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# Visual Attention Segmentation of Genshin Impact Characters: An Eye-Tracking and Hierarchical Clustering Analysis of First-Time Players

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**ABSTRACT**

This study investigates the visual attention patterns of first-time players toward character designs in anime-style role-playing games, using Genshin Impact as the research context. An eye-tracking experiment was conducted with 60 participants to capture gaze behavior during exposure to four-character stimuli. The analysis focused on heatmaps, dwell time, and first fixation points, consistently revealing a dominant focus on the character's body region, regardless of character type or visual variation. Hierarchical clustering further segmented participants into three distinct gaze profiles: lateral scanning, peripheral attention to symbolic elements, and centralized body-centric focus. These findings underscore the importance of adaptive character design strategies that prioritize the body region for conveying emotional and narrative cues while enhancing peripheral elements to improve engagement. The study contributes to the fields of game user experience and visual attention research by integrating eye-tracking data with clustering techniques, offering actionable insights for game developers and interface designers.

**Keyword:** Eye-tracking, game user experience, visual attention

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## 1. INTRODUCTION

The advancement of digital technology has fundamentally reshaped the entertainment industry, with video games emerging as a dominant cultural phenomenon. As a form of interactive media, video games provide immersive experiences where visual elements—such as character models, color schemes, and animations—serve as critical factors in capturing player attention and influencing in-game decision-making (Michailidis et al., 2018; Tanskanen, 2018). Within this framework, character design plays a pivotal role in shaping player perceptions, fostering emotional connections, and guiding gameplay choices (Friedman, 2015).

Despite the growing academic interest in Genshin Impact, prior studies have largely focused on AI implementation in gameplay mechanics (Lutfi et al., 2022), consumer purchasing behavior related to in-game items (Angelia et al., 2021), and visual analysis of individual character aesthetics (Prasetya & Anggapuspa, 2022). However, no empirical research employing eye-tracking methods has yet examined how players distribute their visual attention across multiple character designs in Genshin Impact. Although eye-tracking has been applied in other gaming contexts—such as monitoring gaze behavior in first-person shooter (FPS) games to tailor adaptive gameplay (Antunes & Santana, 2018) and assessing attention in game-based learning environments (Blascheck et al., 2014)—the combination of eye-tracking with hierarchical clustering to analyze visual attention patterns in character design studies remains underexplored. This highlights a clear research gap: there is a lack of objective, data-driven analysis of how first-time players perceive anime-style character elements in complex game environments.

Addressing this gap is essential, as visual attention directly influences user experience and has critical implications for game design optimization. Without quantitative insights into gaze distribution, designers risk overlooking key opportunities to enhance visual engagement and player immersion. Recent advancements in eye-tracking technology now allow for precise measurement of gaze behavior, offering valuable empirical data that can inform both aesthetic decisions and user interface improvements in game development.

In response to this gap, the present study aims to systematically investigate the visual attention patterns of first-time players toward Genshin Impact character designs. By integrating eye-tracking technology with hierarchical clustering techniques, this research seeks to identify distinct clusters of gaze behavior, revealing whether players consistently focus on specific character features—such as the face versus the body—and whether clustering analysis can uncover meaningful patterns in attention allocation.

This study contributes to two novel dimensions in game research: (1) introducing the first eye-tracking analysis of visual perception in Genshin Impact character design, and (2) demonstrating the applicability of clustering methods to categorize gaze behavior in visual game studies. These findings are expected to generate both practical implications for character design optimization and theoretical contributions to user-centered game design frameworks.

## 2. MATERIALS AND METHODS

### 2.1 Materials

This study employed primary data collected from participants' visual attention responses toward character design stimuli in Genshin Impact. The main dataset consisted of eye movement coordinates (X, Y) obtained through the online eye-tracking platform Gazerecorder.com, which allowed for remote data acquisition. In addition to eye-tracking data, demographic information such as age, gender, and prior gaming experience was gathered using Google Forms to support participant profiling.

A purposive sampling technique was used to recruit 60 participants aged between 19 and 23 years. The inclusion criteria ensured the suitability of the sample for the research objectives and were as follows: (1) participants had no prior experience playing Genshin Impact, (2) participants possessed normal or corrected-to-normal vision, and (3) participants reported no diagnosed visual impairments. This selection process aimed to minimize potential biases related to prior game familiarity and visual capacity.

The experimental stimuli consisted of four video clips featuring Genshin Impact characters, each with a duration of 10 seconds. The videos displayed characters performing idle animations against neutral backgrounds, ensuring the participants' attention was directed primarily toward character design features. The eye-tracking output was automatically stored in CSV format, recording gaze coordinates frame by frame for subsequent analysis. To facilitate data processing and visualization, Python programming was utilized within the Google Colab environment, providing a flexible and reproducible analytical workflow.

Several key eye-tracking metrics were analyzed to capture participants' visual behavior. These included:

a) Region of Interest (RoI): Divided into four main zones—head, body, character name, and elemental icon—to map specific gaze targets.
b) Heatmaps: Color-coded representations of gaze intensity distributions across stimuli frames.
c) Dwell Time and First View: Metrics indicating the duration of attention and the sequence of gaze priorities.

All gaze data were exported in CSV format for further statistical analysis, and visualizations such as heatmaps and gaze plots were generated using Python-based tools in the Google Colab platform. This comprehensive approach enabled both quantitative and qualitative assessment of visual attention patterns during character exposure.

## 2.2 Methods

This study employed a quantitative, descriptive exploratory approach to examine visual attention patterns toward character designs in a digital game environment. Data were collected using a webcam-based eye-tracking platform through gazerecorder.com, following established methodologies in mobile and web-based gaze-tracking research (Fu et al., 2024). The visual stimuli comprised four short video clips of different Genshin Impact characters, each with a duration of 10 seconds. These videos were presented against a neutral background to minimize distractions and reduce visual noise. Additionally, demographic information such as age, gender, and gaming experience was collected via Google Forms to support participant profiling.

To quantify visual attention, three primary eye-tracking metrics were analyzed. First, heatmaps were generated to visualize the distribution of gaze points across the character stimuli. Second, dwell time was calculated to measure the duration of participant attention within predefined areas. Third, the first view metric was used to identify the initial focal points of gaze, providing insights into attentional priorities. To support this analysis, Regions of Interest (ROI) were defined using a pixel-based segmentation approach, consistent with established practices in gaze visualization studies (Burch et al., 2020).

Following data collection, the raw gaze data underwent a cleaning and reduction process to extract one representative fixation point per participant per video. This reduction facilitated clearer pattern analysis while maintaining data integrity. For inferential analysis, hierarchical clustering was employed to group participants based on similarities in their gaze behavior. The Average Linkage method was chosen due to its proven effectiveness in categorizing visual attention patterns, particularly in cognitive learning research (Hahn & Klein, 2025). To further enhance data quality and reduce dimensionality, Principal Component Analysis (PCA) was applied prior to clustering, a method widely adopted in gaze-based behavioral studies (Wegner-Clemens et al., 2019).

All data processing, statistical analysis, and visualizations were conducted using Python programming within the Google Colab environment. This computational framework ensured reproducibility and facilitated advanced analytical procedures. The methodological design, including the selection of metrics and analytical techniques, was guided by prior studies in game-based learning and eye-tracking research, thereby ensuring both empirical rigor and relevance to game interface analysis (Kiili et al., 2014). The overall research workflow is illustrated in Figure 1, which presents the sequence of eye-tracking data collection, processing, and analysis steps.

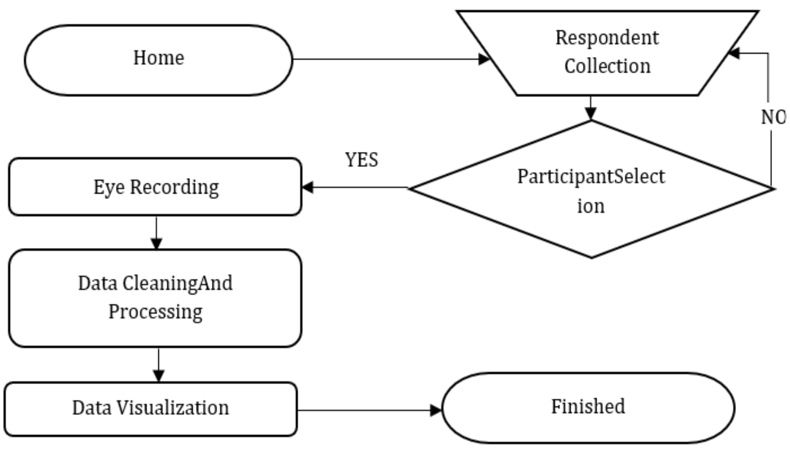


Figure 1. Eye-tracking data processing and analysis flowchart

Ethical considerations were strictly observed throughout the research process. All participants received comprehensive information regarding the study's objectives, procedures, and their right to withdraw at any point. Furthermore, data were anonymized to protect participant confidentiality, and participation was entirely voluntary, in accordance with the ethical standards of academic research.

## 2.3 Eye-Tracking Procedure and Clustering Analysis

This study employed a webcam-based eye-tracking system to capture participants' gaze behavior while viewing Genshin Impact character designs. Eligible participants were instructed to sit comfortably in front of a computer screen to ensure accurate visual engagement. The stimuli consisted of four-character videos, each lasting 10 seconds, resulting in a total exposure time of 40 seconds. The experimental procedure is illustrated in Figure 2, and the visual stimuli are shown in Figure 3.

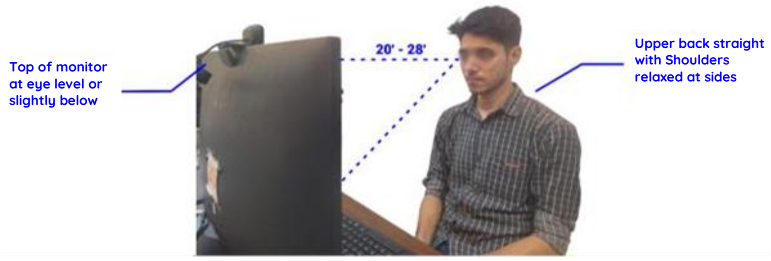


Figure 2. Eye-tracking experimental procedure

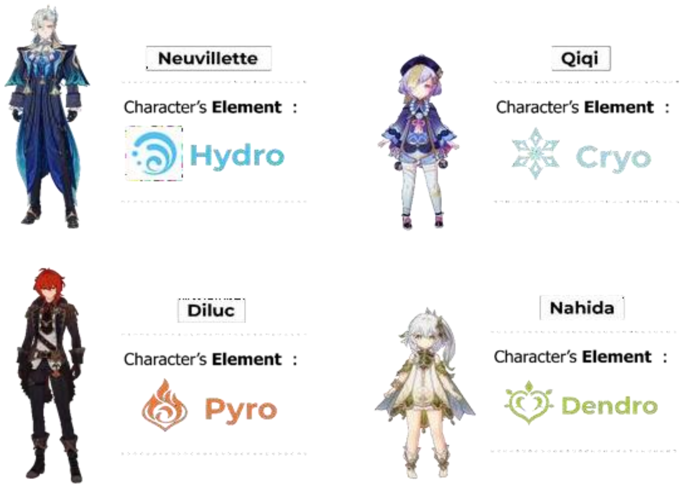


Figure 3. Character design stimuli used in eye-tracking task

Gaze data were collected using gazerecorder.com, which continuously recorded the participants' X and Y gaze coordinates throughout the visual exposure. The analysis focused on key attention metrics, including Regions of Interest (RoI), heatmaps, dwell time, and first view indicators, to capture both spatial and temporal aspects of visual attention. Given the large volume of gaze data points generated per participant, the data were preprocessed by aggregating multiple fixations into a single representative data point per participant, summarizing their dominant gaze behavior for clustering analysis.

To prepare the data for clustering, Principal Component Analysis (PCA) was employed as a dimensionality reduction technique (Kherif & Latypova, 2020; Ng, 2017; Salem & Hussein, 2019; Tharwat, 2016). PCA addresses multicollinearity by transforming correlated gaze variables into orthogonal principal components, allowing for data simplification without significant loss of information. The eigenvalue criterion (>1) was used to determine the number of components retained, ensuring that the major variance in the data was preserved. This step facilitated more stable and interpretable clustering results.

Following dimensionality reduction, hierarchical clustering analysis was performed to identify patterns in gaze behavior across participants. Four linkage methods were tested to compare clustering performance: single linkage, complete linkage, average linkage, and Ward's method (Bakkelund, 2022). The quality of clustering was evaluated using the agglomerative coefficient, and the method with the highest coefficient was selected for dendrogram construction. The overall data analysis workflow, including gaze data collection, PCA preprocessing, hierarchical clustering, and cluster determination, is illustrated in Figure 4.

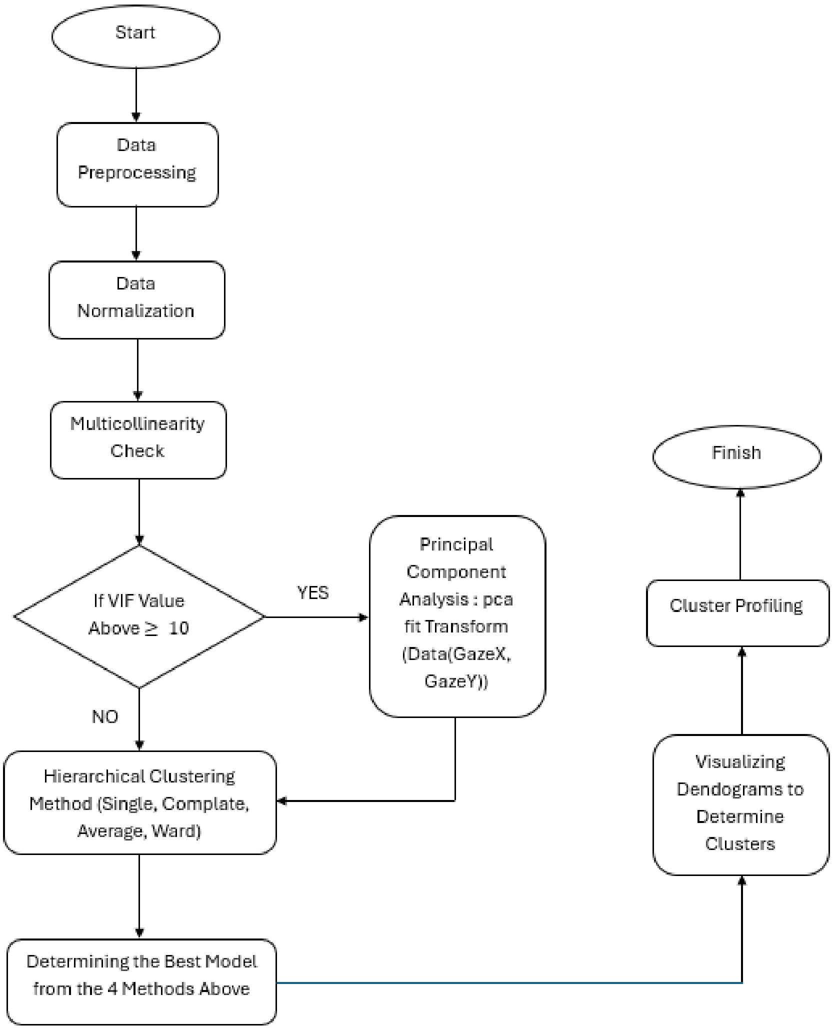


Figure 4. Analytical workflow for hierarchical clustering of gaze data

The optimal number of clusters was determined by analyzing the resulting dendrogram, specifically by identifying the most significant vertical distance cut. This approach ensured meaningful segmentation of participants based on distinct gaze behavior patterns. As a result, the participants were categorized into homogeneous clusters, providing empirical insights into how first-time users allocate visual attention to character design features in anime-style games.

## 3. RESULTS AND DISCUSSION

### 3.1 Visual Attention Mapping

1. Region of Interest (RoI) Identification

The Region of Interest (RoI) mapping was conducted to segment participants' gaze data into specific character features. As shown in Figure 5, each character design was divided into four RoI categories:

a) RoI 1: Character head
b) RoI 2: Character body
c) RoI 3: Character name
d) RoI 4: Character elemental icon

This segmentation enabled a detailed analysis of gaze allocation across different visual components.

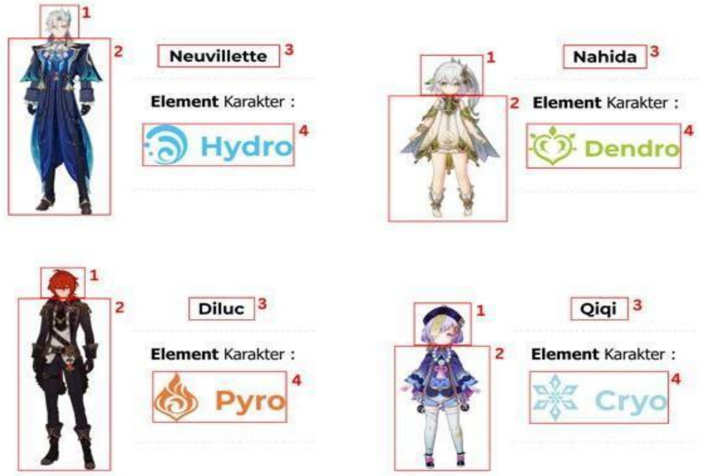


Figure 5. Region of interest (roi) mapping of genshin impact characters

2. Heatmap Analysis

Heatmaps provide a visual representation of gaze distribution and intensity, using color gradients to indicate the duration and focus of participants' gaze points. As illustrated in Figure 6, areas displayed in hot colors (red and orange) represent zones where participants spent more time focusing, while cooler colors (green and purple) indicate less visual attention. The heatmaps consistently showed that RoI 2 (the character's body) attracted the highest gaze intensity across all characters.

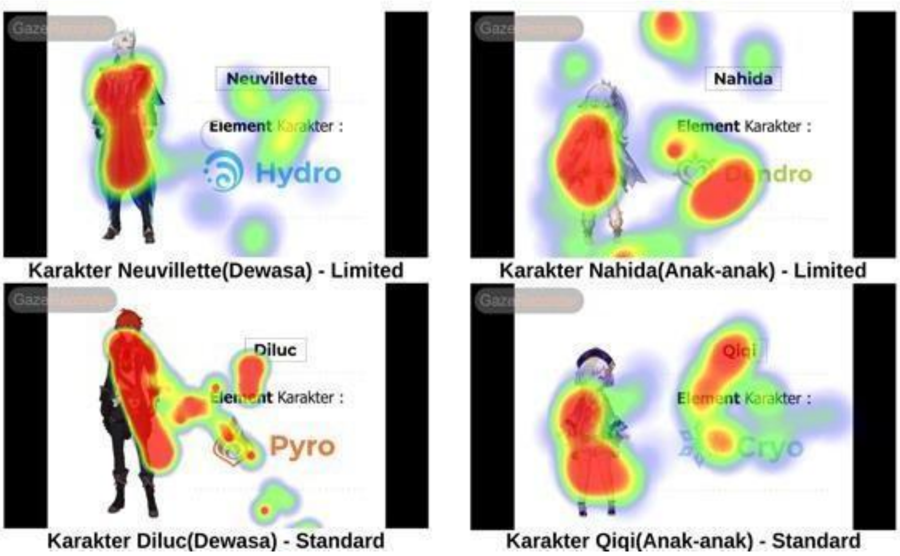


Figure 6. Heatmaps of participants' visual attention across four characters

3. Dwell Time Analysis

Dwell time measures the total duration participants fixated on a specific RoI before shifting their gaze. This metric is critical in understanding sustained attention. As presented in Figure 7, the body region

(RoI 2) received the longest dwell time across most character samples. Notably, for adult characters, the body region consistently dominated dwell time, while for the child character "Qiqi," the least dwell time was recorded on the head region (RoI 1), although the difference with the name region (RoI 3) was marginal (0.03 seconds).

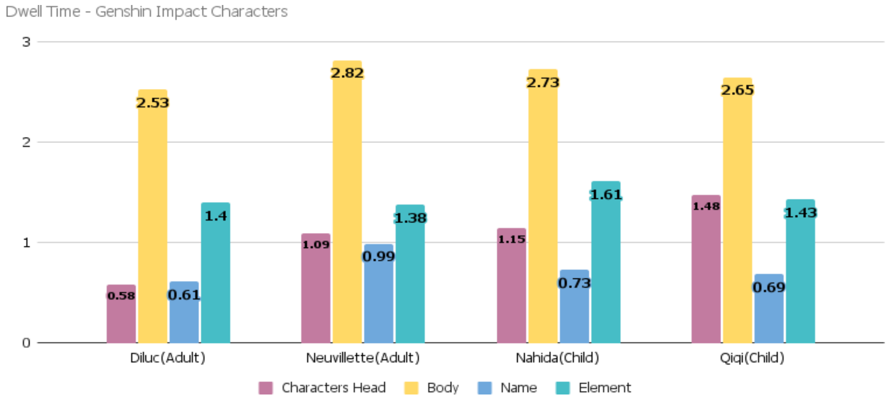


Figure 7. Dwell time distribution across regions of interest

4. First View Analysis

The first view metric identifies which RoI was fixated upon first during the initial exposure. Figure 8 shows the first fixation time across characters. In all four cases, participants first fixated on RoI 2 (body) within the first 2 seconds:

a) Diluc: 1.91 seconds
b) Neuvillette: 1.22 seconds
c) Nahida: 1.39 seconds
d) Qiqi: 1.47 seconds

These results confirm that the body region consistently captures participants' initial visual attention, regardless of character type.

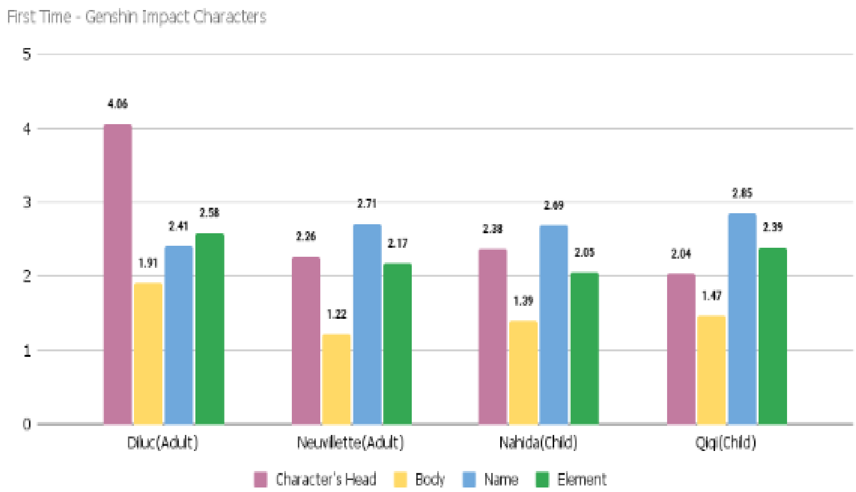


Figure 8. First view timing across characters

## 3.2 Multicollinearity Test

Before performing clustering analysis, a multicollinearity test was conducted to ensure the independence of variables. The Variance Inflation Factor (VIF) was calculated for the gaze coordinates (X and Y). As shown in Table 1, both variables recorded a VIF of 1.14, indicating no multicollinearity since the values are well below the threshold of 10.

Table 1. Variance inflation factor (vif) results

| Variable | VIF Value |
|---|---|
| X | 1.141864 |
| Y | 1.141864 |

## 3.3 Hierarchical Clustering Analysis

1. Agglomerative Coefficient Evaluation

A hierarchical clustering analysis was performed using four agglomerative methods: Single Linkage, Complete Linkage, Average Linkage, and Ward's Method. The agglomerative coefficient was used to determine the clustering quality. As presented in Table 2, the Average Linkage method yielded the highest coefficient (0.8683), indicating superior clustering performance.

Table 2. Agglomerative coefficients for clustering methods

| Method | Agglomerative Coefficient |
|---|---|
| Single Linkage | 0.8273 |
| Complete Linkage | 0.8355 |
| Average Linkage | 0.8683 |
| Ward's Method | 0.8473 |

2. Dendrogram and Cluster Formation

Based on the Average Linkage method, a dendrogram was generated to visualize participant clustering (see Figure 9). The dendrogram revealed three distinct clusters representing different gaze behavior patterns.

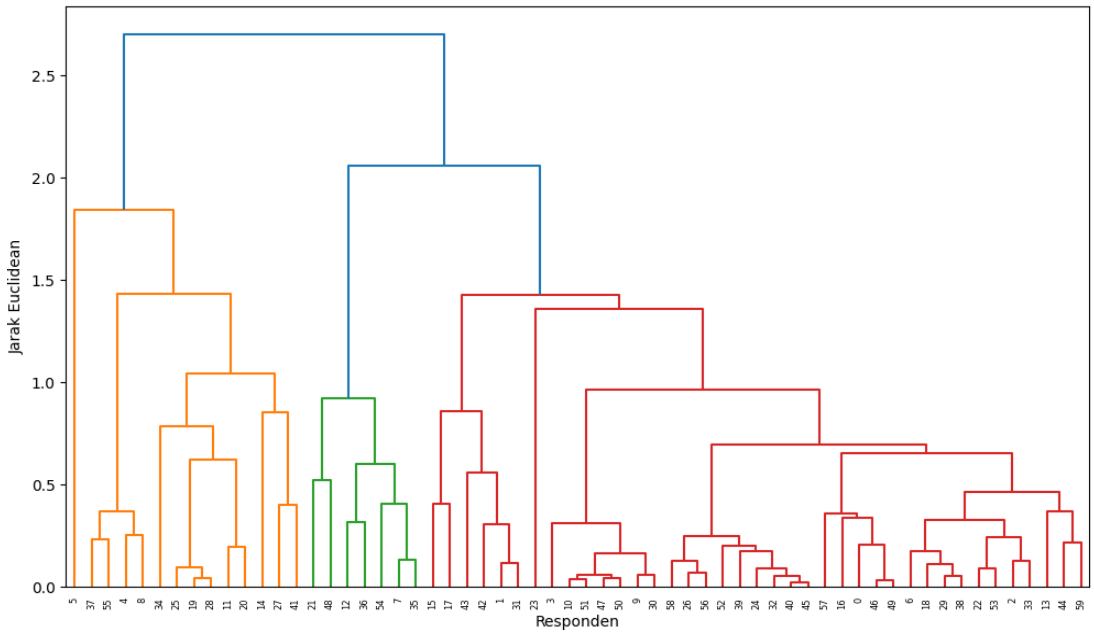


Figure 9. Dendrogram of average linkage clustering

3. Cluster Membership and Gaze Behavior Profiling

The hierarchical clustering analysis using the Average Linkage method produced three distinct clusters, each representing a different pattern of visual attention during character perception tasks. Table 3 summarizes the participant distribution across these clusters.

Cluster 1 includes participants who exhibited lateral scanning behavior, shifting their gaze across different regions of the screen without maintaining prolonged focus on any specific area. Cluster 2 is characterized by participants who directed their attention to peripheral visual elements, such as the elemental icons and character names, suggesting a preference for interface-related details. Cluster 3 represents the largest group, with 39 participants consistently fixating on the character's body region (RoI 2), indicating a dominant central focus pattern.

Table 3. Participant distribution by cluster

| Cluster | Number of Participants | Description |
|---|---|---|
| 1 | 14 | Lateral and dispersed gaze |
| 2 | 7 | Peripheral-focused attention |
| 3 | 39 | Centralized gaze on the body |

4. Gaze Coordinate Profiling and Distance Analysis

To further profile the clusters, the average gaze coordinates (X and Y) for each group were calculated. This provided a quantitative representation of each cluster's focal area on the screen. The results are shown in Table 4.

Table 4. Cluster centroids based on average gaze coordinates

| Cluster | X Coordinate | Y Coordinate |
|---|---|---|
| 1 | -1.3875 | -1.2682 |
| 2 | 1.1462 | -1.0824 |
| 3 | 0.2923 | 0.6495 |

To assess the dispersion of gaze patterns, the Euclidean distance from the origin (0,0) was calculated for each cluster centroid. The results are as follows:

a) Cluster 1: $\sqrt{((-1.3875)^2 + (-1.2682)^2)} = \sqrt{(1.9241 + 1.6073)} = 1.88$

b) Cluster 2: $\sqrt{((1.1462)^2 + (-1.0824)^2)} = \sqrt{(1.3139 + 1.1716)} = 1.58$

c) Cluster 3: $\sqrt{((0.2923)^2 + (0.6495)^2)} = \sqrt{(0.0855 + 0.4219)} = 0.71$

These results confirm that Cluster 3 had the most centralized gaze pattern, with a focus near the body region of the characters. In contrast, Cluster 1 exhibited the widest gaze dispersion, and Cluster 2 maintained attention on peripheral areas of the screen.

## 3.4 Interpretation of Findings

1. Dominant Visual Attention Patterns

The visual attention mapping revealed a consistent focus on the character's body (RoI 2) across all participants and characters. This finding was validated through multiple eye-tracking metrics:

a) Heatmaps demonstrated the highest gaze intensity in RoI 2, visualized by red and orange zones.
b) Dwell Time analysis indicated that participants spent the longest durations fixating on RoI 2.
c) First View measurements showed that RoI 2 was consistently the first area fixated upon, occurring within the first 2 seconds of stimulus exposure.

These results suggest a dominant attentional bias toward the central body region of characters, regardless of character attributes such as age, size, or design complexity.

2. Gaze Behavior Segmentation and User Profiles

The hierarchical clustering analysis provided deeper insights into participant gaze segmentation:

a) Cluster 1 (14 participants): Represented individuals who engaged in exploratory scanning, with lateral gaze dispersion likely indicating a more comprehensive search of the screen.

b) Cluster 2 (7 participants): Comprised participants who prioritized peripheral interface elements, such as icons and text labels, over central features.
c) Cluster 3 (39 participants): Captured the majority of respondents who displayed body-centric gaze behavior, focusing primarily on the character's torso and midsection.

This segmentation highlights the heterogeneity of user visual attention strategies, which is crucial for informing character design, interface layout, and user experience (UX) considerations in game development.

### 3.5 Discussion

The present study demonstrates that participants consistently focused their visual attention on Region of Interest 2 (RoI 2), specifically the character's body, across all character stimuli. This finding was supported by multiple eye-tracking metrics, including dwell time, heatmaps, and first fixation data. The results align with visual salience theory (Itti & Koch, 2001), which posits that visual features such as central positioning, contrast, and design complexity naturally attract attention. Furthermore, the observed gaze pattern is consistent with the central gaze bias (Tatler, 2007), where viewers tend to prioritize the center of the screen during initial visual exploration, reinforcing the prominence of the character's body in early gaze allocation.

These findings differ from prior research in other gaming genres. In first-person shooter (FPS) games, for example, gaze is typically distributed across functional and interactive elements such as weapon reticles and HUD indicators (Antunes & Santana, 2018). Conversely, in anime-style role-playing games (RPGs), players focus more on character aesthetics and narrative visuals, explaining the centralized gaze pattern observed in this study. Similar contrasts are evident in educational game research, where visual attention is directed towards goal-relevant features rather than aesthetic elements (Alemdag & Cagiltay, 2018). These differences emphasize the importance of genre-specific design considerations in gaze-based UX research.

The hierarchical clustering analysis identified three distinct gaze behavior patterns, revealing that character visuals are not uniformly perceived by all users. Some participants exhibited lateral gaze dispersion, while others focused on peripheral symbols such as icons and text labels. The majority, however, displayed a centralized, body-focused gaze pattern. These findings highlight the need for adaptive design strategies in game development, where designers can prioritize the character body for conveying emotional expressions, narrative elements, and interaction triggers, while also considering enhancements to peripheral elements to improve their visual salience.

Despite these contributions, the study has limitations. It did not account for individual differences such as gender, culture, or gaming experience, which may influence gaze behavior. Additionally, only first-time viewers were assessed, leaving open the question of how experience might shift visual attention toward gameplay-relevant elements. The use of static stimuli also limits ecological validity; future research should incorporate dynamic interactions and real-time gameplay to capture gaze behavior in more naturalistic contexts. Further studies integrating affective measures and cross-cultural comparisons are recommended to enrich the understanding of user engagement and visual perception in gaming environments.

## 4. CONCLUSION

This study provides empirical insights into how first-time players allocate visual attention when perceiving character designs in anime-style role-playing games. The eye-tracking results consistently revealed that participants focused predominantly on the body region, regardless of character type or visual variation. This pattern was confirmed through multiple gaze metrics, indicating a dominant body-centric attention tendency during initial exposure to character visuals.

The clustering analysis further identified three distinct gaze behavior profiles, highlighting the variability in user perception. These findings emphasize the importance of adaptive character design strategies that prioritize the body region as a central point for delivering emotional expressions and interactive cues, while peripheral elements may require design adjustments to increase engagement.

This research contributes to the broader field of game user experience and visual attention studies by combining eye-tracking data with clustering techniques to segment gaze behavior. The results provide practical implications for game developers and interface designers aiming to enhance character-based engagement in interactive media.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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