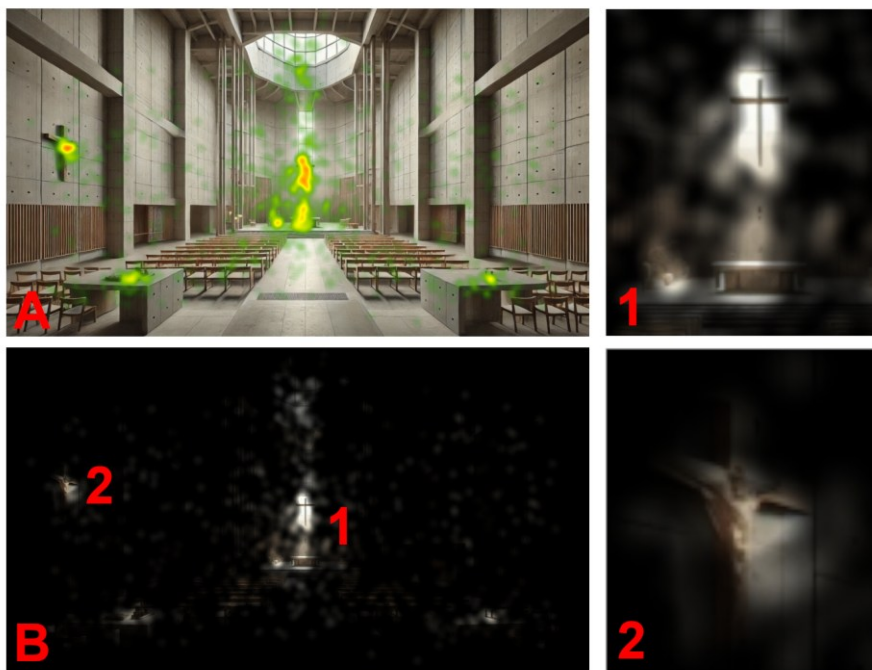


Fig. 17. Image number 11-minimalist Japanese architecture with reinforced concrete elements, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

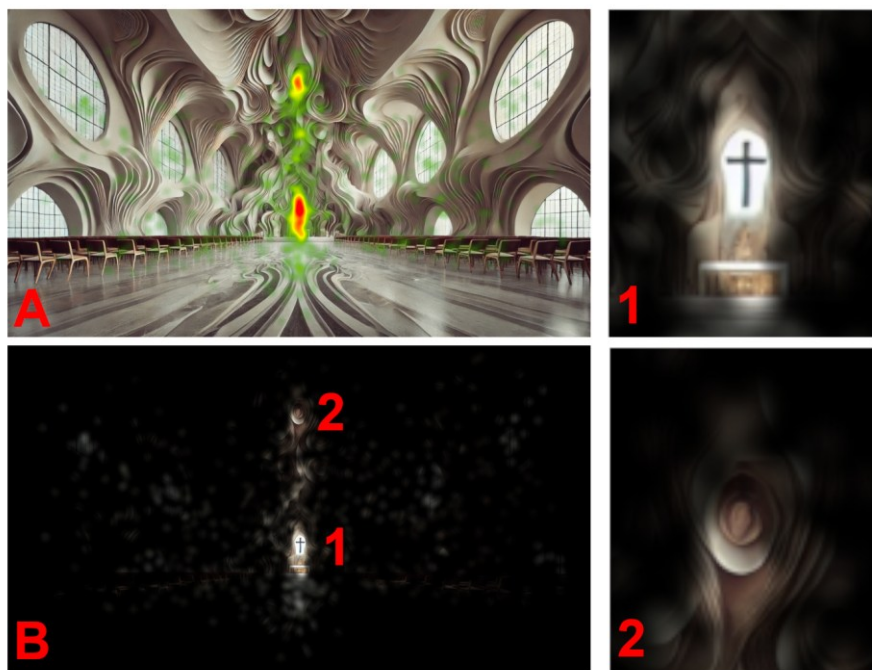


Fig. 18. Image number 12-surrealist, A – results of heat map analysis, B – results of opacity analysis, 1 – first area of greatest interest, 2 – second area of greatest interest.

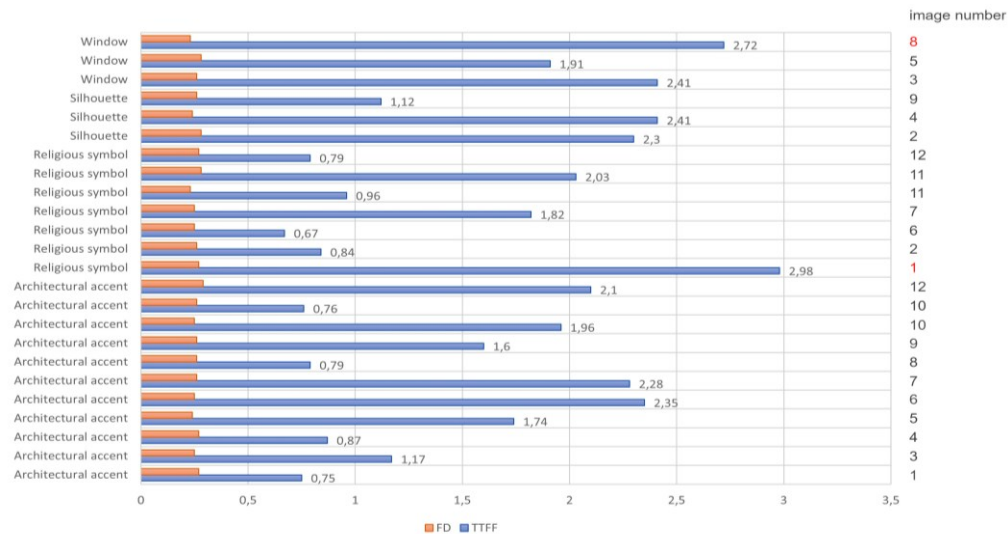


Fig. 19. Graph showing the parameter TTFF, mean time to the first fixation per area of interest, and FD means fixation duration in AOI, obtained in the analyzed 12 visualizations. Significant exceedances at a level of over 2.5 are marked in red.

Table 1 represents the following criteria, which were used in the comparative analysis and comparison charts (Fig. 5-14):

- Image: ordinal number of the examined visualization,
- Spot: 1 - first place of greatest interest, 2 - second place of greatest interest,
- Position: location of the observed element, left, right, centre, top, bottom,
- Subject: silhouette, ornament, architectural accent, religious symbol, window,
- IA: maximum fixations count per unit area (IA expressed in fpa),
- TTFF: mean time to the first fixation per area of interest,
- FD: mean fixation duration in AOI,
- PF: the percentage of participants that fixated at least once within an AOI (in %).

Table 1. Table of various values analyzed in the study in terms of individual images and marked spots. Significant exceedances are marked in red, including for IA over 20, for TTFF and FD over 2.5, and for PF over 0.8.

l	Image	Spot	Position	Subject	IA [fpa]	TTFF [s]	FD [s]	PF [%]
2	1	1	Centre	Architectural accent	24	0.75	0.27	0.88
3	1	2	Right	Religious symbol	10	2.98	0.27	0.51
4	Total	2						
5	2	1	Centre	Religious symbol	12	0.84	0.26	0.83
6	2	2	Left	Silhouette	10	2.30	0.28	0.68
7	Total	2						
8	3	1	Centre	Architectural accent	16	1.17	0.25	0.88
9	3	2	Top	Window	11	2.41	0.26	0.46
10	Total	2						
11	4	1	Centre	Architectural accent	15	0.87	0.27	0.83
12	4	2	Left	Silhouette	10	2.41	0.24	0.52
13	Total	2						
14	5	1	Centre	Architectural accent	19	1.74	0.24	0.88
15	5	2	Top	Window	21	1.91	0.28	0.86
16	Total	2						
17	6	1	Centre	Religious symbol	24	0.67	0.25	0.97
18	6	2	Top	Architectural accent	4	2.35	0.25	0.43
19	Total	2						
20	7	1	Centre	Architectural accent	9	2.28	0.26	0.74

<i>I</i>	Image	Spot	Position	Subject	IA [fpa]	TTF [s]	FD [s]	PF [%]
21	7	2	Top	Religious symbol	6	1.82	0.25	0.63
22	Total	2						
23	8	1	Centre	Architectural accent	18	0.79	0.26	0.95
24	8	2	Top	Window	8	2.72	0.23	0.45
25	Total	2						
26	9	1	Bottom	Architectural accent	13	1.60	0.26	0.69
27	9	2	Center	Silhouette	12	1.12	0.26	0.85
28	Total	2						
29	10	1	Bottom	Architectural accent	8	1.96	0.25	0.66
30	10	2	Centre	Architectural accent	14	0.76	0.26	0.88
31	Total	2						
32	11	1	Centre	Religious symbol	14	0.96	0.23	0.82
33	11	2	Left	Religious symbol	11	2.03	0.28	0.77
34	Total	2						
25	12	1	Centre	Religious symbol	22	0.79	0.27	0.85
36	12	2	Top	Architectural accent	11	2.10	0.29	0.69
37	Total	2						
38	Total	20						

The table below highlights in red the parameters with significant exceedances in the overall scale of results. In visualization no. 1, in position 2, a notable increase in the TTF and FD parameters was observed [14]. A similar increase was observed in visualization no. 8, in position 2. An intriguing aspect of the results showing significant values is that for visualizations no. 1 and no. 8, no corresponding increases in the IA and PF parameters were recorded. The lack of correlation between these parameters suggests several insights. Firstly, despite the highest average time to first fixation and the highest average number of fixations in the selected areas, not all participants exhibited this pattern [17]. For example, in visualization no. 1 in location no. 2, the PF value is 0.51, indicating that only half of the participants fixated on this location. A similar result of 0.45 was observed in visualization no. 8, in location 2, where less than half of the participants observed this area. This discrepancy could be attributed to various factors, including individual characteristics of the participants [18].

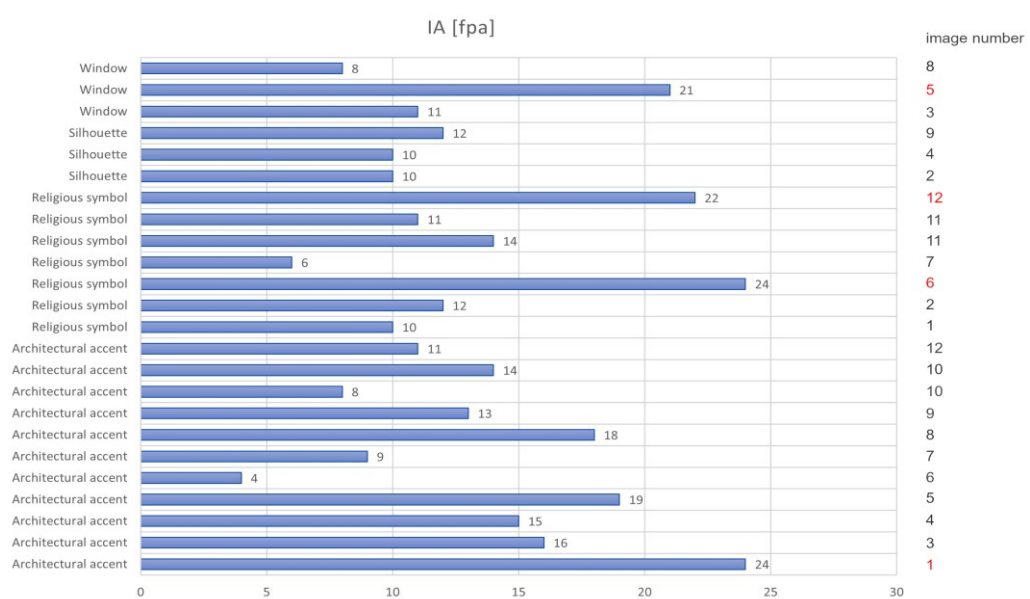


Fig. 20. Graph showing the AI [fpa] maximum fixation count per unit area parameter obtained in the 12 analyzed visualizations. Significant exceedances at a level above 20 are marked in red.

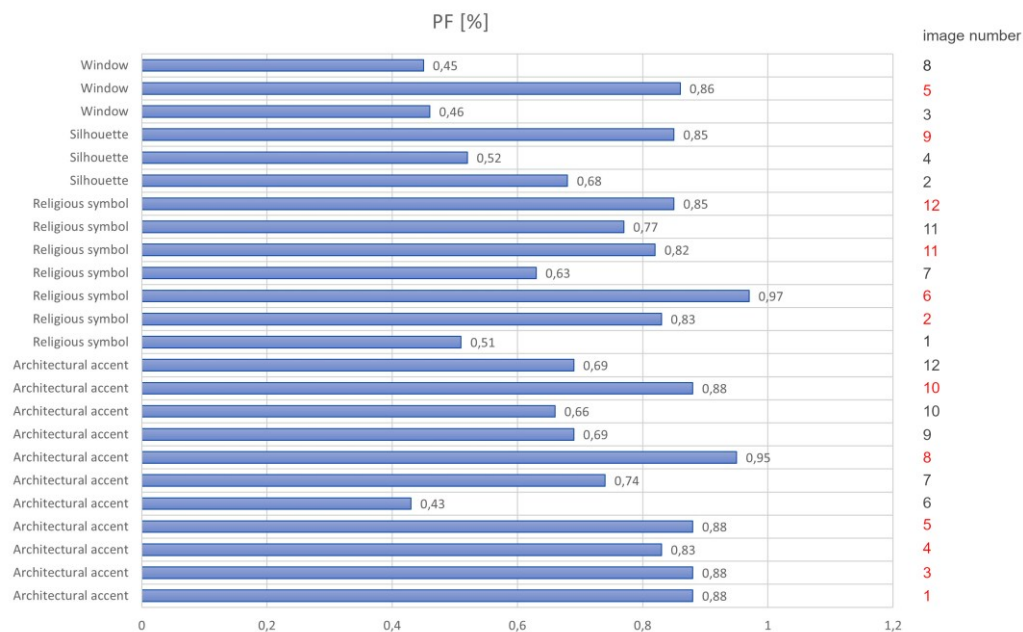


Fig. 21. Graph showing the parameter PF [%], the percentage of participants that fixed at least once within an AOI obtained in the analyzed 12 visualizations. Significant exceedances at the level of over 0.8 are marked in red.

Conclusions

The results obtained from the experiment highlight the significance of the interior's character and its impact on the dynamics of eye movement. Human vision is in a constant state of analysis, continuously processing visual information [16]. This implies that the dynamics of vision are exceptionally high.

The question arises: How can we ensure that human vision is not continually distracted within certain interiors, and how can the level of concentration, particularly in meditative environments, be maximized?

Attention should also be drawn to the results presented in column 9, table 1, which reflect the variation in the number of participants who actually noticed the selected areas. The highest value is 0.97, signifying almost complete attention by participants, while the lowest value is 0.43, indicating that fewer than half of the participants fixated on this location [19].

This considerable variability in fixation rates suggests significant individual differences in attention. It can therefore be concluded that the elevated FD and TTFF values were obtained by a diverse group of participants, with at least 43% showing notable differences in attention. These variations may be linked to individual factors, including personal conditions, reaction time, and perceptual sensitivity.

The results presented in the table also highlight the correlation between the IA and PF indices. In each instance where the IA index exceeds the normative threshold (the highest value used in this study), the PF parameter is similarly elevated [20]. Conversely, this relationship does not hold in reverse; that is, the maximum value of obtained fixations is consistently associated with a large percentage of the study participants. This suggests a strong association between a higher number of fixations and a greater proportion of participants engaging with the focal areas.

The application of eye-tracking technology in architectural design opens up numerous previously unexplored avenues for evaluating spatial quality. This study specifically focused on the analysis of a color palette with neutral properties for human vision [21].

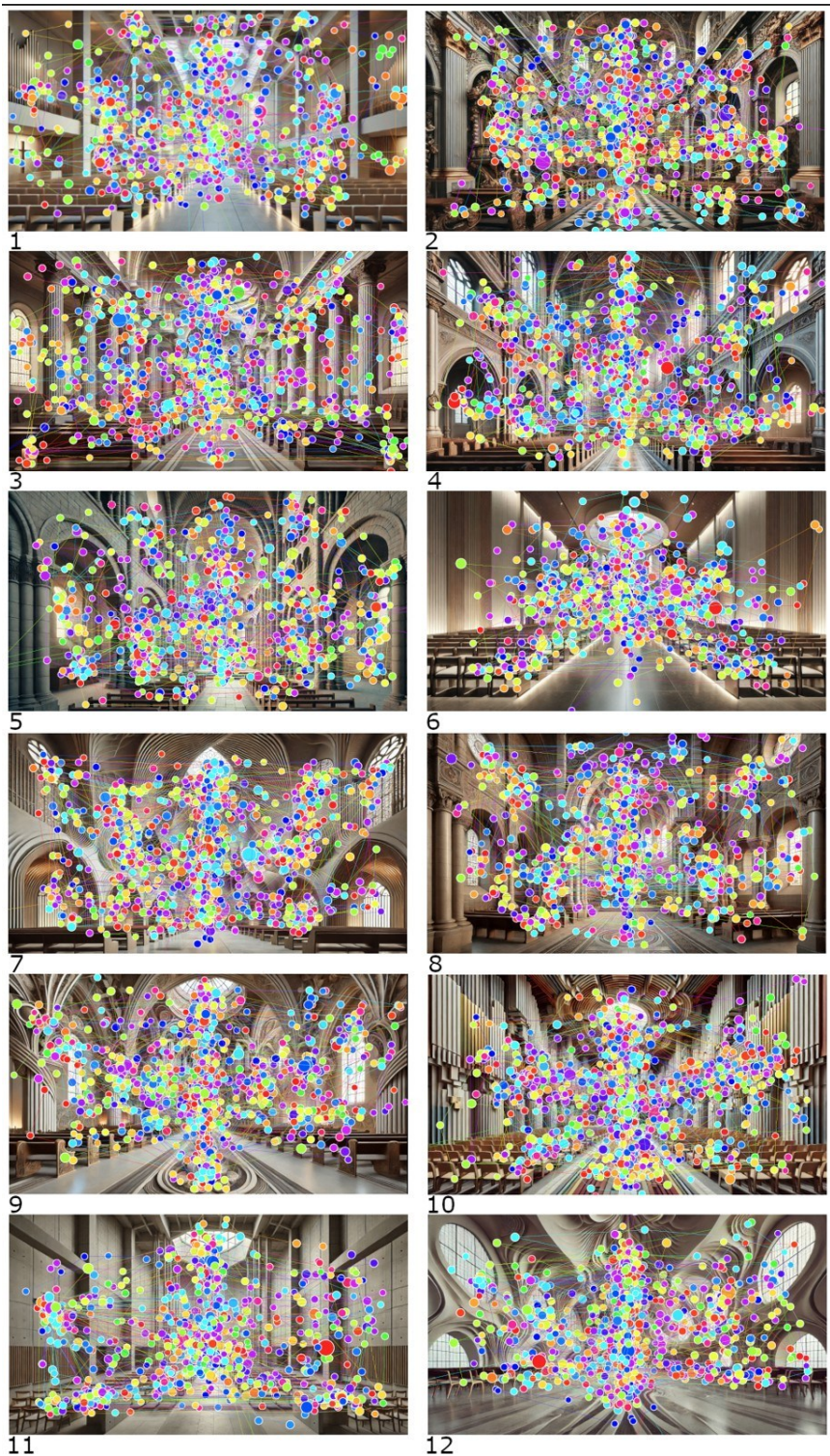


Fig. 22. Analysis of Gaze Plot areas of interest – results.

The results of the experiment provide partial confirmation that the use of such a color range may reduce visual dynamics, thus potentially fostering a higher level of contemplation or meditation within sacred spaces [22]. Furthermore, it was observed, in comparison to previous studies, that visualizations generated using artificial intelligence tools performed equally well in the context of the experiment and in producing reliable results. A notable advantage of these AI-generated visualizations is their photorealism, which closely approximates a photograph of a real interior, to the point of near indistinguishability [23]. Figure 22 illustrates the Gaze Plot results, where an intriguing observation is the absence of any fixations at the edges of the visualization, suggesting that these areas were not considered significant for visual attention.

In conclusion, it can be asserted that when utilized within a defined scope and for specific purposes, artificial intelligence tools can significantly contribute to the acquisition of meaningful and valuable research results [24]. It is also important to recognize that the integration of architectural design with eye-tracking technology holds the potential to yield groundbreaking research outcomes, with tangible implications for the design of architectural spaces.

References

- [1] Y. Liu, Z. Zhou, Y. Xu, *Design Element Preferences in Public Facilities: An Eye Tracking Study*, **Land**, **12**(7), 2023, pp. 1-17. <https://doi.org/10.3390/land12071411>.
- [2] K. Rayner, *Eye movements and attention in reading, scene perception, and visual search*, **Quarterly Journal of Experimental Psychology**, **62**, 2009, pp. 1457-1506. <https://doi.org/10.1080/17470210902816461>.
- [3] S.K. Mannan, K.H. Ruddock, D.S. Wooding, *Automatic control of saccadic eye movements made in visual inspection of briefly presented 2-D images*, **Spatial Vision**, **9**(3), 1995, pp. 363-386, <https://doi.org/10.1163/156856895X00052>.
- [4] W. Krauze, M. Motak, *Neurosciences in architecture. Applied research and its potential in architectural design*, **Teka Komisji Urbanistyki i Architektury Oddział PAN w Krakowie**, **50**, 2022, pp. 330-356. <https://doi.org/10.24425/tkuia.2022.144856>.
- [5] H.J. Rosas, A. Sussman, A.C. Sekely, A.A. Lavdas, *Using Eye Tracking to Reveal Responses to the Built Environment and Its Constituents*, **Applied Sciences**, **13**(21), 2023, pp. 3-25. <https://doi.org/10.3390/app132112071>.
- [6] P. Huddleston, B.K. Behe, S. Minahan, R.T. Fernandez, *Seeking Attention: An Eye-Tracking Study of In-Store Merchandise Displays*, **International Journal of Retail and Distribution Management**, **43**(6), 2015, pp. 561-574. <https://doi.org/10.1108/IJRDM-06-2013-0120>.
- [6] P. Wang, W. Song, J. Zhou, Y. Tan, H. Wang, *AI-Based Environmental Color System in Achieving Sustainable Urban Development*, **Systems**, **11**(3), 2023, pp. 1-16. <https://doi.org/10.3390/systems11030135>.
- [7] W. Kocki, M. Dzieńkowski, *Architectural visual design – eye-tracking analysis of church altars: a case study*, **International Journal of Conservation Science**, **15**(3), 2024, pp. 1346-1347. <https://doi.org/10.36868/IJCS.2024.03.12>.
- [7] M.F. Islam, M.A. Manab, J.J. Mondal, S. Zabeen, F.B. Rahman, M.Z. Hasan, F. Sadeque, J. Noor, *Involution fused convolution for classifying eye-tracking patterns of children with Autism Spectrum Disorder*, **Engineering Applications of Artificial Intelligence**, **139**, pp. 14-15. <https://doi.org/10.1016/j.engappai.2024.109475>.
- [8] M. Lisińska-Kuśnierz, M. Krupa, *Suitability of Eye Tracking in Assessing the Visual Perception of Architecture—A Case Study Concerning Selected Projects Located in Cologne*, **Buildings**, **10**(2), 2020, pp. 1-23. <https://doi.org/10.3390/buildings10020020>.
- [8] E.J. Kim, Y. Kang, *Analyzing image recognition characteristics in landscape architecture: A study using eye tracking with a focus on educational perspectives*, **Frontiers of**

- Architectural Research**, **14**(3), 2024, pp. 797-811.
<https://doi.org/10.1016/j.foar.2024.09.010>.
- [9] G.R. Loftus, *Picture perception: Effects of luminance on available information and information-extraction rate*, **Journal of Experimental Psychology: General**, **114**(3), 1985, pp. 342-356. <https://doi.org/10.1037/0096-3445.114.3.342>.
- [10] G. Lio, R. Fadda, G. Doneddu, J.R. Duhamel, A. Sirigu, *Digit-tracking as a new tactile interface for visual perception analysis*, **Nature Communications**, **10**, 2019, pp. 1-13. <https://doi.org/10.1038/s41467-019-13285-0>.
- [10] A. Bojko, *Informative or Misleading? Heatmaps Deconstructed*, in: **Human-Computer Interaction. New Trends. HCI 2009** (editor: J. A. Jacko), Lecture Notes in Computer Science, 5610, 2009, Springer, Berlin, Heidelberg, https://doi.org/10.1007/978-3-642-02574-7_4.
- [11] R.J.K. Jacob, K.S. Karn, *Eye Tracking in Human-Computer Interaction and Usability Research: Ready to Deliver the Promises*, in: **The Mind's Eye: Cognitive and Applied Aspects of Eye Movement Research**, (editors: J. Hyona, R. Radach, H. Deubel), Elsevier Science, Amsterdam, 2003, pp. 573-605. <https://doi.org/10.1016/B978-0-44451020-4/50031-1>.
- [12] J.B. Hollander, A. Sussman, P. Lowitt, N. Angus, M. Situ, *Eye-tracking emulation software: a promising urban design tool*, **Architecture science review**, **64**(4), 2021, pp. 383-393. <https://doi.org/10.1080/00038628.2021.1929055>.
- [12] Z. Bylinskii, M.A. Borkin, N.W. Kim, H. Pfister, A. Oliva, *Eye Fixation Metrics for Large Scale Evaluation and Comparison of Information Visualizations*, In: **Eye Tracking and Visualization** (editors: Burch, M., Chuang, L., Fisher, B., Schmidt, A., Weiskopf, D.), ETVIS 2015, Mathematics and Visualization, Springer, Cham, 2017, pp. 235-255. https://doi.org/10.1007/978-3-319-47024-5_14.
- [13] S. Erslan, *Eye Tracking Scanpath Analysis Techniques on Web Pages: A Survey, Evaluation and Comparison*, **Journal of Eye Movement Research**, **9**(1), 2015, pp. 1-19. <https://doi.org/10.16910/jemr.9.1.2>.
- [9] Tobii AB, *User Manual – Tobii Studio. Version 3.2 Rev A*, Stockholm, Sweden, 2012.
- [14] B. Wąsikowska, *Eye tracking w badaniach marketingowych*, **Zeszyty na ukowe uniwersytetu szczecińskiego** **863**, **Studia Informatica**, **36**, 2015, pp. 177-192. <https://doi.org/10.18276/si.2015.36-13>.
- [15] K. Rayner, *Eye Movements in reading and Information Processing*, **Psychological Bulletin**, **85**, 1978, pp. 618-660. <https://doi.org/10.1037/0033-2909.85.3.618>.
- [16] W. Tuszyńska-Bogucka, B. Kwiatkowski, M. Chmielewska, M. Dzieńkowski, W. Kocki, J. Pełka, N. Przesmycka, J. Bogucki, D. Galkowski, *The effects of interior design on wellness – Eye tracking analysis in determining emotional experience of architectural space. A survey on a group of volunteers from the Lublin Region, Eastern Poland*, **Annals of Agricultural and Environmental Medicine**, **27**(1), 2020, pp. 113-122. <https://doi.org/10.26444/aaem/106233>.
- [17] W. Einhäuser, C. Atzert, A. Nuthmann, *Fixation durations in natural scene viewing are guided by peripheral scene content*, **Journal of Vision**, **20**(4), 2020, pp.1-15. <https://doi.org/10.1167/jov.20.4.15>.
- [18] D.T. Guarnera, C.A. Bryant, A. Mishra, J.I. Maletic, B. Sharif, *iTrace: Eye Tracking Infrastructure for Development Environments*, in: **Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications, ETRA'18**, **105**, 2018, pp. 1-3. <https://doi.org/10.1145/3204493.3208343>.
- [19] A. Hoffmann, P. Stork, M. Madysa, Y. Borgianni, *How attractive is sustainability in products: A Systematic Review about eye-tracking studies on sustainability labels*, **Journal of Environmental Psychology**, **101**, 2025, pp. 5-6. <https://doi.org/10.1016/j.jenvp.2025.102519>.

- [20] J. Kim, N. Kim, *Quantifying Emotions in Architectural Environments Using Biometrics*, **Applied Sciences**, **12**(19), 2022, pp. 1-22. <https://doi.org/10.3390/app12199998>.
- [21] T.A. Salthouse, C.L. Ellis, *Determinants of Eye-Fixation Duration*, **The American Journal of Psychology**, **93**(2), 1980, pp. 207-234. <https://doi.org/10.2307/1422228>.
- [22] D.J. Kelly, S. Mielliet, R. Caldara, *Culture shapes eye movements for visually homogeneous objects*, **Frontiers in psychology**, **1**, 2010, pp. 1-7, <https://doi.org/10.3389/fpsyg.2010.00006>.
- [23] P. Ugwitz, O. Kvarda, Z. Juríková, C. Šašinka, S. Tamm, *Eye-Tracking in Interactive Virtual Environments: Implementation and Evaluation*, **Applied Sciences**, **12**(3), 2022, pp. 1-30. <https://doi.org/10.3390/app12031027>.
- [24] K. Panetta, Q. Wan, A. Kaszowska, H.A. Taylor, S. Agaian, *Software Architecture for Automating Cognitive Science Eye-Tracking Data Analysis and Object Annotation*, **IEEE Transactions on Human-Machine Systems**, **49**(3), 2019, pp. 268-277. <https://doi.org/10.1109/THMS.2019.2892919>.

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