Context-Aware Adaptive Feedback for Maintaining Healthy Blink Rates During Screen Use

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***Abstract*—Prolonged screen use suppresses blink frequency, increasing the risk of Dry Eye Disease (DED), visual fatigue, and discomfort. While fixed-interval reminders offer a basic solution, their lack of personalization can cause user fatigue, poor compliance, and over-blinking—potentially worsening conditions such as blepharospasm. This paper presents a real-time adaptive feedback system that personalizes blink reminders based on recent user behavior. The system combines clinically grounded thresholds (**15–30 blinks per minute [BPM]**), a sliding window for trend estimation, and randomized exponential backoff to minimize habituation. In a pilot study with 15 participants, the system significantly increased blink frequency compared to a no-reminder baseline ($p < 0.0001$), without inducing over-blinking. Subjective ratings showed high usability (M = 4.0), satisfaction (M = 4.4), and perceived effectiveness (M = 4.6). These findings suggest that adaptive, behavior-sensitive feedback offers a practical and user-friendly approach to supporting ocular health during screen use.**

***Index Terms*—Blink Monitoring, Blink Reminders, Adaptive Feedback, Eye Health, Human-Computer Interaction, Real-Time Sensing**

I. Introduction

Blinking is an essential physiological function that maintains tear film stability and protects the eyes during visual tasks. However, prolonged use of digital devices has been shown to suppress spontaneous blinking, particularly during cognitively demanding activities such as reading, programming, or gaming. This suppression can reduce blink frequency to as low as 5 blinks per minute (BPM)—well below the clinically recommended range of 15–30 BPM—contributing to the rise of Dry Eye Disease (DED), visual fatigue, and reduced task performance [1].

The rise in screen time—averaging 3.2 hours daily—has been associated with prevalent ocular symptoms such as tired eyes (39.8%), dryness (31.5%), discomfort (30.8%), and strain (30.6%), affecting users during at least half of their device use [2]. Recognizing this as a growing public health concern, the WHO has urged countries to integrate eye care into national health strategies [3]. In alignment, the present system supports daily prevention by providing adaptive, real-time feedback to sustain healthy blink behavior during screen use.

To mitigate blink suppression, prior systems have implemented fixed-interval blink reminders. While these approaches can temporarily improve blink frequency, they often operate independently of users' real-time physiological states. As a result, reminders may be poorly timed or overly frequent, contributing to annoyance, user fatigue, and reduced compliance over time. Furthermore, many existing interventions focus solely on increasing blink rates, overlooking the potential consequences of over-blinking—which can cause discomfort or aggravate conditions such as blepharospasm, a neurological disorder characterized by involuntary eyelid closure and ocular strain [4].

Maintaining an optimal blink rate is not only a matter of comfort—it is closely tied to long-term ocular health, cognitive performance, and digital wellbeing. **While previous systems have addressed blinking from a reactive or rule-based perspective, there remains a need for proactive, behavior-sensitive feedback that adapts to individual patterns in real time.**

In response, we propose a context-aware adaptive feedback system designed to promote healthy blink behavior during screen-based tasks. Rather than relying on pre-set intervals, the system continuously monitors blinking through a webcam and adjusts reminder timing based on real-time trends. It integrates: (1) a **sliding window** mechanism for estimating blink frequency over a 1-minute window, (2) **threshold-based decision logic** grounded in clinical norms (15–30 BPM), and (3) a **randomized exponential backoff** strategy that delays subsequent prompts to minimize habituation and maintain user attention.

Although the individual components (e.g., sliding window, thresholds) may appear simple, their combined use in a dynamic, adaptive loop provides a novel balance between responsiveness and user tolerance—contributing a lightweight, personalized approach to blink regulation without requiring intrusive hardware or complex gaze tracking. **This framing shifts the focus from one-time blink reminders to continuous interaction support, making the system relevant to broader applications in digital health and attention-aware interfaces.**

This study explores how low-cost, non-intrusive sensing—via standard webcams—can power personalized interventions. Unlike gaze tracking or eye movement analytics, our method focuses on blink frequency, offering a direct and interpretable metric for ocular wellness. The system builds on prior work in blink detection [5] and real-time adaptive sensing [6], offering a lightweight framework for integration into everyday computing environments.

Research Aim: This study investigates whether combining passive, real-time blink sensing with adaptive feedback can help sustain healthy blink patterns during screen use—without causing user discomfort or disrupting workflow.

We evaluated the system through a pilot study involving 15 participants, each completing a screen-reading task under one of three conditions: no reminder (baseline), fixed-interval reminder, and adaptive feedback. The results showed that the adaptive system significantly increased blink frequency compared to the baseline, while avoiding the over-blinking observed in the fixed-interval condition. Subjective ratings further indicated high usability (mean = 4.0, SD = 0.71), satisfaction (mean = 4.4, SD = 0.55), and perceived effectiveness (mean = 4.6, SD = 0.55), suggesting that adaptive feedback offers a more effective and user-friendly approach to supporting healthy blink behavior during prolonged screen use.

The rest of this paper is organized as follows: Section II reviews related literature on blink regulation and adaptive sensing. Section III describes the system architecture and design logic. Section IV presents experimental results, and Sections V and VI discuss findings, limitations, and future directions.

II. Related Work

Blink rate (15–30 BPM) declines during screen use, increasing DED and fatigue risk [7]–[9]. This section reviews blink interventions, their limitations, and related adaptive wellness technologies.

A. Digital Interventions for Blink Regulation

Several digital interventions aim to counter blink reduction. Ashwini et al. [7] used fixed reminders (8/min), improving blink rates and DED symptoms—with lasting effects. Even the control group (1/min) showed modest gains.

Furqan et al. [10] used a decoy technique based on Nudge Theory. Although some users' blink patterns changed, the effects were not statistically significant.

Despite their benefits, fixed-timing approaches ignore real-time physiological changes and risk causing over-blinking or fatigue, which may worsen conditions like blepharospasm [4].

Tsubota et al. [11] introduced Maximum Blink Interval (MBI)—the longest time one can keep their eyes open—as a personalized metric for blink interventions and a passive DED diagnostic tool, validated through a mobile app.

Together, these studies highlight the potential of blink interventions, while also revealing a need for solutions that are both adaptive and behaviorally sensitive.

B. Adaptive Feedback in Wellness Systems

Adaptive systems that tailor feedback to real-time behavior have shown effectiveness in wellness applications [12], [13]. However, existing approaches lack physiological integration and are not intended for blink regulation.

The present work extends prior efforts by incorporating blink-specific sensing and adaptive feedback. It introduces three key innovations:

- Real-time blink detection using webcam-based Eye Aspect Ratio analysis to monitor physiological states.
- Sliding window trend estimation to smooth blink fluctuations and avoid responses to outliers.
- Randomized exponential backoff to minimize user fatigue and reduce habituation to feedback.

By targeting both under- and over-blinking, our system offers a lightweight, adaptive solution for ocular wellness during screen use. Unlike fixed-interval methods, it tailors feedback to individual blink patterns, enabling more precise and context-aware intervention.

III. System Design And Implementation

This section describes the system architecture and logic for adaptive feedback based on real-time blink monitoring, and explains how the system interacts with users.

A. Overview and Architecture

The system uses a webcam to capture eye activity, which is analyzed in real time using the Eye Aspect Ratio (EAR) algorithm [5] to detect blinks. Blink frequency is monitored using a sliding window of recent activity, and based on this information, the system makes decisions to either prompt the user or defer intervention.

As shown in Fig. 1, the control logic responds dynamically: when blinking behavior deviates from clinically healthy norms (15–30 BPM), a visual reminder is issued, and the timer resets. If blinking remains within the target range, the system applies an exponential backoff mechanism to space out future reminders—helping reduce user fatigue and habituation.

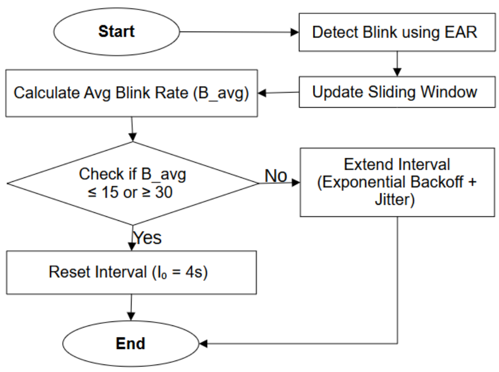


Fig. 1. Control flow of the adaptive feedback system.

B. Real-Time Blink Estimation and Decision Logic

Blink behavior is estimated using a 60-second sliding window (three 20-second segments, updated every 20 seconds) to smooth fluctuations while remaining responsive. This approach aligns with prior work on real-time, behavior-aware feedback [14].

The window size was selected based on pilot testing, which evaluated 1–6 intervals. A three-interval (1-minute) window offered the best balance of stability and responsiveness, aligning with the clinical blink range of 15–30 BPM (≈5–10 blinks per 20 seconds).

The average blink rate over the window is computed as:

$$B_{\text{avg}} = \frac{1}{W} \sum_{i=t-W+1}^{t} B_i \tag{1}$$

where:

- $W = 3$: Number of intervals in the window
- B_i: Blink count in the i^{th} 20-second segment

The system compares B_{avg} against a clinically accepted blink rate range of 15–30 BPM. If the average falls outside this range, a visual reminder is triggered, and the reminder interval is reset to a base value $I_0 = 4$ seconds. This value was selected through pilot testing to ensure that reminders are frequent enough to prompt action, but not so frequent as to cause annoyance.

If the blink rate remains within the target range, the system applies a randomized exponential backoff strategy to delay the next reminder, helping to reduce habituation:

$$I_{t+1} = \begin{cases} I_0, & \text{if } B_{\text{avg}} \notin [T_{\min}, T_{\max}] \\ \min(2I_t + J, I_{\max}), & \text{otherwise} \end{cases} \tag{2}$$

where:

- $I_0 = 4$s: The base interval used when blink behavior is outside the healthy range.
- $I_{\max} = 60$s: The maximum reminder delay was set based on pilot testing, which found that delays over 60 seconds diminished user awareness and reduced blink intervention effectiveness.
- $J \sim U(0, I_{\max} - I_0)$: A uniformly sampled random jitter used to add variability.

Jittered exponential backoff, capped at $I_{\max}$introduces timing variability to prevent habituation by making feedback less predictable and more salient.

Algorithm 1 outlines the system's runtime logic, which continuously monitors blink data and adapts reminder timing based on physiological thresholds.

C. Implementation

The adaptive blink reminder system was implemented in Python using the PyQt6 framework. It ran on a laptop with a 13th Gen Intel Core i7-1355U (1.70 GHz) and 16 GB RAM, and was tested in a quiet, controlled indoor setting.

To support real-time monitoring, the system displayed blink rate using a semicircular gauge (Fig. 3) with a central numeric value and a color-coded arc for instant interpretation.

The arc was divided into four regions:

- **Red (left)**: Too low (<15 BPM)
- **Green**: Healthy (15–25 BPM)
- **Yellow**: Elevated but acceptable (26–30 BPM)

Algorithm 1 Adaptive Feedback Algorithm for Real-Time Blink Regulation

Initialize: $W = 3$, $I_0 = 4$, $I_{\max} = 60$, $T_{\min} = 15$, $T_{\max} = 30$
Initialize: $I_1 \leftarrow I_0$, time interval index $i \leftarrow 1$
while system is active **do**
  Wait for I_i seconds
  Record blink count B_i during current interval
  if $i \geq W$ **then**
    Compute $B_{\text{avg}} \leftarrow \frac{1}{W} \sum_{j=i-W+1}^{i} B_j$
    if $B_{\text{avg}} < T_{\min}$ or $B_{\text{avg}} > T_{\max}$ **then**
      $I_{i+1} \leftarrow I_0$ ▷ Trigger immediate reminder
    else
      Sample $J \sim \text{Uniform}(0, I_{\max} - I_0)$
      $I_{i+1} \leftarrow \min(2I_i + J, I_{\max})$
    end if
  end if
  $i \leftarrow i + 1$
end while

Fig. 2. Illustration of a participant using the system during the experiment.

- **Red (right)**: Excessive (>30 BPM)

This intuitive design enabled users to self-regulate blink behavior without interrupting tasks.

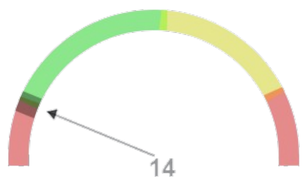
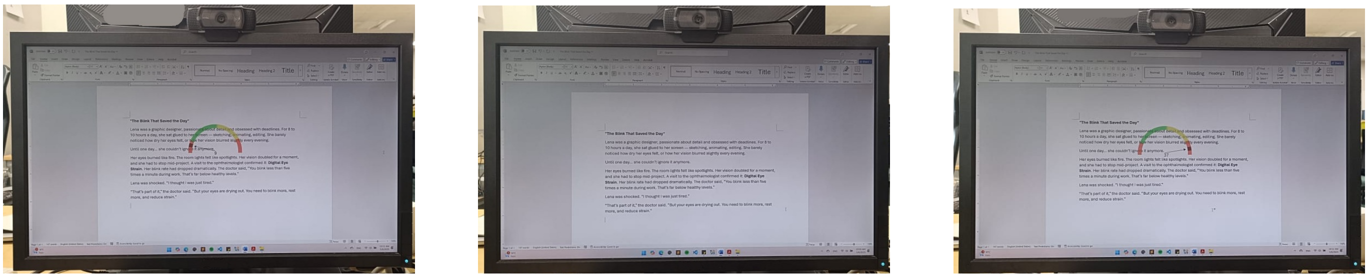


Fig. 3. Real-time blink rate feedback gauge showing numeric and color-coded status.

In addition to the gauge, the system employs popup notifications to deliver adaptive feedback when blink behavior deviates from the recommended range. As shown in Fig. 4, reminders are triggered based on current blink status to facilitate real-time behavioral correction.

IV. Pilot Study Results

This section reports findings from a pilot study evaluating the adaptive blink feedback system using both quantitative (blink frequency) and qualitative (user feedback) measures to assess its impact on blink behavior and user experience.



(a) Low blink rate detected (b) Healthy blink rate (c) Excessive blinking detected

Fig. 4. Visual reminders shown on the monitor in response to (a) low, (b) healthy, and (c) excessive blink rates.

A. Participants and Experimental Setup

Fifteen participants (12 males, 3 females; $M_{\text{age}} = 29.4$, $SD = 4.5$) completed a five-minute screen-based reading task in a controlled laboratory setting. To ensure consistency across participants and conditions, blink activity was segmented into seven fixed intervals per participant, yielding 105 blink samples in total.

All participants reported normal or corrected-to-normal vision and an average daily screen time of over 4 hours (SD = 1.6), reflecting habitual use of digital devices.

Participants were randomly assigned to one of three groups ($n = 5$ each): (1) **Baseline** with no feedback, (2) **Fixed-Interval** reminders triggered below 15 BPM, and (3) **Adaptive** reminders based on real-time, context-aware blink analysis.

In the adaptive condition, participants could modify the base reminder interval (default: 4s); only one selected 6s. Blink activity was recorded using a 1920×1080 webcam at 30 fps and detected in real time via the validated, non-intrusive Eye Aspect Ratio (EAR) method [5].

After completing the reading task, participants in the Adaptive group completed a questionnaire evaluating usability, perceived effectiveness, and interface clarity using a 5-point Likert scale. Feedback from other groups was not collected, as the study focused on assessing the performance of the adaptive feedback mechanism.

B. Blink Rate Trends Across Conditions

To analyze blink trends, raw blink counts (20s intervals) were processed into progressive 1-minute averages using a sliding window of size three. This smoothing technique helped identify trends while mitigating sensitivity to short-term fluctuations.

Fig. 5 illustrates the distribution of blink rates across conditions. The adaptive system maintained values more consistently within the clinically recommended range (15–30 BPM), whereas the baseline condition showed rates predominantly below 15 BPM, and the fixed-interval reminder condition frequently exceeded 30 BPM—suggesting potential overcompensation.

To improve transparency and verifiability, Table I presents the descriptive statistics for each group. These include the minimum, 25th percentile (Q1), median, 75th percentile (Q3), and maximum blink rates. Providing these numerical values

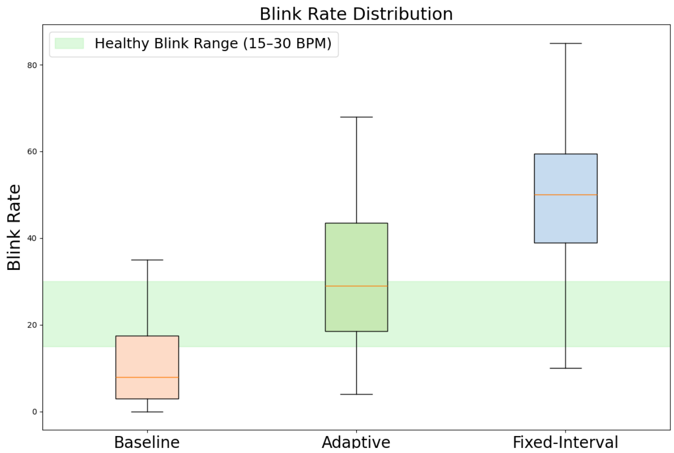


Fig. 5. Blink rate distribution across all conditions.

complements the figure and allows a clearer understanding of the distributions.

TABLE I
DESCRIPTIVE STATISTICS OF BLINK RATES ACROSS CONDITIONS (BPM)

Condition	Min	Q1	Median	Q3	Max
Baseline (No Reminder)	0	2.0	4.0	6.0	12
Fixed-Interval Reminder	10	15.0	17.0	20.0	29
Adaptive Reminder	4	6.0	10.0	15.0	30

C. Statistical Comparison

Given the small sample size and non-normal distribution of blink rates, we employed non-parametric statistical methods. A global **Kruskal–Wallis H test** was first conducted to assess overall group differences, yielding a significant result ($H = 56.57$, $p < 0.0001$), which justified further pairwise comparisons.

To confirm the appropriateness of these tests, we assessed the assumption of homogeneity of variance using **Levene's Test**, which indicated no significant differences in variances across conditions ($p = 0.19$). As such, the use of non-parametric methods was deemed valid.

Post-hoc analysis was conducted using pairwise **Mann–Whitney U tests**. To control for multiple comparisons, we applied a Bonferroni correction that included the

Kruskal–Wallis H test in the count of comparisons ($\alpha = 0.05/4 = 0.0125$). All three comparisons remained statistically significant under the corrected threshold, as shown in Table II.

TABLE II
PAIRWISE MANN–WHITNEY U TEST RESULTS WITH BONFERRONI-ADJUSTED P-VALUES

Comparison	U	Adj. p-value
Baseline vs Adaptive	161.0	< 0.0001
Baseline vs Fixed-Interval	45.5	< 0.0001
Adaptive vs Fixed-Interval	296.5	0.0009

To estimate the magnitude of differences, we computed **Cliff's Delta** (δ), a rank-based effect size measure. All values indicated **large effects** ($|\delta| > 0.474$), suggesting practical relevance (Fig. 6). However, we acknowledge that Cliff's Delta assesses distributional dominance but does not directly reflect how close each group's blink rate was to the clinical target.

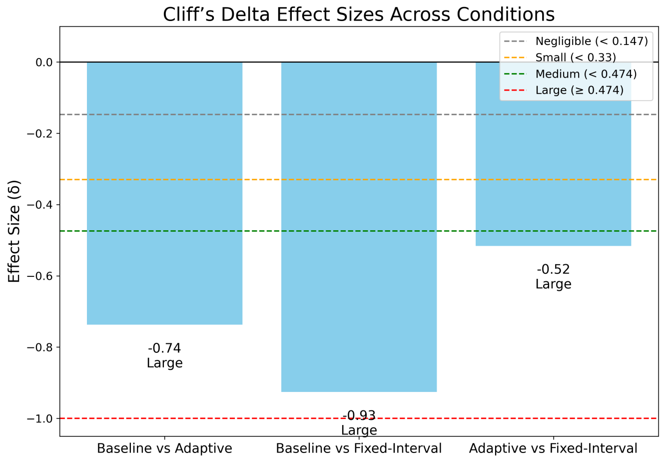


Fig. 6. Cliff's Delta effect sizes for all condition comparisons.

To supplement the effect size analysis, we report **median blink rates** and their deviations from the optimal clinical midpoint of 22.5 BPM. Table III presents these values: the Adaptive condition had a median of 15.0 BPM (deviation: 7.5), Fixed-Interval 20.0 BPM (deviation: 2.5), and Baseline 4.0 BPM (deviation: 18.5). These deviations offer a clearer view of practical effectiveness in maintaining the target blink range of 15–30 BPM.

TABLE III
MEDIAN BLINK RATES AND DEVIATION FROM CLINICAL MIDPOINT (22.5 BPM)

Condition	Median BPM	Deviation from 22.5 BPM
Baseline	4.0	18.5
Fixed-Interval	20.0	2.5
Adaptive	15.0	7.5

D. Subjective Evaluation

Participants in the adaptive group completed a questionnaire immediately after the session, in the same environment. The aim was to capture their immediate impressions regarding system usability, feedback clarity, and perceived impact on blink behavior.

The questionnaire included three main items: overall satisfaction, usability, and perceived effectiveness in supporting healthy blinking. Each was rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The results were as follows:

User Ratings:

- **Satisfaction:** $M = 4.4$, $SD = 0.55$
- **Usability:** $M = 4.0$, $SD = 0.71$
- **Perceived Effectiveness:** $M = 4.6$, $SD = 0.55$

In addition to numerical ratings, participants were invited to respond to two optional open-ended questions: (1) "What did you like about the system?" and (2) "What would you like to improve?" These qualitative responses offered deeper insights into user experience beyond the scope of Likert-scale items. Key themes from the comments are summarized below:

Positive Comments:

- "I think that none of the features are unnecessary."
- "The system helped me realize when I wasn't blinking enough."
- "None." (reported by multiple participants, indicating general satisfaction)

Suggested Improvements (verbatim):

- "The font for the currently selected number of seconds (for notification duration) is a little bit hard to read."
- "Notification still blinking every x seconds when durations were equal — felt a little distracting."
- "Maybe a better User interface."
- "The visual cue... may be too much information to process in the short duration that it is displayed. Perhaps a simplified visual cue would be better."
- "The system assumes that the user understands the auditory and visual cues... In the future it would be interesting if the system leverages phenomena that induce this behavior naturally."

These insights validate the system's usability and effectiveness while also offering valuable suggestions for improving clarity, interface design, and the timing of reminders.

V. DISCUSSION

This study explored how context-aware adaptive feedback supports healthier blink behavior during screen use—a key factor in preventing Dry Eye Disease (DED) and digital eye strain. Results show that adaptive feedback increased blink rates and maintained them within the clinical 15–30 BPM range, avoiding over-blinking commonly induced by fixed-interval systems.

The system's use of a sliding window estimator and exponential backoff enabled responsiveness to short-term trends rather than isolated anomalies, promoting smoother, more natural blinking patterns. Unlike the abrupt changes seen with fixed intervals, the adaptive method maintained stable regulation over time.

While the core logic relies on simple rules and clinically grounded thresholds, its real-time, behavior-sensitive loop demonstrates the feasibility of delivering adaptive support without complex sensing or computation. This balance between simplicity and responsiveness makes it suitable for low-cost deployment in general-purpose computing environments.

Statistical results supported these trends. A Kruskal–Wallis H test showed significant group differences, and Bonferroni-adjusted Mann–Whitney U tests confirmed large effects across all comparisons. **We also verified homogeneity of variance across groups using Levene's Test ($p = 0.19$), which supported the use of Mann–Whitney U tests. While the Brenner–Munzel test could be more robust in the presence of unequal variances, we chose Mann–Whitney U for its interpretability and compatibility with Cliff's Delta. However, we acknowledge the Brenner–Munzel method as a valuable alternative for future work, particularly in studies with larger sample sizes or variance heterogeneity.**

Subjective results aligned with the quantitative findings. Adaptive group participants reported high satisfaction (4.4), usability (4.0), and perceived effectiveness (4.6). They appreciated the feedback gauge and suggested refinements to fonts, visuals, and customization—highlighting opportunities for improved clarity and personalization.

Still, limitations remain. The small sample (N = 15), gender imbalance, and brief task duration limit generalizability and long-term insights. Environmental factors—e.g., posture, lighting, and screen position—may also affect detection accuracy and feedback perception.

To move beyond fixed thresholds and general rule-based logic, future work should investigate the integration of machine learning or user modeling techniques to support deeper personalization. This could enable the system to adapt to individual blink patterns, task contexts, or user preferences over time—enhancing engagement and long-term compliance. **Moreover, broader application domains such as digital wellness, attention-aware computing, or preventive eye health interventions may benefit from the core methodology proposed here.**

Future studies should explore longer deployments in ecologically valid contexts such as remote work, mobile devices, or VR. **As the system evolves, combining physiological sensing with adaptive intelligence could help realize more generalizable, user-aware feedback systems that extend beyond the blink regulation use case.**

VI. Conclusion

This study presented a real-time adaptive feedback system to encourage healthy blinking during screen use. By combining sliding window estimation, clinically grounded thresholds, and randomized backoff, the system delivers responsive yet unobtrusive support for ocular wellness.

Pilot results showed increased blink frequency without overcorrection, outperforming both baseline and fixed-interval conditions in statistical and practical terms. User feedback confirmed the system's usability and acceptability, underscoring its promise for wider deployment.

More broadly, this work advances health-supportive human-computer interaction by demonstrating how passive sensing can enable personalized, real-time wellness interventions. As screen time grows, adaptive systems like this may help mitigate visual discomfort and promote sustainable digital habits.

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