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Article

Generational Differences in Visual Engagement: Applying the Visual Interaction Analysis (VIA) Methodology Composed of Eye Tracking and Virtual Reality

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Abstract: Understanding visual engagement in marketing is crucial for optimizing user experience and enhancing campaign effectiveness. This study introduces the Visual Interaction Analysis (VIA) methodology, utilizing advanced eye-tracking technology within immersive virtual reality (VR) environments to examine generational and gender differences in visual engagement after exposure to advertising materials. Using the Cognitive 3D platform for precise data capture, this research analyzed fixation patterns—total fixations, duration of fixations, and average duration per fixation—across Millennial and Generation Z cohorts. The analysis involved 44 participants, who were exposed to three posters in controlled VR settings. Results revealed significant generational differences: Generation Z demonstrated more focused attention, with higher fixation counts and longer total fixation durations compared to Millennials, suggesting that differences in media consumption and technological adaptation influence engagement strategies. However, both generations showed a similar depth of engagement, as indicated by the average duration per fixation. Gender analysis within Generation Z further revealed that female participants engaged for longer periods per fixation, indicating deeper processing of visual information. This methodology offers a robust framework for quantifying visual engagement, providing actionable insights that can help marketers tailor strategies and optimize campaign designs before launch.

Keywords: Visual Interaction Analysis; Eye Tracking; Virtual Reality; Consumer Behavior; Sustainable Marketing; User Experience Design

1. Introduction

In the contemporary digital era, the intricate understanding of consumer behavior and the optimization of user experience (UX) design are fundamental to devising effective marketing strategies [1], [2].With the proliferation of digital content across diverse platforms, capturing and analyzing visual engagement has become a cornerstone of impactful marketing [3], [4], [5]. Effective visual marketing strategies and user-centered designs not only elevate brand perception but also drive higher conversion rates and foster customer loyalty [6], [7].

However, the analysis of visual attention and interaction patterns presents significant challenges [8], [9], [10]. Traditional methodologies often depend on subjective measures and fail to encapsulate the intricate dynamics of visual engagement in fluid environments [11]. Existing analytical tools frequently lack the precision required to pinpoint specific areas of interest and do not yield actionable insights into user behavior, thereby constraining the efficacy of marketing and UX initiatives [12].

This study introduces a novel methodology known as Visual Interaction Analysis (VIA), which integrates advanced eye-tracking technology with the immersive capabilities of virtual reality (VR). VIA provides a robust framework for rigorously testing and evaluating communication strategies

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within precisely controlled environments. By utilizing the software Unity for creating virtual spaces, VIA accurately measures attention, identifies focal points, and offers detailed insights into user engagement, enabling data-driven decisions before the launch of marketing campaigns. This approach not only reduces financial risks but also significantly enhances the effectiveness of marketing and UX strategies [13].

Here, we will outline the theoretical foundations and existing research relevant to VIA; including the integration of eye-tracking and VR. This paper aims to demonstrate how VIA can profoundly impact the fields of marketing and UX design by offering a more nuanced and effective way to understand and engage modern consumers.

2. Literature Review

In the rapidly evolving landscape of digital technology, virtual reality (VR) presents novel opportunities for the strategic testing and optimization of marketing communications [14]. This emerging approach leverages VR not just as a medium for user interaction but as a sophisticated tool for pre-launch evaluation of marketing strategies [15], [16], [17]. This literature review introduces a pioneering methodology that integrates key cognitive theories—Visual Attention Theory, Cognitive Load Theory, Embodied Cognition, and Human-Computer Interaction—to establish a new paradigm in marketing research (see figure 1). By synthesizing insights from cognitive psychology and human-computer interaction, this proposed methodology aims to harness immersive VR environments for the efficient testing and refinement of marketing media. These theories are interwoven to provide a nuanced framework that enhances our understanding of user behavior in complex digital settings, thereby enabling marketers and researchers to optimize resource allocation and campaign effectiveness through targeted, empirical analysis.

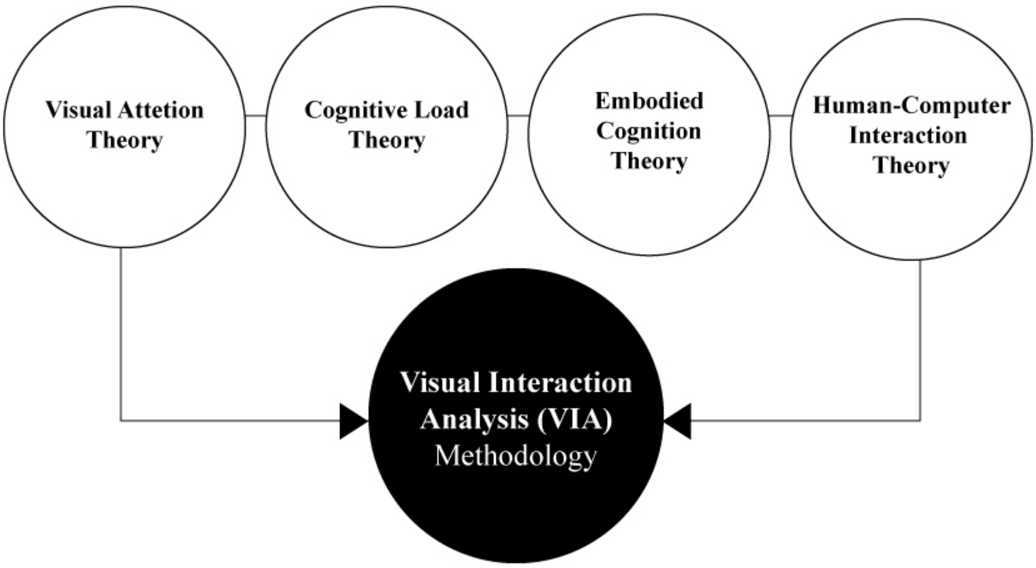

Figure 1. Interconnection of Theories Applied to Visual Interaction Analysis in VR. ***Note:*** *This figure illustrates how Visual Attention Theory, Cognitive Load Theory, Embodied Cognition, and Human-Computer Interaction converge to form the Visual Interaction Analysis (VIA) methodology, facilitating an integrated approach to studying user experience in virtual environments.*

2.1. Visual Attention Theory

Visual Attention Theory was first discussed in the context of cognitive psychology, where it focuses on how humans selectively process visual information in their environment [18]. This theory is particularly relevant in virtual reality (VR) settings, where consumer interaction and engagement are influenced by what visually captures and retains their attention [19]. By employing eye-tracking technology, researchers like Meißner, et al. (2019) have been able to measure quantitatively where

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users focus and for how long, providing empirical evidence of visual preferences and behaviors [20]. This data is crucial for optimizing the placement and design of content within virtual spaces to ensure that key messages and products are effectively highlighted. As shown by subsequent studies (e.g., Bigne et al. (2024); Kim et al. (2024), understanding these visual engagement patterns can directly influence decision-making processes in digital environments [21], [22]. Thus, Visual Attention Theory offers a foundational approach for studying consumer interactions in VR, guiding the strategic presentation of stimuli to enhance user engagement and commercial outcomes [23].

2.2. Cognitive Load Theory

Cognitive Load Theory, initially conceptualized by Sweller (1991), addresses the limits of mental capacity in working memory [24]. This theory is particularly applicable in virtual reality (VR) settings where the design of environments can either facilitate or hinder cognitive processing [25]. By balancing informational complexity and user interface usability, this theory guides the creation of VR environments that prevent cognitive overload, thus enhancing user interaction and learning [26]. Implementations of Cognitive Load Theory in VR have been extensively studied, with researchers such as Martínez-Molés et al. (2024) focusing on how streamlined design and intuitive navigation can reduce cognitive strain, thereby improving information processing and decision-making [27]. Further research by Kang et al. (2020) explores how different methods of presenting information in VR—such as virtual stores or interactive advertisements—affect user comprehension and choices. The findings from these studies contribute to a better understanding of effective VR design principles that align with human cognitive capacities [28].

2.3. Embodied Cognition

Embodied Cognition, as discussed by Andy Clark (1999), posits that cognitive processes are fundamentally shaped by the body's interactions with its environment [29]. Clark emphasizes the complex interplay between neural systems and the wider world, suggesting that this interaction transforms both the subject matter and the theoretical framework of cognitive science. This perspective is crucial in virtual reality (VR), where the design of immersive environments should align with natural human behaviors and instincts to optimize cognitive outcomes [30]. The theory emphasizes the importance of physical actions within VR, such as navigation and object manipulation, in shaping cognitive processes and influencing user behavior [31]. Studies in this domain, such as those by Kharoub et al. (2019), investigate how VR interface designs that mimic natural movements can enhance user satisfaction and engagement [32]. By focusing on creating intuitive and immersive experiences, researchers aim to leverage the principles of embodied cognition to improve the effectiveness and interactivity of virtual environments [33]. This approach not only aids in the development of more user-friendly VR systems but also deepens our understanding of the cognitive impacts of embodied interactions in digital spaces[34].

2.4. Human-Computer Interaction (HCI)

HCI has evolved from its early focus on ergonomics to a comprehensive, user-centered discipline [35]. Initially influenced by the ergonomic design of computer systems in the mid-20th century, HCI now integrates psychological insights and advanced technology to enhance user interaction, emphasizing accessibility and user-friendly design [36]. In virtual reality (VR), the principles of HCI are pivotal in crafting user interfaces that not only provide intuitive navigation but also enhance user engagement and facilitate desired behavioral outcomes such as increased purchase intentions or improved learning experiences [37]. HCI research in VR encompasses a broad spectrum of elements including menu design, interaction techniques, and feedback mechanisms [38]. Studies in this area, conducted by experts such as Lou et al. (2021), aim to ensure that VR environments are accessible, efficient, and user-friendly [39]. By applying HCI principles to VR, researchers strive to create interfaces that are both effective in meeting user needs and conducive to achieving specific goals, ultimately making VR experiences more engaging and productive [40].

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Table 1. Summary of Research and Key Findings in VR According to Applied Theories.

Theory	Key Principles	Implications for Consumer Behavior	Integration and Enhancement by VIA
Visual Attention Theory	Focuses on how and why certain visual elements capture attention based on salience, relevance, and task demands.	Influences which marketing elements are noticed and processed by consumers, affecting engagement and decision-making.	VIA uses real-time eye tracking to precisely measure which elements draw consumer attention, optimizing design elements in virtual environments.
Cognitive Load Theory	Asserts that cognitive load affects how effectively information is processed; optimal load enhances learning.	Too much or too little information can overwhelm or under-stimulate, impacting consumer understanding and retention.	VIA designs visual stimuli in VR to balance informational content, thus optimizing cognitive load for better comprehension and interaction.
Embodied Cognition	Suggests that cognitive processes are influenced by the body's interactions with its physical environment.	Consumer decisions are affected by physical and simulated interactions with products, influencing preferences and behaviors.	VIA utilizes VR to simulate realistic consumer-product interactions, providing insights into behavioral responses in near-realistic settings.
Human-Computer Interaction (HCI)	Principles aim to optimize the interface design for usability, accessibility, and satisfaction.	Good HCI design leads to better user experiences, higher satisfaction, and more effective interaction with digital products.	VIA incorporates HCI principles to ensure that VR environments are intuitive and user-friendly, enhancing the reliability and quality of data collected.

The VIA methodology exemplifies a holistic integration of multiple cognitive theories, transcending the traditional application of these frameworks in isolation. This methodological fusion strategically enhances the virtual reality (VR) user experience by addressing a spectrum of user interaction dynamics, including visual attention, cognitive processing, physical interaction, and interface usability. Such an integrated approach ensures that the VR environment is not only engaging but also cognitively attuned to the user's needs.

Furthermore, the synergy among these theories within the VIA framework significantly improves the quality of individual user experiences. It establishes a comprehensive and systematic protocol for researchers and developers engaged in VR design. By leveraging these combined insights, the VIA methodology pioneers a new paradigm in the development of immersive and interactive virtual environments, characterized by their scientific robustness and user-centered design.

To further illustrate the current landscape of technological applications in VR and related fields, the following table compares various advanced studies that employ technologies such as eye-tracking and VR to understand and enhance consumer interactions. This comparative analysis highlights where VIA stands in relation to existing methodologies and its unique contributions to the field.

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Table 2. Comparison of Technological Studies in Marketing and UX.

Study/Reference	Technology Used	Key Metrics Analyzed	Application Area	Major Findings
Guo et al. (2016) [41]	Eye-Tracking	Product interest, design optimization	New Product Development (NPD)	Eye-tracking identifies design elements that capture attention and influence product preferences.
Micu et al. (2018) [42]	Artificial Intelligence	Social Media Engagement metrics, campaign effectiveness	Social Media Marketing	AI improves campaign effectiveness through targeted content and predictive analytics.
Peukert et al. (2019) [43]	Virtual Reality	Purchase behavior, user experience	Virtual Retail Environments	VR enhances the shopping experience, potentially increasing user engagement and purchase intent.
Fan et al. (2020) [44]	Augmented Reality	Consumer behavior, purchase intention	Retail, Marketing	AR increases purchase intentions by enhancing the shopping experience with interactive elements.
Chylinski et al. (2020) [45]	Augmented Reality	User engagement, marketing effectiveness	Marketing	AR enhances customer engagement by providing immersive and interactive product visualizations.
Pedersen et al. (2021) [46]	Eye-Tracking	Visual attention, user interaction	Retail, Product Design	Eye-tracking provides insights into consumer preferences and behavior in retail environments.

Unlike broader applications of eye-tracking in studies like those by Guo et al. (2016) and Pedersen et al. (2021) that span various aspects of product interaction and retail environments, VIA concentrates on meticulously evaluating how individuals engage with media within virtual spaces. By stripping away extraneous environmental factors, VIA ensures that the eye-tracking data collected is highly specific to the media being tested. This allows for precise adjustments to media design based on direct measures of visual engagement, optimizing elements such as placement, size, and content to maximize consumer attention and retention.

VIA's use of virtual reality goes beyond enhancing user experience generally, as described in Peukert et al. (2019). Instead, VIA employs a minimalistic VR setup to specifically test the impact of isolated media elements on user behavior. This focused approach facilitates a controlled study of the effectiveness of different media presentations, enabling marketers to fine-tune advertisements before they are launched into more complex real-world or digital settings.

Building on the engagement strategies seen in AR studies by Fan et al. (2020) and Chylinski et al. (2020), VIA applies these technologies not just to enhance general marketing effectiveness but to specifically refine media content. By embedding AR elements in a distraction-free VR environment, VIA can assess how augmentations affect user interaction with advertisements, providing actionable insights that are crucial for the pre-launch optimization of marketing campaigns.

VIA provides a targeted, scientifically rigorous approach to media testing. This precision is crucial for developing marketing materials that are not only visually compelling but also highly effective in capturing and maintaining consumer attention. The integration of eye-tracking with VR and AR in a focused setting allows VIA to deliver data-driven insights that significantly enhance the predictive accuracy and effectiveness of pre-launch media optimizations.

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3. Methodology

Visual Interaction Analysis (VIA) study is designed to harness cutting-edge eye-tracking technology within immersive virtual reality (VR) environments to probe the variations in consumer behavior across generational cohorts—specifically Millennials and Generation Z—when interacting with marketing stimuli.

3.1. System Overview

The VIA system integrates several advanced technological components to create a controlled setting where consumer interactions with digital marketing materials can be precisely measured and analyzed. The system is comprised of the Meta Quest Pro VR headset, Unity software for virtual environment setup, and Cognitive3D for the collection and analysis of eye-tracking data (see figure 2).

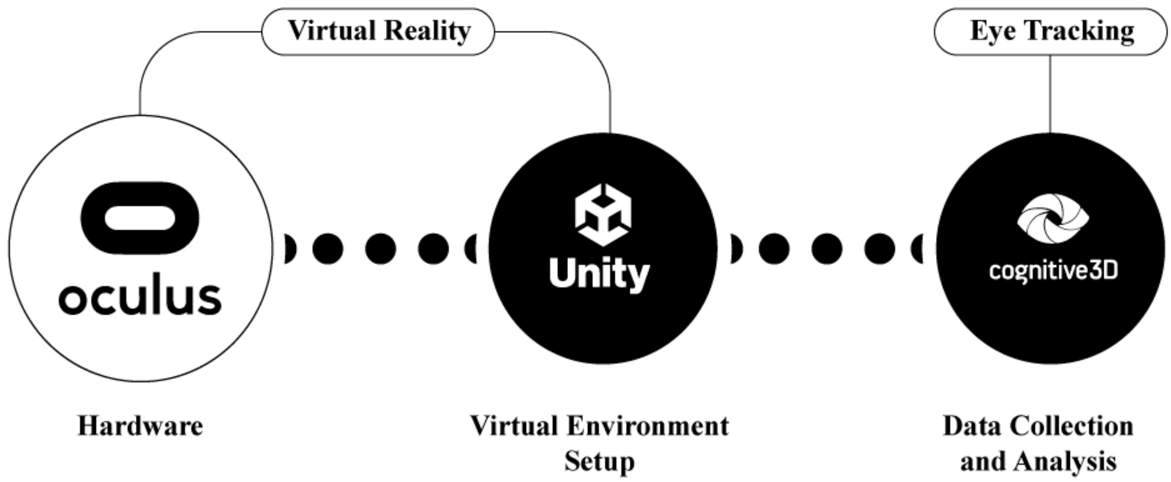

Figure 2. Integration Flowchart of the Visual Interaction Analysis (VIA) Methodology.

3.1.1. Meta Quest Pro

In this study, the Meta Quest Pro VR headset, which comes equipped with advanced integrated eye-tracking technology, was utilized to capture detailed eye movement data. The Meta Quest Pro features high-precision sensors that record the condition of the pupils using infrared LED light, crucial for accurately tracking gaze direction and pupil dilation. The headset operates at a screen update rate of 90 Hz, ensuring high-resolution images and fluid video playback, which are essential for precise eye-tracking analysis (see figure 3).

One of the key features of the Meta Quest Pro is its automatic lens calibration system. Each headset includes adjustable lenses that are calibrated automatically to match each participant's visual acuity. This feature ensures that every user experience clear, sharp images, which is critical for reducing potential artifacts in eye-tracking data due to visual distortions.

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Figure 3. VR Equipment, Meta Quest Pro.

3.1.2. Unity

The virtual environments for the study were created using Unity, a leading game development platform renowned for its capability to construct immersive virtual spaces. Unity allowed for the design of realistic marketing scenarios where participants could interact, thereby facilitating the controlled presentation of marketing posters within a simulated gallery setting (see figure 4).

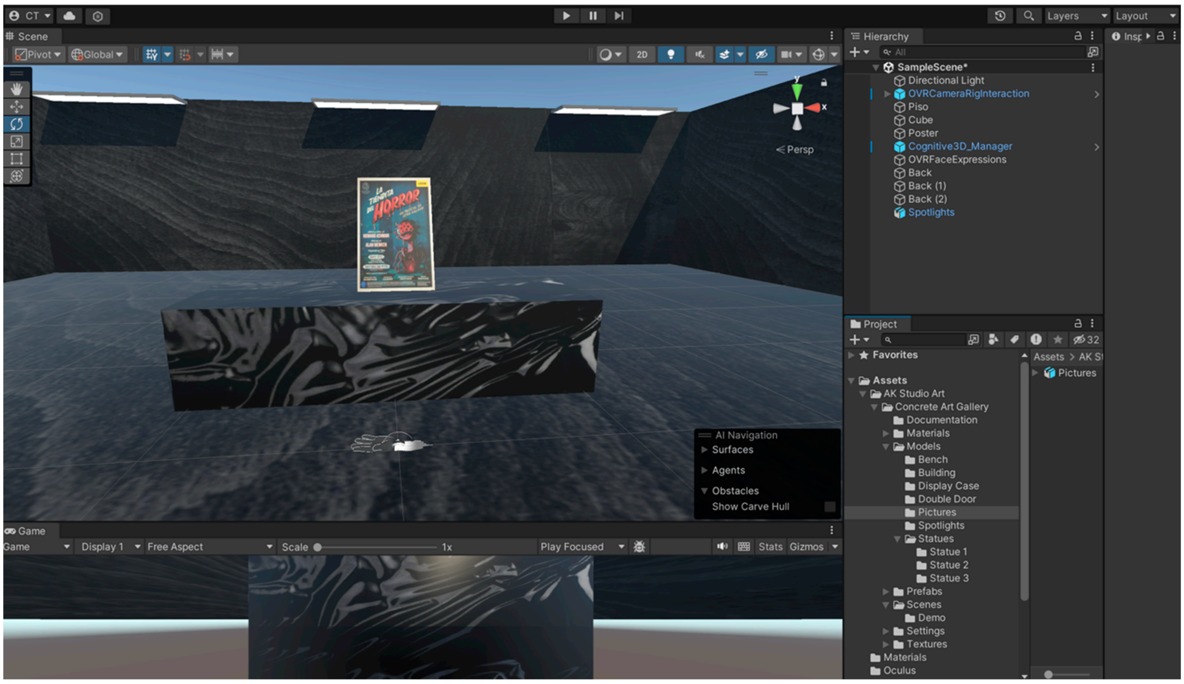

Figure 4. Unity Software Interface for VR Environment Design.

3.1.3. Cognitive 3D

For the analysis of the eye-tracking data, Cognitive 3D was employed. This advanced analytics platform specializes in analyzing user interactions within virtual environments and provided comprehensive metrics on where participants looked, how long they focused on specific elements, and their gaze patterns across different stimuli. Such data is vital for gauging consumer behavior in virtual marketplaces and optimizing the design of marketing materials to enhance viewer engagement (see figure 5).

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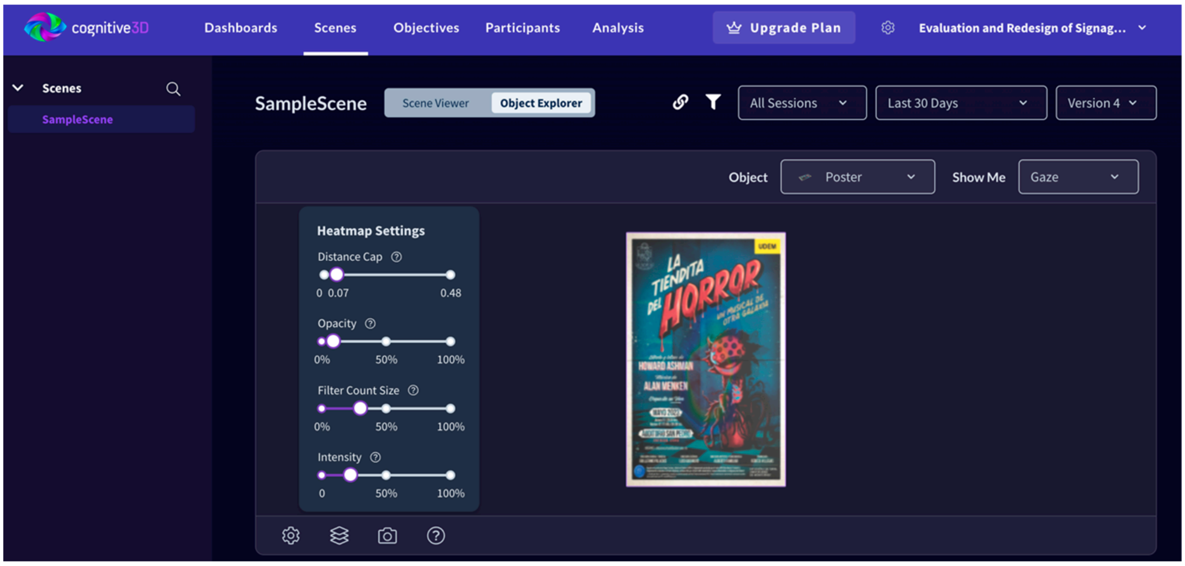

Figure 5. Cognitive 3D Analytics Dashboard for Eye-Tracking Data.

3.2. Experimental Design

The experimental design of the Visual Interaction Analysis (VIA) study leverages the integration of advanced eye-tracking technology within immersive Virtual Reality (VR) environments, facilitated by Unity software and Cognitive3D analytics. This setup aims to elucidate the variations in consumer behavior across generational cohorts—specifically Millennials and Generation Z—when interacting with marketing stimuli.

This methodological approach allows for a nuanced exploration of how different generational cohorts engage with and process marketing communications within a VR context, providing valuable insights into effective marketing strategies tailored to diverse demographic segments.

3.3. Participants

In this research, 44 participants were engaged in a VR eye-tracking experiment to assess visual engagement with marketing material (see table 3). These participants were classified into two generational cohorts: Generation Z and Millennials. The Generation Z cohort comprised 19 individuals, including 13 men (68%) and 6 women (32%), ranging in age from 18 to 26 years. The Millennial cohort consisted of 25 individuals, including 15 men (60%) and 10 women (40%), aged between 28 and 38 years. Each participant was exposed to a sequence of marketing posters within a virtual reality environment, and their eye movements were meticulously recorded.

The participants displayed a diverse range of educational backgrounds, with 80% holding a college degree, 16% having postgraduate qualifications, and a smaller proportion, 5%, having completed only high school. In terms of occupation, the majority, 68%, were students, reflecting the youthful demographic of the study, while the remaining 32% were employed across various sectors. This mix provides a broad perspective on different user interactions with the VR technology.

Regarding their experience with VR technology, the levels varied among participants: 32% had low experience, 45% medium, and 23% high. This variety in VR familiarity is crucial for understanding how different levels of prior exposure to VR technology can influence the engagement and interaction patterns in virtual environments. Additionally, the frequency of technology usage among participants also varied, with 23% using technology infrequently, 36% at a moderate rate, and 41% frequently engaging with technology. This information is integral to analyzing how habitual interactions with technology can affect responses to virtual marketing stimuli.

This comprehensive profiling of participants ensures that the study captures a wide array of responses based on varied technological familiarity and demographic backgrounds. The diversity in age, gender, and technological experience within each generational cohort allows for an in-depth analysis of how different demographic groups respond to visual marketing stimuli in a controlled,

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immersive setting. This approach aims to elucidate generational differences in visual engagement and provide insights into designing effective marketing strategies tailored to specific audience segments.

Table 3. Sample profile (N=44).

Category	Subcategory	Frequency	Percentage
Gender			
	Female	16	36%
	Male	28	64%
Generation			
	Gen Z	19	43%
	Millennial	25	57%
Age Range			
	18-20	11	25%
	21-23	5	11%
	24-26	3	7%
	28-30	13	30%
	31-34	10	23%
	35-38	2	4%
Education Level			
	High School	2	5%
	College	35	80%
	Postgraduate	7	16%
Occupation			
	Student	30	68%
	Employed	14	32%
VR Experience Level			
	Low	14	32%
	Medium	20	45%
	High	10	23%
Technology Usage Frequency			
	Low	10	23%
	Medium	16	36%
	High	18	41%

3.4. Data Collection and Analysis

Data collection in the Visual Interaction Analysis (VIA) study is primarily facilitated by the Cognitive 3D plugin, which is intricately integrated with the Meta Quest Pro headset. This setup enables the precise capture of detailed eye-tracking metrics that are critical for assessing the visual engagement of participants with marketing stimuli within virtual reality (VR) environments. The process involves recording eye movement data as participants interact with marketing posters designed in the Unity environment.

3.4.1. Data Collection Process

During the experiment, participants wear the Meta Quest Pro headset, which records eye movements through its built-in eye-tracking technology. As participants view the series of marketing materials, the environment, meticulously designed in Unity to be highly neutral, ensures that the participants' attention is solely focused on the marketing content and not distracted by the virtual space itself. This strategic design choice enhances the validity of the visual attention data captured (see figure 6).

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In this study, participants were exposed to a poster designed for the experiment. The poster was presented in a controlled sequence, with an exposure duration of 90 seconds. During the 90-second exposure, participants were not able to switch between posters or interact with any other elements, ensuring that their attention remained focused solely on the visual stimulus presented. The exposure process was automatically administered within the virtual environment, and eye-tracking data were collected in real-time throughout the entire viewing period.

Figure 6. Application of VIA Methodology in Musical Theater Marketing. Note: The image depicts a participant using the VIA setup to engage with a virtual advertisement for 'La Tiendita del Horror.' The left panel shows the user equipped with VR hardware, and the right panel displays the user's perspective, focusing on the promotional poster within the virtual environment.

The Cognitive 3D plugin then captures several key metrics of visual attention, allowing for a precise analysis of how participants engage with the displayed materials.

Heat Maps: These are generated to visually represent the concentration of visual attention within the environment, highlighting areas that attract the most gaze.

Total Fixation Counts (TF): This metric quantifies the number of discrete instances where participants' gazes are fixated on specific elements, providing a direct measure of engagement.

Total Duration of Fixations (TDF): It reflects the cumulative time spent by participants focusing on different elements, indicating the depth of visual engagement.

Average Duration per Fixation (ADF): This measure offers insights into the engagement depth by calculating the average duration of each fixation, which helps infer the cognitive effort or interest elicited by the content.

Participants are given 90 seconds to engage with each poster, starting from their first fixation. This standardized exposure time ensures consistency in data collection across participants, facilitating comparative analysis.

3.4.2. Initial Setup and Pre-experiment Orientation

Before beginning the main data collection phase, participants engage with the Meta Quest Pro "First Steps" application for 20 to 30 minutes. This preliminary session is designed to familiarize them with the VR environment and reduce variability in their responses due to unfamiliarity with VR controls and interfaces.

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3.4.3. Data Analysis

Following data collection, the gathered metrics are analyzed using Analysis of Variance (ANOVA) to evaluate the impact of the presented visual marketing strategies on the two generational cohorts—Millennials and Generation Z. This statistical method helps determine whether there are significant differences among the groups based on the following hypotheses:

Hypothesis 1 (H1): There are generational differences in the total number of fixations (TF), indicating variations in initial visual attraction to the marketing elements.

Hypothesis 2 (H2): Variations in the total duration of fixations (TDF) reflect differing levels of engagement with the content, with potential implications for marketing strategy effectiveness.

Hypothesis 3 (H3): Differences in the average duration per fixation (ADF) suggest variations in cognitive processing, potentially influenced by generational characteristics.

The results from this analysis will provide valuable insights into how different generational cohorts engage with and process marketing communications in immersive VR settings. These findings will help tailor marketing strategies to better align with the preferences and behaviors of these distinct groups, enhancing the efficacy and impact of future marketing efforts.

4. Results

This study examined the eye-tracking data of participants across two different generations—Millennials and Generation Z—and by gender within Generation Z to investigate the variations in visual attention. The participants consisted of individuals from both generations with a distribution across genders, focusing on three primary metrics: Total Fixations (TF), Total Duration of Fixations (DTF), and Average Duration per Fixation (DPF).

The ANOVA results for TF and DTF between Millennials and Generation Z show significant differences, indicating that the two generations exhibit distinct patterns of visual attention in terms of both the number and total duration of their fixations. Specifically, the large F-values (TF: $F_{(1, 42)} = 282.54$, $p < 0.0001$; DTF: $F_{(1, 42)} = 639.37$, $p < 0.0001$) suggest a strong generational effect on these metrics. This implies that Generation Z participants may engage differently with visual stimuli compared to Millennials, possibly due to generational variations in media consumption and technology use.

Conversely, the Average Duration per Fixation (DPF) did not differ significantly between the two groups ($F_{(1, 42)} = 0.15$, $p = 0.6969$), indicating that while the overall engagement and duration might differ, the average time spent per fixation is consistent across generations. This uniformity suggests that once engaged, the depth of processing or attentional focus per item does not vary significantly between Millennials and Generation Z (see table 4).

Table 4. Comparison of Visual Attention Patterns between Generation Z and Millennials.

Variable	Sum of Squares	Degrees of Freedom	*F*-Value	*P*-Value
TF				
Generation	10171.84	1	282.54	0.00
Residual	1512.05	42		
TDF				
Generation	287.34	1	639.37	0.00
Residual	18.87	42		
ADF				
Generation	0.000036	1	0.15	0.69
Residual	0.009927	42		

Within Generation Z, the analysis of gender differences revealed no significant disparities in Total Fixations (TF: $F_{(1, 20)} = 1.09$, $p = 0.3088$) or Total Duration of Fixations (DTF: $F_{(1, 20)} = 1.09$, $p = 0.3088$). This outcome suggests that male and female participants from Generation Z exhibit similar patterns in the quantity and total time of their visual engagements.

However, a significant difference was observed in the Average Duration per Fixation (DPF) between genders ($F_{(1, 20)} = 11.83$, $p = 0.0026$), with women possibly displaying a longer average fixation

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duration compared to men. This finding might indicate deeper or more sustained processing of visual information by female participants within this generation, reflecting potential cognitive and perceptual differences in how visual information is processed between genders (see table 5).

Table 5. Gender-Based Visual Engagement Differences within Generation Z.

Variable	Sum of Squares	Degrees of Freedom	*F*-Value	*P*-Value
TF				
Gender	32.63	1	1.09	0.3088
Residual	598.33	20		
DTF				
Gender	0.84	1	1.09	0.3088
Residual	15.32	20		
DPF				
Gender	2.28E-33	1	11.83	0.0026
Residual	3.85E-33	20		

The data from this study suggest that while there are generational differences in how visual stimuli are engaged with, the inherent depth of processing per fixation remains consistent across generations. Within Generation Z, gender differences in visual attention patterns are minimal except in the duration per fixation, hinting at deeper cognitive processing differences. These insights could be pivotal for designing educational tools, marketing strategies, and digital content tailored to specific demographic groups based on their unique visual attention patterns (see table 6).

Table 6. Gender-Based Visual Engagement Differences within Millenials.

Variable	Sum of Squares	Degrees of Freedom	*F*-Value	*P*-Value
TF				
Gender	39.82	1	0.95	0.3422
Residual	841.27	20		
DTF				
Gender	0.26	1	2.08	0.1646
Residual	2.47	20		
DPF				
Gender	0.000552	1	1.18	0.2906
Residual	0.009375	20		

Within the Millennial generation, the statistical analysis did not reveal significant differences between genders in any of the visual attention metrics analyzed. Specifically, the ANOVA results indicate no significant disparities in Total Fixations (TF: $F_{(1, 20)} = 0.95$, $p = 0.3422$) or Total Duration of Fixations (DTF: $F_{(1, 20)} = 2.08$, $p = 0.1646$). These outcomes suggest that both male and female Millennials exhibit similar patterns in the quantity of fixations and the total time spent on visual engagements.

Additionally, there was no significant difference in the Average Duration per Fixation (DPF: $F_{(1, 20)} = 1.18$, $p = 0.2906$) between genders. This result implies that the duration for which male and female Millennials focus on a single visual point is comparable, indicating no significant gender-based differences in how visual information is processed in terms of fixation duration.

The analysis of eye-tracking data highlights distinct visual engagement patterns between Millennials and Generation Z, with Generation Z showing notably higher levels of visual engagement, possibly reflecting their different media consumption and technological immersion. For Millennials, no significant gender differences were found in any visual attention metrics, indicating uniform visual engagement behaviors across genders within this group. Within Generation Z, while overall engagement levels were similar across genders, females exhibited longer durations per fixation, suggesting deeper processing. These insights reveal nuanced differences in visual attention that can guide content strategies tailored to each generation's unique characteristics.

The heat maps from the VR eye-tracking experiment, obtained using Cognitive 3D technology, represented in figure 4, where (a) for Generation Z and (b) for Millennials, provide compelling visual evidence of the differences in visual engagement patterns between the two generational cohorts. Image (a) shows more concentrated areas of heat, particularly around dynamic elements of the poster, indicating that Generation Z participants generally fixated longer and more frequently on these areas. This observation aligns with the quantitative findings where Generation Z demonstrated a higher total number of fixations and total duration of fixations than Millennials.

Conversely, image (b) illustrates a more dispersed engagement across the poster for Millennials, suggesting a broader but less intense focus. The lower intensity of heat map areas in image (a) correlates with the statistically significant lower fixation counts and durations found in the Millennial cohort. This pattern may reflect the generational differences in media consumption habits, with Millennials possibly being less prone to focus intensively on singular visual elements compared to the more digitally native Generation Z, as captured by the advanced tracking capabilities of Cognitive 3D (see figure 7).

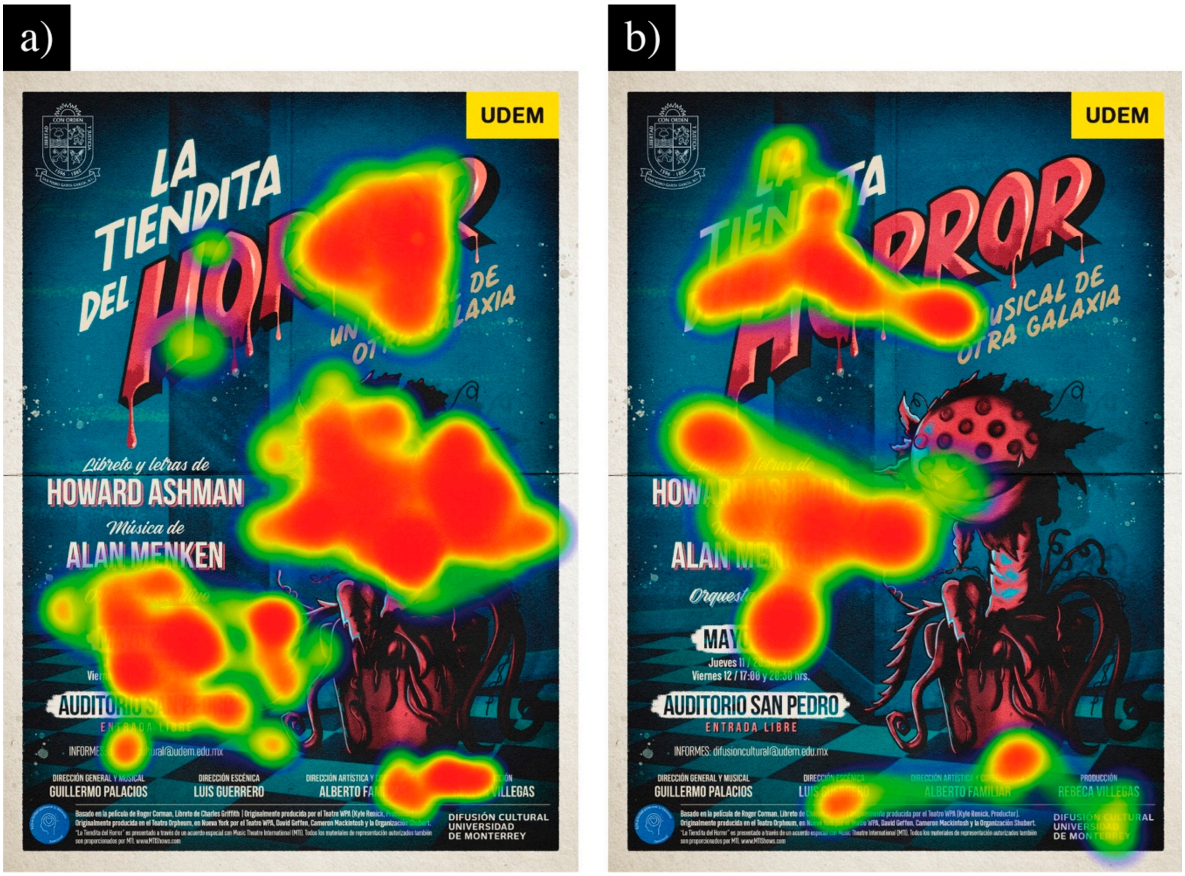

Figure 7. Heat Map Comparisons of Eye-Tracking Data Between Generation Z and Millennials. *Note:* (a) Heat map visualization of eye-tracking data from Generation Z participants showing focused engagement on specific elements of the poster. (b) Heat map from Millennial participants displaying a more dispersed visual attention pattern across the poster.

4. Discussion

4.1. Theoretical Contributions

This study's application of the Visual Interaction Analysis (VIA) methodology within a virtual reality (VR) framework offers a comprehensive perspective on the nuanced dynamics of visual engagement across both generational and gender divides. By leveraging eye-tracking technology and immersive VR environments, this research contributes to the growing body of empirical evidence

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supporting Visual Attention Theory, emphasizing the variability in how different demographic groups process visual stimuli.

The findings confirm that Generation Z participants exhibit more concentrated and intense visual engagement compared to Millennials, as indicated by their higher total number of fixations and fixation durations. This supports the theory that digital nativity in Generation Z leads to more focused attention spans when interacting with visually rich, immersive environments. Moreover, a significant gender difference within Generation Z was found in the Average Duration per Fixation (DPF), where female participants displayed longer fixation durations. This suggests that women may engage in deeper cognitive processing, which could be indicative of greater attention to detail or higher emotional involvement when interacting with visual stimuli. These gender differences are in line with previous studies that propose women are more likely to engage with complex or emotionally charged content in a more sustained manner, adding a layer of depth to the understanding of Visual Attention Theory in digital contexts.

Additionally, the study advances Cognitive Load Theory by showing how generational and gender differences influence the management of cognitive resources in VR environments. The longer fixation durations observed among female Generation Z participants imply a heightened cognitive load when processing visually dense stimuli. This suggests that, for content aimed at this demographic, balancing visual richness with cognitive simplicity is crucial to avoid overwhelming users and ensuring optimal engagement. These insights are pivotal for creating user-centered designs that align with the cognitive and perceptual capacities of different demographic groups.

4.2. Practical Implications

This research has significant practical implications for the design of marketing strategies and user experiences in virtual environments. By identifying the distinct visual engagement patterns of Millennials, Generation Z, and gender differences within Generation Z, marketers and UX designers can better tailor content to resonate with specific audience segments.

For female Generation Z participants, the data suggests that they are more likely to engage with content that is both visually rich and emotionally resonant, as their longer fixation durations indicate deeper cognitive engagement. Marketing materials aimed at this group should focus on visually detailed and emotionally compelling content, ensuring that it provides sufficient cognitive challenge without leading to overload. For Generation Z, marketing strategies should emphasize dynamic, interactive elements that capture their attention and encourage sustained engagement.

In contrast, for Millennials, the data shows that they tend to engage less intensely with singular visual elements, suggesting that a broader array of content that encourages exploration might be more effective. Marketing materials aimed at this group could benefit from a less immersive, more diverse approach that allows for multitasking and non-linear interaction.

The precise measurement capabilities provided by Cognitive 3D technology enhance the ability to fine-tune marketing campaigns before full-scale deployment. By capturing real-time data on how different demographic groups engage with visual stimuli, marketers can optimize content and layout, reducing financial risk and increasing campaign effectiveness.

4.3. Limitations and Future Research

While this study offers valuable insights into generational and gender-based differences in visual engagement, several limitations should be acknowledged. First, the sample size and cultural context may limit the generalizability of the findings. The participants were drawn from a specific cultural and demographic background, which may not reflect the visual engagement behaviors of other populations. Future research should aim to include a more diverse and representative sample, incorporating participants from various cultural and socio-economic backgrounds to explore how these factors may influence visual engagement patterns in VR environments.

Second, the controlled nature of the VR environment, while beneficial for isolating specific variables, does not fully replicate the complexities of real-world settings where multiple stimuli compete for attention. Future studies could explore the impact of more complex, real-world-like VR

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environments where users must navigate competing visual and auditory stimuli. This would provide a more holistic understanding of how users engage with content in less controlled, everyday environments.

Another limitation lies in the relatively short duration of exposure to the marketing materials. While the standardized exposure time ensures comparability across participants, it may not reflect real-world engagement where users interact with content at varying durations. Future research could incorporate longitudinal designs to examine how visual engagement patterns evolve over longer periods and in response to repeated exposures.

Lastly, the study focused primarily on eye-tracking metrics such as fixations and fixation durations. While these metrics provide important insights into visual attention, they do not capture the full spectrum of cognitive and emotional engagement with content. Future studies could integrate additional physiological measures such as pupil dilation or galvanic skin response to capture a more comprehensive picture of the emotional and cognitive responses elicited by visual stimuli in VR environments.

5. Conclusion and Futures Directions

This study represents a significant advancement in understanding how different generations and genders engage visually with marketing content in virtual reality environments. By employing the Visual Interaction Analysis (VIA) methodology alongside sophisticated eye-tracking technology, this research not only delineates the distinct visual engagement patterns of Millennials and Generation Z but also provides valuable insights into gender-based differences, particularly within Generation Z. The use of advanced technologies such as Cognitive 3D enabled precise data capture and analysis, enhancing the robustness of our findings.

While both VR and eye-tracking are established technologies, their combined application in this study facilitated a nuanced exploration of generational and gender behaviors in a controlled virtual setting. The insights gained here contribute substantially to the fields of digital marketing and user experience design, offering data-driven strategies to optimize visual engagement across diverse demographic groups.

From the analysis, it became evident that Generation Z participants displayed a more intense focus on specific elements, with female participants in particular exhibiting longer fixation durations than their male counterparts. This suggests deeper cognitive processing of visual stimuli among women in Generation Z, aligning with research that highlights greater attention to detail in complex visual environments. Millennials, on the other hand, demonstrated a broader but less concentrated engagement pattern, suggesting different priorities and media consumption habits. These findings highlight the need for tailored marketing approaches that cater to the unique preferences and behaviors of each generation and gender group.

Despite these insights, the study's reliance on a controlled VR environment also points to its limitations. Real-world applications often involve more complex and less predictable user interactions, suggesting the need for further research in more dynamic settings. Future work should also consider expanding the demographic and cultural scope of participants to enhance the generalizability of the results. Including a more diverse sample would help validate whether the generational and gender-based differences observed here hold across varied cultural contexts.

Additionally, future research could explore deeper integrations of biometric tracking technologies, such as pupil dilation or galvanic skin response, to assess emotional responses alongside visual engagement. This would provide a more comprehensive understanding of how users emotionally and cognitively interact with marketing stimuli in VR environments, complementing the visual attention data captured through eye-tracking. Moreover, advancements in VR technology could allow for the creation of more detailed and realistic simulations, potentially uncovering new aspects of user behavior that were not feasible to study with current technological constraints.

In conclusion, this research underscores the transformative potential of integrating eye-tracking with VR to understand and enhance user engagement. The inclusion of gender-based analysis further

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enriches our understanding of how different demographic groups interact with visual stimuli in virtual environments. As technology continues to evolve, so too will the opportunities to refine and expand the VIA methodology, ensuring that virtual marketing strategies remain effective and relevant in an increasingly digital and diverse future.

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Data Availability Statement: We encourage all authors of articles published in MDPI journals to share their research data. In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required. Suggested Data Availability Statements are available in section "MDPI Research Data Policies" at https://www.mdpi.com/ethics.

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