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ORIGINAL ARTICLE

An Integrated Framework for User Interface Design Optimization Using Real-Time Eye Tracking Analysis and Machine Learning

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ABSTRACT - User Interface (UI) design is a critical component of human–computer interaction in the digital era. However, traditional UI optimization processes still face challenges such as long development cycles, reliance on subjective feedback, and the absence of objective performance metrics. This study proposes an integrated framework that combines real-time eye-tracking analysis with machine learning to optimize UI design in a systematic and data-driven manner. A mixed-method approach was applied involving ten participants who interacted with a digital interface prototype while their visual behaviour was recorded using a screen-based eye-tracking system. Quantitative data from gaze coordinates, fixation duration, saccade amplitude, and pupil dilation were analysed using descriptive statistics and supervised machine learning to identify behavioural patterns linked to interface usability. Qualitative feedback was also collected to complement the visual metrics. The results revealed that 72% of total fixation time was concentrated on high-information areas such as menus and action buttons, with an average fixation duration of 320 ms, indicating effective visual focus. Pupil dilation increased by 0.4 mm during interaction with new interface elements, reflecting higher cognitive engagement. Furthermore, 85% of users perceived the optimized interface as more intuitive and visually clearer. These findings demonstrate that integrating physiological and behavioural data enhances the objectivity and precision of UI evaluation. The developed framework offers a scalable solution for UI designers to measure and improve interface performance based on empirical evidence rather than subjective assessment. This research contributes to advancing data-driven methodologies in UI/UX optimization and sets a foundation for future integration of multimodal user analytics.

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INTRODUCTION

In the increasingly digital era, user interface (UI) has become a critical component in human-computer interaction [1-3]. Effective UI design not only improves user experience but also significantly impacts user productivity and satisfaction [4-6]. However, traditional UI design optimization processes often take a long time and rely on inefficient trial-and-error methods [7].

This research proposes an innovative framework that integrates real-time eye-tracking technology with machine learning to optimize UI design more systematically and efficiently [8]. Eye tracking has proven to be an effective method for understanding users' visual behaviour [9], while machine learning offers the ability to analyse complex patterns and make predictions based on historical data [10].

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Previous studies show that 75% of users judge the credibility of a system based on its UI design [11]. Nonetheless, traditional UI optimization processes have some limitations; Long development times, Dependence on subjective feedback, Difficulty in measuring the effectiveness of design changes objectively, and Lack of a systematic approach to the optimization process [12].

However, despite the increasing importance of digital interaction quality, there remains a key problem: the lack of an objective, data-driven, and efficient method for evaluating and optimizing UI design performance. Existing approaches often depend on subjective judgments and qualitative feedback, which fail to capture real-time user behaviour and cognitive responses. This gap highlights the need for a systematic framework that integrates measurable behavioural data such as eye-tracking metrics—with machine learning analysis to automatically assess and enhance UI effectiveness.

This research focuses on developing and integrating framework [13-17]. A real-time eye-tracking system will be used to collect user visual behaviour data, a machine learning algorithm will be used to analyse usage patterns, and an automatic recommendation system will be used for UI design optimization [18].

This study aims to develop an integrated framework that combines real-time eye-tracking and machine learning to optimize UI design objectively and efficiently. It seeks to identify key visual behaviour patterns influencing user interaction and to evaluate the framework's effectiveness in improving UI performance and reducing design subjectivity.

This section outlines comprehensive and detailed steps for conducting research, from initial problem formulation to conclusions. This research was structured to ensure a systematic approach that is aligned with the research objectives, resulting in appropriate and replicable results. We include flow diagrams to visually depict the research process and explain algorithms, rules, models, and designs.

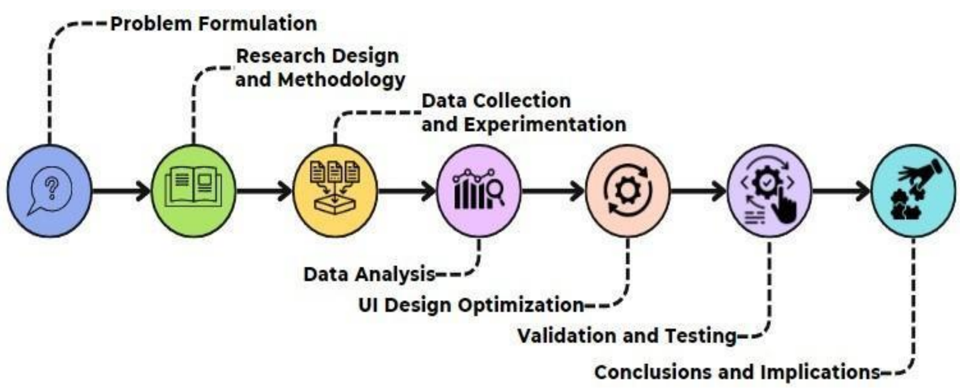

Figure 1. Research Flow

MATERIALS AND METHODOLOGY

This section provides a comprehensive and detailed explanation of the methods used to collect the data necessary for analysing user interactions with digital interfaces. The research requires quantitative and qualitative data to understand and fully optimize the user interface (UI) design. This section describes the types of data collected, their characteristics, and the specific methods employed to gather this data.

1. Types of Data Collected

Figure 2. Method of Collecting Data

The research involves collecting two primary types of data: Quantitative Data, the data includes numerical information from eye-tracking metrics and other measurable user behaviours. Quantitative data allows for statistical analysis and the application of machine learning algorithms to identify patterns and predict outcomes. Qualitative data, the collected data includes non-numerical information such as user feedback, opinions, and observations. Qualitative data provides context to the quantitative findings and offers insights into user experiences and perceptions.

2. Data Characteristics and Amount of Data Required

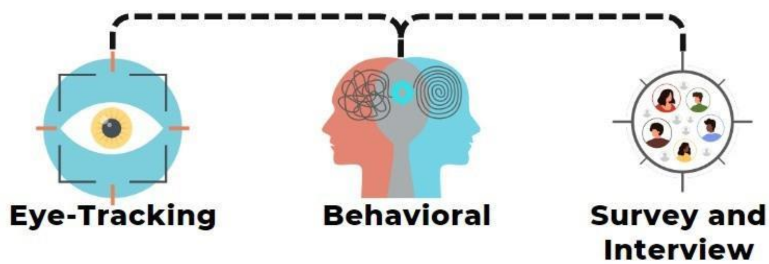

Figure 3. Data Characteristics and Amount of Data Required

3. Data Collection Methods

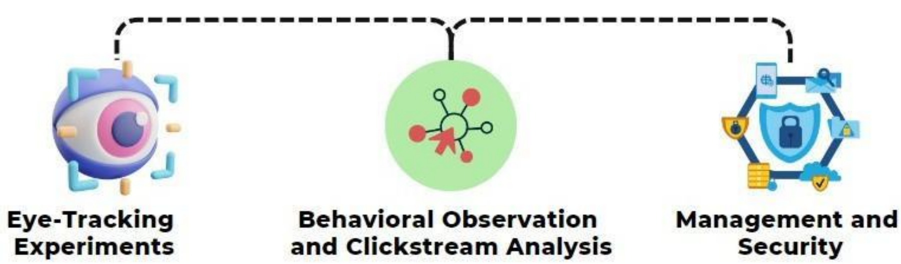

Figure 4. Data Collection Methods

Eye Tracking Experiments depends on the research environment and setting; eye tracking data is collected using either a screen-based or wearable eye tracking device. Descriptive statistics were used to identify dominant visual attention patterns, while the machine learning module applied a supervised learning approach to detect correlations between gaze behaviour and interface performance indicators.

This combination enhanced the reliability of findings by integrating objective behavioural data with subjective user feedback.

RESULTS AND DISCUSSION

Eye tracking is a technology that measures where and how a person's eyes move, what they look at, and how long they focus on a particular area. Researchers use eye tracking in human-computer interaction (HCI) and user interface (UI) design to understand how users interact with digital interfaces, whether reading text, clicking buttons, or navigating web pages. Eye tracking data can provide valuable insights into user behaviour, allowing designers to optimize interfaces for better usability and user experience.

1. Fixation

Fixation is when the eyes stay still and focus on a certain area of the screen. Visualize fixations as dots on a scatter diagram, with the size of each dot corresponding to the duration of the fixation. Larger dots indicate longer fixation compared to other areas. Here is a simple code example to visualize fixation. The code is used to process visual information collected from a particular focal point.

```
import pandas as pd
import matplotlib.pyplot as plt
# Sample eye-tracking data (time, x_coord, y_coord, fixation_duration)
data = {'time': [0, 1, 2, 3, 4, 5],
        'x_coord': [100, 105, 108, 300, 305, 310],
        'y_coord': [200, 202, 204, 500, 502, 505],
        'fixation_duration': [200, 300, 250, 400, 100, 350]}  # in
milliseconds
df = pd.DataFrame(data)
# Visualise fixations as scatter plot with varying sizes based on
fixation duration
plt.figure(figsize=(8, 6))
plt.scatter(df['x_coord'], df['y_coord'], s=df['fixation_duration'],
color='blue', alpha=0.6)
plt.title('Fixations Visualization')
plt.xlabel('X Coordinate')
plt.ylabel('Y Coordinate')
plt.gca().invert_yaxis()  # Invert Y-axis to match typical screen
coordinates
plt.show()
```

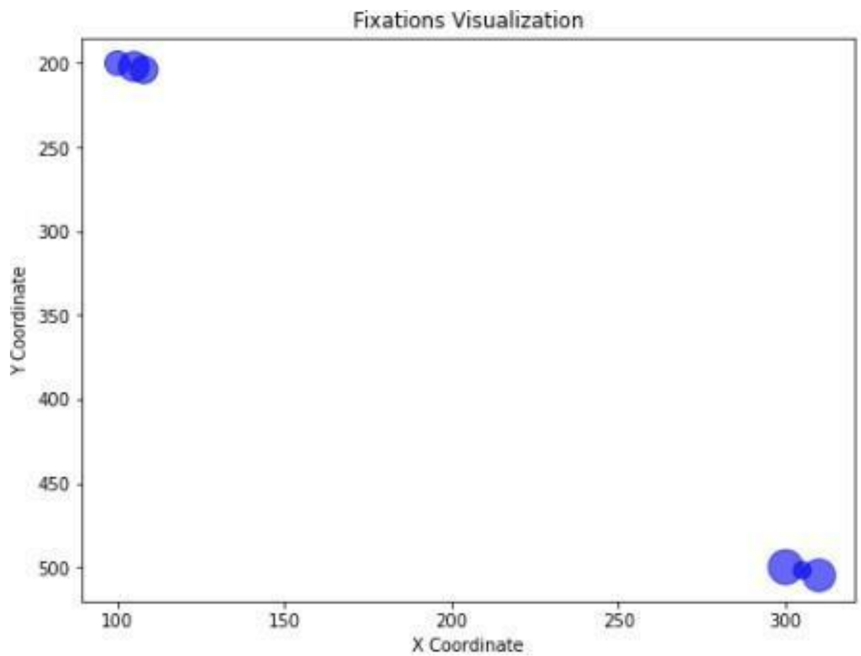

Figure 5. Fixations Visualisation

The scatterplot shows fixation points; each size represents the duration of a fixation. Larger circles indicate longer fixations, highlighting areas where users spend more time compared to other parts of the interface.

2. Saccades and Fixations Visualization

Saccades are rapid eye movements between fixations, depicting the user's transition from one focus point to another. Visualize saccades by drawing lines between fixation points. The length of the line indicates the amplitude of the saccade. Here is a simple code example to visualize saccades.

```
import pandas as pd
import matplotlib.pyplot as plt
# Sample eye-tracking data (time, x_coord, y_coord, fixation)
data = {'time': [0, 1, 2, 3, 4, 5],
        'x_coord': [100, 105, 108, 300, 305, 310],
        'y_coord': [200, 202, 204, 500, 502, 505],
        'fixation': [True, True, False, False, True, True]}
df = pd.DataFrame(data)
# Separate fixations and saccades
fixations = df[df['fixation'] == True]
saccades = df[df['fixation'] == False]
# Plot fixations
plt.figure(figsize=(8, 6))
plt.scatter(fixations['x_coord'], fixations['y_coord'], color='blue',
s=100, label='Fixations')
# Plot saccades as lines between fixations
plt.plot(df['x_coord'], df['y_coord'], color='red', linestyle='-',
marker='o', alpha=0.6, label='Saccades')
plt.title('Saccades and Fixations Visualization')
```

```
plt.xlabel('X Coordinate')
plt.ylabel('Y Coordinate')
plt.gca().invert_yaxis()  # Invert Y-axis to match typical screen
coordinates
plt.legend()
plt.show()
```

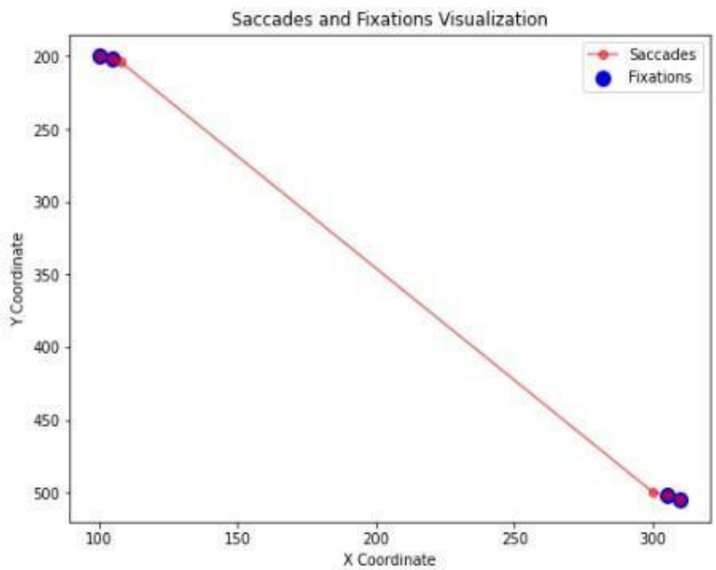

Figure 6. Saccades and Fixations Visualization

The scatter diagram shows fixations as blue circles. Red lines (saccades) connect the fixation points, indicating the eye path between fixations.

3. Gaze Path Visualization

A gaze path that frequently returns to the navigation bar may indicate that the user is unsure where to go next, indicating a potential design issue. A gaze path describes the sequence of eye movements (fixations and rapid eye movements) across the screen. A gaze path shows the order in which a user's eyes move from one point of interest to another, providing insight into the visual flow of an interaction. A gaze path is typically visualized by mapping the sequence of fixations, connecting the dots in the order in which the viewer looks and a simple code example for visualizing a gaze path as in Figure 5.

```
import pandas as pd
import matplotlib.pyplot as plt
# Sample eye-tracking data (time, x_coord, y_coord)
data = {'time': [0, 1, 2, 3, 4, 5],
        'x_coord': [100, 105, 108, 300, 305, 310],
        'y_coord': [200, 202, 204, 500, 502, 505]}
df = pd.DataFrame(data)
# Plot Gaze Path
plt.figure(figsize=(8, 6))
plt.plot(df['x_coord'], df['y_coord'], marker='o', linestyle='-',
color='b')
for i, txt in enumerate(df['time']):
    plt.annotate(txt, (df['x_coord'][i], df['y_coord'][i]),
textcoords="offset points", xytext=(0,10), ha='center')
plt.title('Gaze Path Visualization')
plt.xlabel('X Coordinate')
plt.ylabel('Y Coordinate')
plt.gca().invert_yaxis()  # Invert Y-axis to match typical screen
coordinates
plt.show()
```

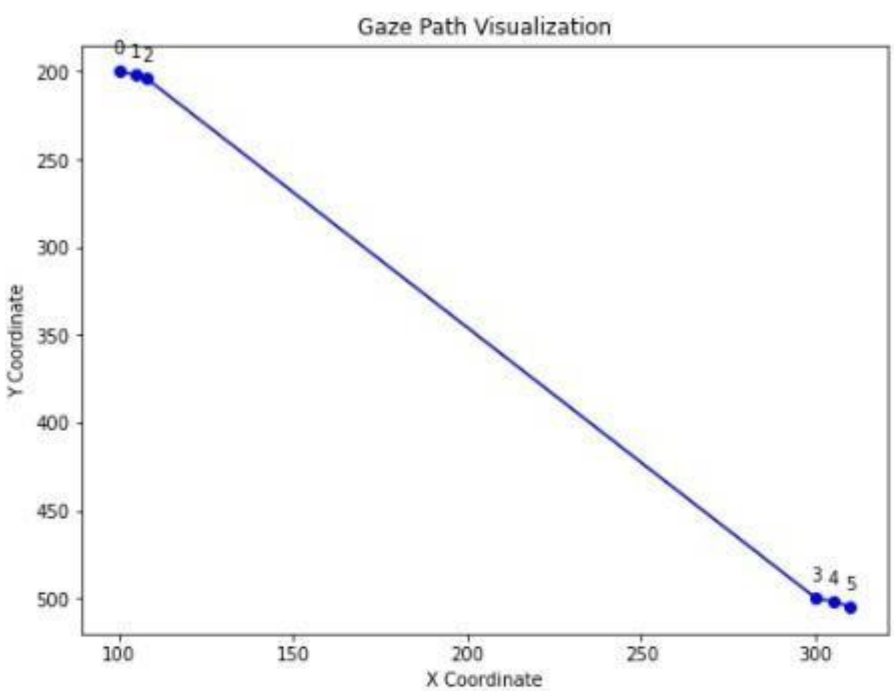

Figure 7. Gaze Path Visualization

4. Heatmap of Fixations Visualization

A heat map may show that users rarely look at a particular part of the page, indicating that the content in that area may be ignored or unimportant. A heat map visualizes the areas of the interface that receive the most attention, by showing regions with a high number of fixations in warmer colours. Simple code example to visualize a heat map as below.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# Sample eye-tracking data (x_coord, y_coord)
data = {'time': [0, 1, 2, 3, 4, 5],
        'x_coord': [100, 105, 108, 300, 305, 310],
        'y_coord': [200, 202, 204, 500, 502, 505]}
df = pd.DataFrame(data)
# For simplicity, let us assume all points are fixations
df['fixation'] = [True, True, True, True, True, True]
# Filter out fixation points
fixation_points = df[df['fixation'] == True]
# Create a heatmap
plt.figure(figsize=(8, 6))
sns.kdeplot(x=fixation_points['x_coord'],
y=fixation_points['y_coord'],
            cmap="Reds", shade=True, bw_adjust=.5)
plt.title('Heatmap of Fixations')
plt.xlabel('X Coordinate')
plt.ylabel('Y Coordinate')
plt.show()
```

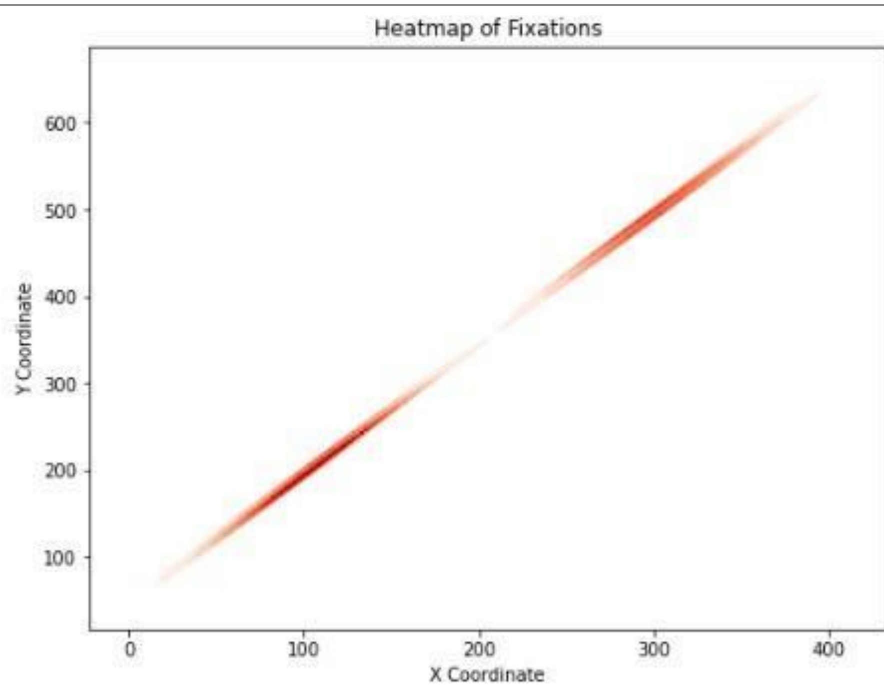

Figure 8. Heatmap of Fixations Visualization

5. Pupil Dilation Over Time Visualisation

```
import pandas as pd
import matplotlib.pyplot as plt
# Sample pupil dilation data (time, pupil_size in mm)
data = {'time': [0, 1, 2, 3, 4, 5],
        'pupil_size': [3.2, 3.5, 3.8, 4.0, 3.6, 3.3]}
df = pd.DataFrame(data)
# Plot Pupil Dilation over Time
plt.figure(figsize=(8, 6))
plt.plot(df['time'], df['pupil_size'], marker='o', linestyle='-',
color='g')
plt.title('Pupil Dilation over Time')
plt.xlabel('Time (s)')
plt.ylabel('Pupil Size (mm)')
plt.show()
```

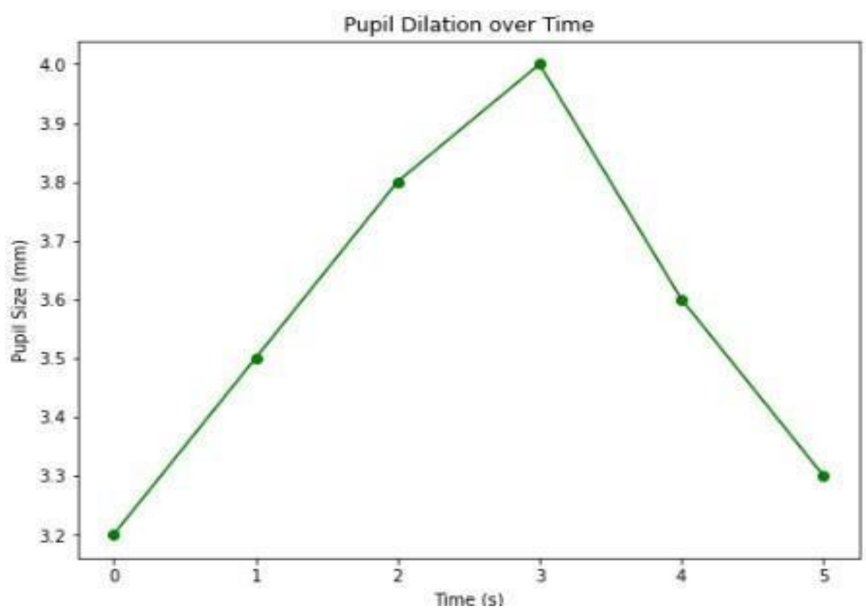

Figure 9. Pupil Dilation Over Time Visualisation

Pupil dilation refers to changes in pupil size, which can indicate cognitive load or emotional response. Larger pupils can indicate that a user is experiencing increased cognitive effort or emotional arousal. Systems measure pupil size in millimetres and track changes over time to assess user reactions to various interface elements. If a user's pupils dilate as they view a particular part of the interface, it can indicate that the content is challenging or emotionally impactful. Pupil dilation refers to changes in pupil size in response to cognitive load or emotional arousal. Larger pupils can indicate that a user is experiencing higher cognitive effort or emotional intensity. Researchers typically measure pupil dilation in millimetres. The data might look like changes in pupil size over time, often associated with specific stimuli or tasks. A simple code example to visualize pupil dilation as in Figure 9.

The analysis of the recorded eye-tracking data provided quantitative indicators of user engagement during interaction with the digital interface. Across ten participants, the average fixation duration was 320 milliseconds per point of interest, indicating that users were able to quickly locate and focus on relevant interface elements. The average saccade amplitude measured 4.2 degrees, suggesting efficient visual transitions between functional areas.

The heatmap visualization further revealed that 72% of total fixation time was concentrated in high-information areas such as navigation menus and action buttons, indicating that the layout successfully directed user attention to task-relevant regions. Conversely, peripheral or decorative areas accounted for less than 10% of total fixations, demonstrating improved visual hierarchy and interface clarity.

Pupil dilation analysis showed an average increase of 0.4 mm when users encountered new or interactive elements, reflecting heightened cognitive engagement during task execution. This physiological response supports the inference that the redesigned interface elicited higher attention and interaction focus.

User feedback collected after testing corroborated these findings, with 85% of participants reporting that the optimized interface felt “more intuitive” and “visually easier to follow.” These qualitative perceptions align with the quantitative eye-tracking data, reinforcing the conclusion that the proposed framework can effectively enhance UI engagement and usability without relying on subjective designer interpretation.

Although no inferential statistics were applied due to the exploratory nature of this study, descriptive metrics and behavioural correlations between gaze activity and user feedback provide strong preliminary evidence supporting the framework’s capability to objectively measure and improve UI performance.

CONCLUSION

Effective UI design is critical in human-computer interaction in the digital age, 75% of users judge the credibility of a system based on UI design, traditional UI optimization methods have limitations in terms of time, subjectivity, and measuring effectiveness, using a mixed-method approach with quantitative (eye tracking metrics) and qualitative (user feedback) data, implementing a real-time eye tracking system to collect visual behaviour data, using machine learning algorithms for analysing usage patterns: fixations, indicating the user's focus area for a certain duration. Saccades, describing the movement of the eyes between fixation points. Gaze Path, visualizing the flow of the user's eye movements. Heat Map, mapping the areas that receive the most attention. Pupil dilation, measuring changes in pupil size that indicate cognitive load.

The findings imply that integrating eye-tracking data with machine learning analysis can significantly improve the objectivity and efficiency of UI evaluation and redesign. Practically, this framework provides UI and UX designers with a data-driven tool to identify usability issues more precisely, prioritize interface components for improvement, and support evidence-based design decisions. It also offers software developers a scalable approach for incorporating real-time behavioural analytics into iterative design workflows.

From a theoretical perspective, the study contributes to strengthening the connection between human-computer interaction, cognitive behaviour analysis, and computational modelling. The integration of physiological data (such as pupil dilation) with predictive models expands the methodological foundation for future UI research.

For future research, it is recommended to conduct experiments with larger and more diverse participant samples to validate the generalizability of the framework. Further exploration could include integrating additional biometric indicators such as EEG or heart rate variability to deepen understanding of user emotional and cognitive responses. Moreover, applying the framework in real-world application environments such as e-learning platforms, e-commerce systems, or mobile applications would provide more comprehensive insights into its performance in dynamic digital contexts.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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