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Context-aware Adaptive Blink Monitoring and Feedback for Supporting Healthy Blinking during Screen Use

Muhammad Furqan Rasyid,[1*] Tomokazu Matsui,[1,2] Yuki Matsuda,[2,3] Hirohiko Suwa,[1,2] and Keiichi Yasumoto[1,2]

[1]Nara Institute of Science and Technology, 8916-5 Takayama-cho, Ikoma, Nara 630-0192, Japan
[2]RIKEN, Center for Advanced Intelligence Project, 1-4-1 Nihonbashi, Chuo-ku, Tokyo 103-0027, Japan
[3]Faculty of Environmental, Life, Natural Science, and Technology, Okayama University, Okayama 700-0082, Japan

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Reduced spontaneous blinking during screen use contributes to eye discomfort and symptoms associated with digital eye strain. Although reminder-based applications attempt to address this behavior, most rely on fixed reminders that do not adapt to changes in blink patterns over time. This lack of personalization can lead to user fatigue, poor compliance, and excessive blinking. In this paper, we present EyeWise 1.1, a lightweight, real-time feedback system that uses webcam-based eye aspect ratio (EAR) detection, a 60 s sliding window to estimate blink rate, and an adaptive reminder engine that delivers cues only when blinking falls outside the target range of 15–30 blinks per minute (BPM). To reduce repeated interruptions during stable periods, the reminder engine incorporates randomized exponential backoff. The system further includes a configurable, nudge-based interface designed to remain understandable briefly while minimizing distraction during ongoing work. We evaluated EyeWise 1.1 in a controlled laboratory study with 15 participants across three conditions: baseline (no feedback), fixed reminders, and adaptive reminders (EyeWise 1.1). Blink activity was segmented into 105 fixed windows (seven per participant) to examine within-session blink-rate distributions; participant-level summaries were then used for statistical testing to account for within-participant dependence. Results indicated that the adaptive condition improved blink behavior relative to baseline by reducing time spent in low-blink-rate periods and maintaining blink rates within the predefined range. Compared with fixed reminders, the adaptive condition showed comparable blink-rate outcomes while appearing less likely to push blink rates above the upper threshold. In post-study questionnaires administered to the adaptive condition, participants reported high satisfaction ($M = 4.4$), ease of use ($M = 4.0$), and perceived effectiveness ($M = 4.6$). Overall, these findings suggest that blink-sensitive adaptive feedback is a promising approach for supporting healthier blinking during routine screen use and can provide a positive user experience.

[*]Corresponding author: e-mail: rasyid.muhammad_furqan.ri4@naist.ac.jp
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1. Introduction

Blinking maintains tear-film stability and protects the ocular surface. Prolonged screen use, however, suppresses spontaneous blinking, often reducing it to around 5 blinks per minute (BPM) during demanding tasks such as reading and programming. This contributes to dry eye disease (DED), visual fatigue, and reduced performance.(1)

A normal blink rate typically ranges from 15 to 20 BPM(2) with rates above 30 BPM considered excessive. Both low and high blink rates can affect overall health. To monitor both insufficient and excessive blinking during screen use, in this study, we used a threshold range of 15–30 BPM.

Daily screen exposure averaging 3.2 h has been associated with high rates of eye-related complaints, including fatigue (39.8%), dryness (31.5%), discomfort (30.8%), and visual strain (30.6%), with symptoms occurring during at least half of users' device sessions.(1) Recognizing the growing public health burden of digital eye strain, the World Health Organization has emphasized the need for preventive and accessible eye-care strategies.(2) Motivated by this context, we aim to develop a real-time system that supports blink behavior within an operational control band to promote behavioral stability during screen use, rather than to serve as a medical diagnostic threshold, using lightweight, personalized feedback.

Several software programs have been developed to address reduced blinking, yet the majority rely on simple timer-based reminders or basic rules rather than adapting to the user.(3) Although these tools increase awareness, they do not adapt to moment-to-moment changes in blink patterns and may accidentally trigger excessive blinking, causing annoyance or distraction. Recent work on adaptive interfaces and digital nudging highlights the value of feedback that responds to user state while maintaining low intrusiveness;(4) however, no system has yet integrated real-time blink monitoring with adaptive reminder logic specifically designed to prevent digital eye strain.

To address these gaps, we propose EyeWise 1.1, a context-aware adaptive feedback system that continuously monitors blinking through a standard webcam and adjusts reminder timing based on real-time behavior. The system integrates a 60 s sliding window estimator of blink frequency, threshold-based decision logic, and a randomized exponential-backoff mechanism that varies reminder timing to reduce habituation. Although each component is simple, their combination into a continuous adaptive loop provides a lightweight yet responsive approach to blink regulation without requiring intrusive hardware or complex gaze-tracking technologies.

This study is conducted to design and implement a real-time blink-aware adaptive feedback system that supports healthier blinking during screen use, to quantitatively evaluate its effects relative to baseline and fixed-interval reminders, and to assess user perceptions of system usability, comfort, and perceived effectiveness. Through this work, we contribute a configurable, lightweight computer-vision system for real-time blink monitoring, an adaptive reminder engine that selectively triggers feedback when blinking deviates from a defined reference range.

This study extends our earlier prototype work(5) by

a) providing a more detailed presentation of system design decisions, including an enhanced user-configurable interface guided by nudging principles;

b) offering refined technical explanations of blink detection, sliding window aggregation, and adaptive-interval logic to improve the system's clarity, transparency, and reproducibility;
c) examining blink rate distributions in accordance with participant medians and incorporating inferential analyses at the participant level; and
d) articulating clearer future research directions, including opportunities for extended real-world deployment beyond the short experimental sessions in this study, interface refinement, and personalized threshold adaptation.

By situating EyeWise 1.1 within current research on digital eye strain, adaptive feedback, and preventive eye-care technologies, in this work, we advance the development of unobtrusive behavior-support systems that promote sustained ocular comfort during everyday computer use.

2. Related Work

Research on blink regulation during screen use spans ophthalmology, computer vision, and human–computer interaction (HCI). In this section, we review prior work across four complementary strands: (1) the physiological mechanisms underlying blink suppression and digital eye strain, (2) sensor-based methods for detecting and monitoring blink behavior, (3) software-based interventions designed to restore healthy blinking, and (4) adaptive feedback approaches aimed at reducing disruption while supporting sustained behavior change. Together, these strands provide the conceptual and technical context for this study.

2.1 Blink physiology and digital eye strain

Digital eye strain (DES) refers to a cluster of visual and ocular symptoms—such as dryness, irritation, blurred vision, and headaches—linked to the prolonged use of digital displays.(6,7) A core mechanism is reduced spontaneous blinking: during relaxed conditions, adults typically blink around 15–20 times per minute, whereas continuous screen viewing can depress this rate to 3–7 BPM, substantially increasing tear-film instability and ocular surface stress.(6) Therefore, clinical and ergonomics guidelines emphasize the importance of frequent blinking and breaks (e.g., the "20–20–20 rule") as low-cost strategies to mitigate DES.(8)

While these recommendations highlight blinking as a modifiable behavior, they are usually implemented through generic instructions or simple timer-based reminders, without the continuous monitoring of actual blink activity. As a result, they provide limited insight into how blinking evolves during specific tasks such as inadequate and excessive blinking, and they cannot adapt feedback to moment-to-moment changes in blink rate—limitations that motivate real-time sensing and intervention systems such as EyeWise 1.1.

2.2 Blink detection and monitoring methods

A wide range of sensing modalities have been explored for blink detection, including electro-oculography (EOG), infrared eye tracking, wearable devices, and commodity cameras. Webcam-based approaches are particularly attractive for everyday desktop use because they require no additional hardware and can be deployed purely in software.

Eye aspect ratio (EAR) has emerged as a simple yet effective geometric descriptor for webcam-based blink detection. By utilizing dlib's 68-point facial landmark model, EAR determines the ratio between the vertical and horizontal distances of periocular landmarks. This ratio decreases sharply during eyelid closure, providing a reliable metric for identifying blinks in real time.(9) EAR-based methods are computationally lightweight, run in real time on standard central processing units (CPUs), and have been successfully applied to drowsiness detection, driver monitoring, and general-purpose blink counting. However, most prior work focuses on detection accuracy in controlled settings and does not directly translate blink estimates into tailored behavioral feedback.

In this work, we build on the EAR-based webcam approach for its practicality and efficiency, and extend prior monitoring-only systems by tightly coupling real-time blink estimates with an adaptive feedback engine and user-facing visualizations.

2.3 Digital interventions for blink regulation

Several software tools have been proposed to actively encourage blinking during screen-based tasks. Nosch *et al.* introduced *Blink Blink*, a desktop animation that periodically prompts users to blink; the system increased blink frequency and improved dry-eye symptoms during computer work, although benefits were tied to fixed reminder schedules and short-term training sessions.(10) Ashwini *et al.* later evaluated "blink software" in a randomized controlled trial with visual display terminal users, showing that high-frequency reminders (8 prompts per minute) improved both blink rate and subjective dry-eye scores compared with a low-frequency control (1/min).(3)

More recently, mobile and cross-platform applications for digital eye strain and dry-eye management have proliferated, offering blink reminders, break timers, and eye exercises. A scoping review of app stores identified numerous tools for dry-eye management and blink training but noted a large variation in quality, limited clinical validation, and predominantly fixed-timing designs.(11) Similarly, smartphone-based blink-training applications combining structured exercises with adherence tracking have shown symptom improvements, yet these systems also depend on preprogrammed schedules rather than real-time adaptation.(12)

Collectively, these interventions demonstrate that software-based reminders can effectively enhance blink frequency and improve ocular comfort. However, they share key limitations: reminder timing is typically fixed or user-defined rather than based on ongoing blink status, most systems do not distinguish between inadequate and excessive blinking, and feedback is often blind to task context, increasing the risk of habituation or unnecessary interruption. EyeWise 1.1 addresses these gaps by using a sliding window estimate of blink rate to trigger feedback only when behavior falls outside a practical threshold and by explicitly visualizing both insufficient and excessive eye blinking to support a more appropriate behavioral regulation.

2.4 Adaptive and behavior-sensitive feedback systems

Adaptive feedback has been widely examined in HCI as a strategy for balancing user support with minimal disruption. Prior work on adaptive visualizations and learning interfaces shows that adjusting information density or break timing based on indicators of cognitive load can enhance both task performance and user comfort.[13–15] From a behavior-change perspective, digital nudging and behavior change support systems offer design principles for subtly guiding user actions through mechanisms such as visual emphasis, defaults, and soft reminders, while preserving user autonomy.[4,16]

Despite these advancements, the application of adaptive and behavior-sensitive feedback to blink regulation remains limited. Existing blink-support tools primarily rely on static reminder intervals, and although wearable systems have explored inducing reflexive blinks, these prototypes focus narrowly on timing appropriateness and are not integrated into everyday desktop workflows.[17] Consequently, current approaches lack moment-to-moment personalization and do not account for ongoing changes in physiological state.

EyeWise 1.1 addresses these gaps by operationalizing adaptive feedback through three mechanisms: (1) a sliding window estimator that continuously evaluates blink rate and triggers feedback only when behavior exceeds a practical reference threshold, (2) a randomized exponential-backoff algorithm that extends reminder intervals during periods of healthy blinking to reduce habituation, and (3) a configurable, nudge-informed interface that allows users to adjust reminder parameters while subtly discouraging premature system exit. This integration of real-time sensing, adaptive timing, and nudging-based design represents a novel contribution within blink-regulation technologies.

3. System Design and Implementation

EyeWise 1.1 is implemented as a lightweight, real-time system that monitors blink behavior through a standard webcam and adapts reminder timing based on the user's moment-to-moment blinking patterns. In this section, we outline the core components that enable the system's operation: (1) the overall architecture and data flow, (2) the blink-detection pipeline based on facial landmarks and EAR, (3) the adaptive reminder logic that regulates feedback using a sliding window estimator and exponential backoff, and (4) the configurable user interface that supports personalized reminder settings. Together, these components form an integrated framework that provides selective, minimally intrusive feedback to support healthier blinking during screen use.

3.1 Overview and architecture

EyeWise 1.1 is designed as a lightweight, real-time system that monitors blink behavior through a standard webcam and delivers adaptive feedback only when blinking deviates from a practical reference range. As illustrated in Fig. 1, the system consists of five core modules: (i) a Webcam Capture Module, which acquires live video frames; (ii) a Blink Detection Module, which estimates eye state using facial landmarks and EAR; (iii) a Blink Analysis Module, which computes recent blink frequency using a 60 s sliding window estimator; (iv) a Decision Engine, which evaluates whether the current blink rate falls outside the 15–30 BPM threshold; and (v) an Adaptive Interval Adjustment Module, which resets or expands the reminder interval on the basis of the outcome of the decision stage. All processes are performed

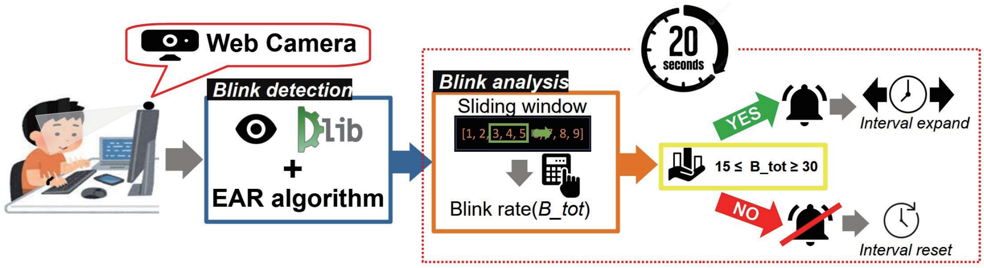


Fig. 1. (Color online) System overview.

locally on a standard CPU without requiring specialized sensors, enabling practical and unobtrusive deployment on everyday computers.

During operation, the system processes each frame to detect the eyes and compute EAR values, which are then used to identify blinks. Blink counts are continuously accumulated into a 60 s sliding window, updated every 20 s. This window length balances responsiveness and stability: shorter windows tend to fluctuate, whereas longer windows delay the detection of meaningful behavioral changes. The resulting windowed blink frequency (B tot) is compared with the predefined threshold range of 15–30 BPM to determine whether the user is blinking less, within the healthy range, or blinking excessively.

Based on this analysis, the Decision Engine either resets the reminder interval or expands it depending on blink status. When blinking falls outside the threshold, a reminder is triggered immediately; when blinking remains stable, the system defers reminders and delegates control to the adaptive timing mechanism described in Sect. 3.3. This architecture enables EyeWise 1.1 to deliver reminders only when necessary, reduce habituation, and provide a personalized level of support without requiring intrusive sensors or gaze-tracking technologies.

3.2 Real-time blink detection

Blink detection is a core component of EyeWise 1.1. The system first estimates facial landmarks and then applies EAR to classify eye states (open/closed).

Facial landmarks. To extract periocular features, we use the dlib 68-point facial landmark model,[18] which returns 68 (x, y) points, including the right eye (36–41) and left eye (42–47). Figure 2 shows the landmark configuration used for eye-region extraction. A face detector first localizes the face bounding box, after which a landmark predictor fits the 68 points within the detected region. This approach has been widely used in face alignment and webcam-based blink detection.

EAR-based blink decision. Using the detected eye landmarks, we compute EAR following the method proposed by Soukupová and Čech,[19] which has been widely adopted for real-time blink monitoring.[9] EAR is defined as

$$EAR = \frac{\left(\| P2 - P6 \| + \| P3 - P5 \|\right)}{2 \cdot \| P1 - P4 \|}, \quad (1)$$

Fig. 2. (Color online) Illustration of the 68-point facial landmark model.

where $P1$–$P6$ denote the six landmark points defining the eye contour. Figure 3 illustrates the EAR geometry for (a) an open eye and (b) a closed eye.

EAR decreases sharply during eyelid closure while remaining stable during normal gaze. To reduce asymmetry effects and minor landmark noise, we use the average EAR from both eyes.

$$EAR_{avg} = \frac{EAR_{left} + EAR_{right}}{2} \tag{2}$$

A blink is registered when EAR_{avg} falls below a threshold T_{EAR} for at least consecutive frames. In our implementation, we set T_{EAR} = 0.20 and N = 3 at 30 fps (≈100 ms minimum closure duration). We increment a closure counter while $EAR_{avg} < T_{EAR}$; when EAR_{avg} rises above the threshold, a blink is recorded if the temporal condition is satisfied. We found T_{EAR} = 0.20 to be stable in our recordings, including cases where participants wore eyeglasses, although performance can vary with lighting and reflections.

To address detection reliability, we performed a small ground-truth spot-check using publicly available blink video data and nonparticipant test recordings collected by the authors (no participant videos were used or retained). Blink events were manually reviewed to confirm that detected events aligned with visible eyelid closures. Detected blink events are then forwarded to the sliding window estimator (Sect. 3.3) to compute short-term blink frequency for adaptive feedback decisions.

3.3 Adaptive reminder interval calculation

Blink behavior is estimated to be using a fixed-length sliding window of 60 s, updated every 20 s. Each update aggregates blink counts from the three most recent, non-overlapping 20 s segments, yielding a rolling estimate of short-term blink frequency. This design smooths short-term fluctuations while remaining responsive to real-time changes, following prior work on behavior-aware feedback systems.[20]

Let b_i denote the number of blinks counted in the i-th non-overlapping 20 s segment, and let w = 3 denote the number of segments in the 60 s window (i.e., 60/20). Thus, the windowed blink count W corresponds to the total number of blinks observed over the most recent 60 s (blinks/min). Because consecutive window estimates overlap, they form part of a continuous control process and are not statistically independent.

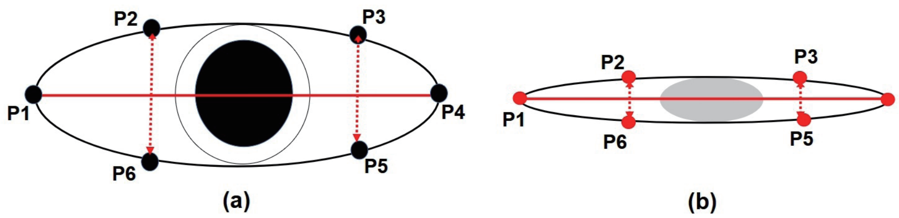


Fig. 3. (Color online) Illustration of (a) an open eye and (b) a closed eye.

As part of the Decision Engine illustrated in Fig. 1, the system evaluates W and determines whether feedback should be triggered or whether the reminder interval should be adjusted. The windowed blink count W is computed as

$$W = \sum_{i=n-w+1}^{n} b_i , \tag{3}$$

or, when fewer than w segments are available,

$$W = \sum_{i=1}^{n} b_i . \tag{4}$$

A reminder is triggered when W falls below 15 blinks (inadequate and excessive blinking) or exceeds 30 blinks (excessive blinking). In either case, the reminder interval is reset to the user-defined base interval. When blinking remains within the practical reference range of 15–30 BPM, the system suppresses the reminder and applies a randomized exponential backoff to reduce habituation by varying the interval duration. While a fixed reference range was used for consistency across participants, future iterations may incorporate personalized thresholds based on individual baseline behavior or task context.

The next reminder interval is computed as

$$I_{next} = I_{base} + U + \left(0, \min\left(2I_{current}, I_{\text{limit}}\right) - I_{base}\right), \tag{5}$$

where $U(a, b)$ denotes a uniform random distribution and $I_{current}$ denotes the most recently scheduled reminder interval (initialized to I_{base} at session start). In our implementation, we used I_{base} = 4 s and I_{limit} = 60 s. The uniform term in Eq. (5) was sampled using Python's standard library RNG (random.uniform) with bounds α = 0 and $b = \min\left(2I_{\text{current}}, I_{\text{limit}}\right) - I_{\text{base}}$. The RNG was not seeded, so the exact reproduction of the random sequence is not guaranteed across runs. This mechanism progressively lengthens intervals during sustained healthy blinking while enforcing the upper bound I_{limit}, ensuring that feedback remains timely but minimally intrusive.

3.4 User interface and configurable reminder settings

The user interface is designed to be minimal, intuitive, and highly configurable, enabling users to tailor reminder behavior according to their preferences. Figure 4 presents the three primary components of the system interface: (a) the main dashboard, (b) the settings dashboard, and (c) the monitoring interface. To improve clarity, each interface element is annotated using labels (A–K).

Table 1 shows the function of each labeled element in Fig. 4, covering the main dashboard (A–C), the settings dashboard (D–J), and the monitoring interface (K).

To enhance usability, the interface incorporates concepts from digital nudging.(4) For example, the Close buttons (C, J) are intentionally smaller than the Setting and Start buttons (B, I), subtly guiding users to remain engaged with the system rather than exit prematurely. The small button is prioritizing task-relevant controls while maintaining a clearly visible opt-out as well. Key configuration parameters—such as reminder interval (E), duration (F), and size (G)—use larger, bold text to emphasize their importance. Figure 5 illustrates the available reminder sizes, enabling users to balance salience and intrusiveness, whereas Fig. 6 presents the selectable on-screen reminder positions, allowing users to place cues in locations that minimize distraction. Additional "Explanation" and "Example" buttons accompany several settings to support user understanding.

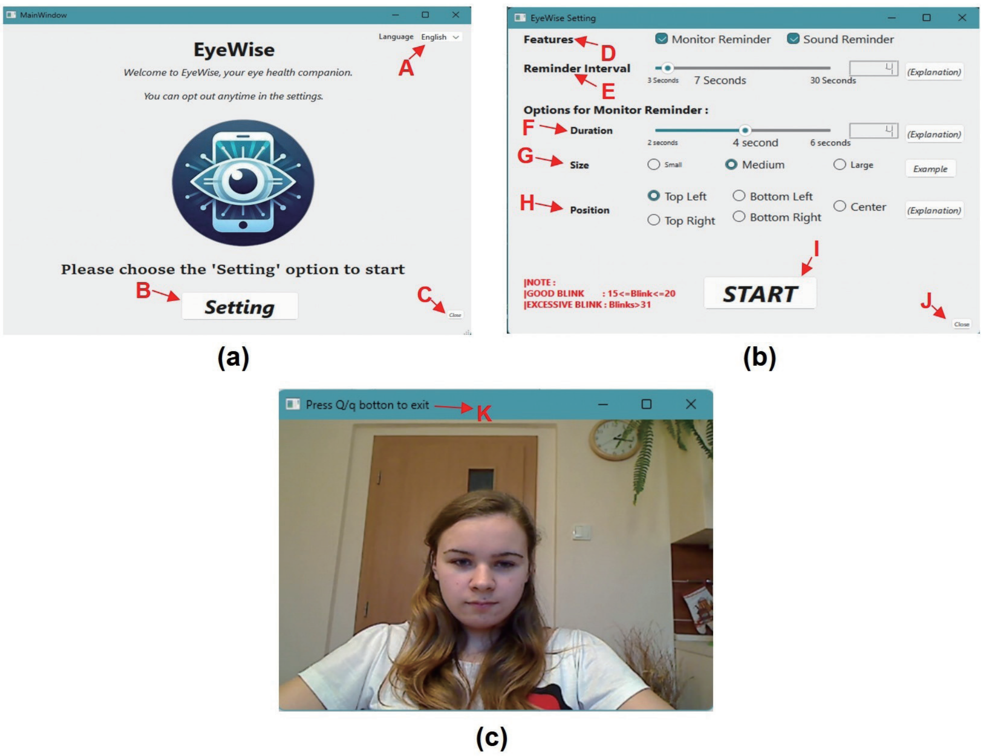


Fig. 4. (Color online) User interface components with annotated labels: (a) main dashboard (A–C), (b) settings dashboard (D–J), and (c) monitoring interface (K).

Table 1
Dashboard and settings components corresponding to Fig. 4.

Label	Component description	Functionality
A	Language selector	Switch between English and Japanese interfaces
B	Settings button	Navigate from the main dashboard to the settings dashboard
C	Close button	Exit the application
D	Reminder modality	Choose visual reminder, audio reminder, or both
E	Reminder interval	Adjust how frequently reminders may appear
F	Reminder duration	Set how long visual cues remain visible
G	Reminder size	Select reminder size (small/medium/large; see Fig. 5)
H	Reminder position	Choose on-screen location (top/bottom/center; see Fig. 6)
I	Start button	Begin real-time blink monitoring and feedback
J	Close button	Exit from the settings dashboard
K	Exit command	Stop monitoring, user must press Q/q button

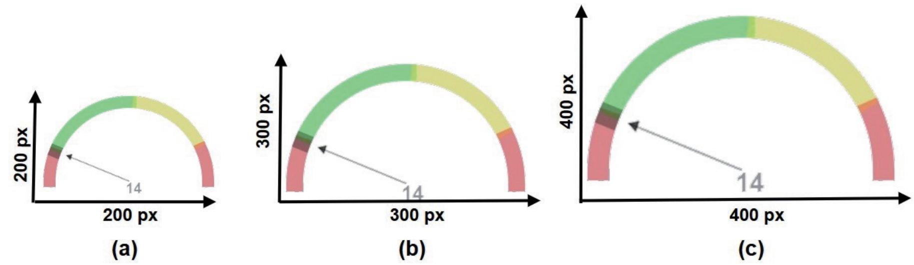


Fig. 5. (Color online) Reminder size options: (a) small, (b) medium, and (c) large.

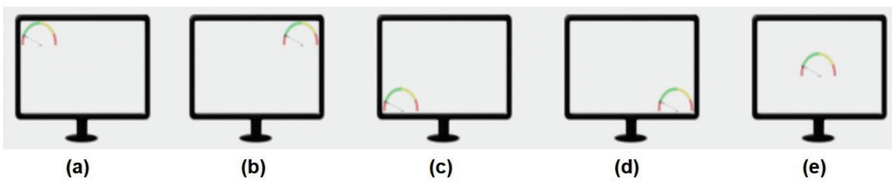
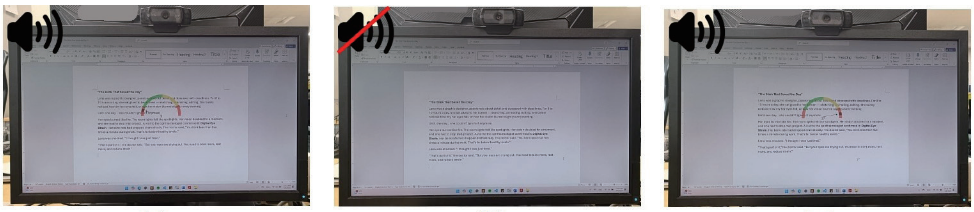


Fig. 6. (Color online) Reminder position options: (a) top left, (b) top right, (c) bottom left, (d) bottom right, and (e) center.

The visual reminder consists of a semicircular gauge divided into four color-coded regions: red for a low blink rate (below 15 BPM), green for the healthy range (15–25 BPM), yellow for a slightly elevated rate (26–30 BPM), and red for an excessive rate (above 30 BPM). This intuitive design allows users to monitor their blink frequency briefly without interrupting their primary task.

During operation, the system continuously analyzes blink activity. The interface responds to three conditions based on the user's blink rate relative to predefined zones (Fig. 7). Optional visual and/or auditory reminders can be activated accordingly, with audio reminders provided only when explicitly enabled via the settings menu [Fig. 4(b), D].

Reminders are delivered only when the blink frequency falls outside the reference range of 15–30 BPM. When the blink behavior remains within this range, both visual and/or auditory cues are suppressed. This selective feedback ensures that the system remains minimally intrusive while providing timely corrective support when necessary.



(a) (b) (c)

Fig. 7. (Color online) Interface states and optional reminders in response to (a) a low blink rate, (b) a healthy blink rate, and (c) an excessive blink rate.

4. Experimental Evaluation

In this section, we outline the experimental framework used to evaluate the effectiveness and user experience of the EyeWise 1.1 system. Specifically, it describes (1) the study design and experimental conditions used to compare reminder strategies, (2) objective measures, (3) the statistical analyses applied to assess changes in blink behavior, (4) the subjective evaluation procedures used to capture user perceptions of usability and feedback clarity, and (5) a technical comparison with existing state-of-the-art (SOTA) blink interventions. Together, these components provide a comprehensive assessment of system performance under controlled laboratory conditions.

4.1 Participants and experimental setup

Fifteen participants (12 males, 3 females; *M* age = 29.4, *SD* = 4.5) completed a 5 min screen-based reading task in a controlled laboratory setting. All participants reported normal or corrected-to-normal vision and an average daily screen time exceeding 4 h (*SD* = 1.6), reflecting habitual digital device use.

To ensure consistency across conditions, blink activity was segmented into seven fixed intervals per participant, yielding 105 total blink samples. Participants were randomly assigned to one of the three groups (n = 5 each):

- Baseline: No feedback was provided to the participant, as shown in Fig. 8(a).
- Fixed-interval: Visual prompts were triggered whenever the estimated blink rate fell below a fixed threshold of 15 BPM. To mimic standard software interventions, this condition used a dual-bar interface (red and green bars), as shown in Fig. 8(b).
- Adaptive (EyeWise 1.1): Reminder timing was adjusted in real time on the basis of the result of context-aware analysis using the new semicircular gauge, as shown in Fig. 8(c).

While the EyeWise 1.1 system is fully configurable, parameters were standardized to ensure a fair comparison. In the Adaptive condition, the base reminder interval I_{base} was set to a default of 4 s; only one participant opted to increase this to 6 s. In the Fixed-interval condition, the interval was set to 1 min, indicating that the system checked the threshold once per minute and triggered a reminder when the rate was below 15 BPM. Table 2 provides the results of a detailed comparison of the notification logic, visual interfaces, and target blink behaviors for all three experimental conditions.

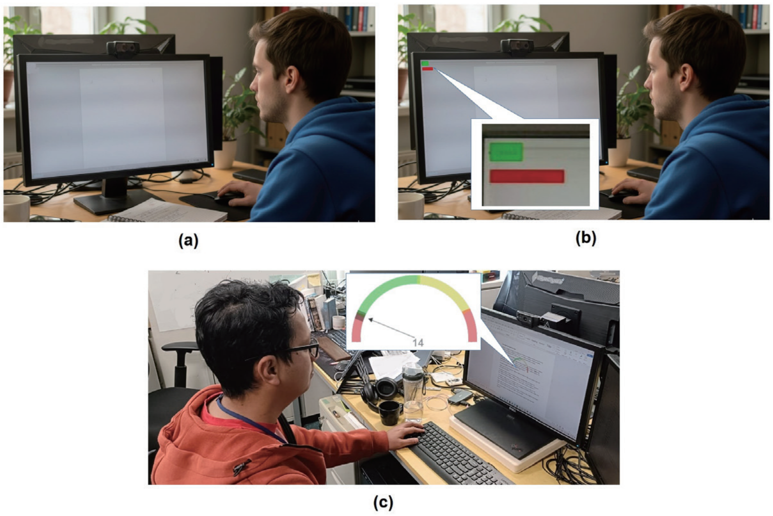


Fig. 8. (Color online) Participants using (a) Baseline, (b) Fixed-interval intervention, and (c) Adaptive intervention.

Table 2
Configuration summary of Baseline, Fixed-interval, and Adaptive conditions.

Feature	Baseline	Fixed-interval (Standard)	Adaptive (EyeWise 1.1)
Notification logic	No reminders	Static: triggers at a fixed 15 BPM threshold	Adaptive: uses a 60 s sliding window and randomized backoff
Visual interface	N/A	Dual-bar: simple red and green bars representing blink status	Semicircular gauge: four-zone, nudge-informed color scale
Blink focus	None	Primarily targets low blink rates (<15 BPM)	Targets both low and excessive blinking (15–30 BPM)
Configurability	N/A	Not adjustable during the study	Configurable, though standardized for this study

The study was conducted in a quiet room under controlled lighting. Participants were seated approximately 60 cm from a 24 in. monitor, and blink data were captured using a webcam configured at 1920 × 1080 resolution and 30 fps. EyeWise 1.1 was implemented in Python (PyQt6) and executed on a Windows 11 (24H2) laptop with a 13th Gen Intel Core i7-1355U CPU (1.70 GHz) and 16 GB of RAM.

The technical constants used for blink detection and the adaptive notification logic are shown in Table 3. We selected an EAR threshold = 0.2 based on established computer vision research, which identifies this value as an optimal benchmark for robust blink detection across diverse facial structures.[9] Figure 8(b) illustrates a participant using the system with these standardized settings during the experimental session to ensure consistent evaluation.

After the task, participants in the Adaptive group completed a questionnaire evaluating usability, perceived effectiveness, and interface clarity on 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. No video recordings were stored; only derived blink metrics were logged to a CSV file for offline analysis.

Table 3
Technical parameters used in the experimental session.

Parameter	Symbol	Description	Value	Rationale for selection
EAR threshold	T_{EAR}	Threshold for eye closure detection	0.2	Established benchmark for robust blink detection[9]
Blink confirmation	N	Consecutive frames to confirm a blink	3	Mitigates noise from ocular micro-movements or jitters
Sliding window	W	Duration for BPM estimation	60 s	Ensures statistical stability of BPM calculation
Update rate	i	Frequency of sliding window refreshes	20 s	Balances system responsiveness with data consistency
Backoff base	I_{base}	Initial interval for exponential backoff	4 s	Prevents notification overcrowding and user annoyance
Max interval	I_{limit}	Maximum time allowed for reminders	60 s	Guarantees support during periods of intense focus

4.2 Blink rate distributions across conditions

The primary outcome was each participant's median BPM during the session, which yields one independent value per participant for inferential testing. Figure 9 shows these participant-level blink rates across the three conditions. During each experimental session, raw blinks were counted and converted to BPM using the standardized sliding window duration and update frequency defined in Table 3. By taking the median blink rate across all window estimates for each individual, we established a single representative value per participant (Baseline: n = 5; EyeWise 1.1: n = 5; Fixed-interval: n = 5) to reduce the effect of short-term behavioral noise.

To complement Fig. 9, Table 4 shows participant-level descriptive statistics (minimum, Q1, median, Q3, maximum).

Window-level estimates were used to visualize within-session dynamics (Fig. 9) and to support the system's closed-loop control logic; they were not treated as independent samples. The distributions show clear descriptive separation across conditions.

a) Baseline (no reminder): Participant medians were consistently below the reference band, reflecting suppressed blinking during reading.
b) Fixed-interval reminder: Participant medians were substantially higher than the reference band, suggesting a tendency toward elevated blinking.
c) Adaptive (EyeWise 1.1): Medians were closer to the threshold band than the fixed-interval reminder condition and higher than baseline; some participants still exceeded 30 BPM.

These summaries characterize central tendency and variability without assuming normality, and provide context for the non-parametric hypothesis tests reported in Sect. 4.3.

4.3 Statistical comparison

Inferential analyses were conducted at the participant level. Although blink rate was estimated over multiple overlapping windows within each session, window-level values from the same participant are not statistically independent. Therefore, each participant contributed a single outcome value computed as the participant median blink rate across windows (Baseline: n = 5; EyeWise 1.1: n = 5; Fixed-interval: n = 5). Because the participant-level distributions were

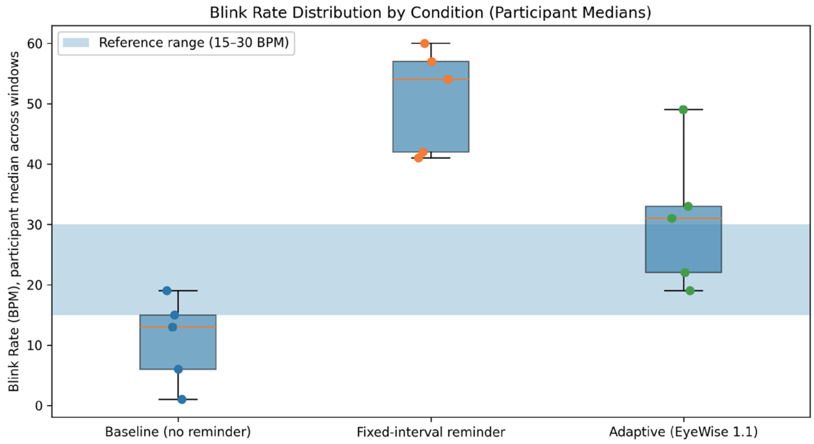


Fig. 9. (Color online) Blink-rate distribution by condition (participant medians). The shaded band indicates the threshold range used (15–30 BPM) as a visual benchmark.

Table 4
Participant-level descriptive statistics of blink rate (BPM) by condition (n = 5 per condition).

Condition	*Min*	Q1	*Median*	Q3	*Max*	n
Baseline (no reminder)	1.0	6.0	13.0	15.0	19.0	5
Fixed-interval reminder	41.0	42.0	54.0	57.0	60.0	5
EyeWise 1.1	19.0	22.0	31.0	33.0	49.0	5

small-sample and non-normal, we used rank-based non-parametric tests.

We first performed a Kruskal–Wallis H test to evaluate overall differences among the three independent conditions. The test showed a significant effect of condition on participant-level blink rate, $H(2) = 11.34$, $p = 0.00346$, with a large effect size ($\varepsilon^2 = 0.778$), indicating that at least one condition differed from the others.

To identify which pairs differed, we conducted two-sided Mann–Whitney U tests for the three pairwise comparisons and applied a Bonferroni correction across the three post-hoc tests ($\alpha = 0.05/3 = 0.0167$). For clarity, Table 5 reports both the unadjusted two-sided p values and the Bonferroni-adjusted values ($p_{adj} = p \times 3$). The significance decision is equivalent whether using the unadjusted p values with the Bonferroni-adjusted threshold (raw $p < 0.0167$) or using p_{adj} with $\alpha = 0.05$.

Under this conservative threshold, Baseline vs EyeWise 1.1 ($p = 0.01597$) and Baseline vs Fixed-interval ($p = 0.00794$) were significant, whereas EyeWise 1.1 vs Fixed-interval was not ($p = 0.03175$). We additionally report Cliff's delta (δ) as a non-parametric effect size; all pairwise effects were large ($|\delta| \geq 0.84$), indicating substantial separation between conditions despite the small sample size. Complete test statistics are summarized in Table 5.

Overall, these results provide statistical support that both reminder conditions increased blink rate relative to baseline. While the Adaptive–Fixed comparison did not reach the Bonferroni-adjusted threshold, the large effect size suggests a meaningful difference that should be retested with a larger sample.

Table 5
Non-parametric statistical comparison of participant-level blink rate (participant median across windows). Bonferroni threshold for pairwise tests: $\alpha = 0.05/3 = 0.0167$.

Test/Comparison	Statistic	P (two-sided)	p_{adj} (Bonferroni × 3)	Significant	Effect size
Kruskal–Wallis (3 groups)	$H(2) = 11.34$, $\varepsilon^2 = 0.778$	0.00346	—	Yes	—
Baseline vs EyeWise 1.1	$U = 0.5$	0.01597	0.04791	Yes	$\delta = -0.96$
Baseline vs Fixed-interval	$U = 0.0$	0.00794	0.02382	Yes	$\delta = -1.00$
EyeWise 1.1 vs Fixed-interval	$U = 2.0$	0.03175	0.09525	No	$\delta = -0.84$

4.4 Subjective evaluation

To complement the quantitative analysis, participants in the Adaptive (EyeWise 1.1) condition (n = 5) completed a brief post-session questionnaire capturing within-condition impressions of usability, clarity of feedback, and perceived effectiveness. Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Mean (M) and standard deviation (SD) ratings were as follows:

a) Satisfaction: $M = 4.4$, $SD = 0.55$,
b) Usability: $M = 4.0$, $SD = 0.71$, and
c) Perceived effectiveness: $M = 4.6$, $SD = 0.55$.

Overall, participants reported positive impressions of the adaptive feedback, indicating that the system was easy to use and perceived as helpful for supporting blink awareness during reading.

Participants also provided optional open-ended responses describing what they liked and what could be improved. Because these comments were collected only from the Adaptive condition and the sample size was small (n = 5), we interpret them as formative design input rather than evidence for cross-condition comparisons. We performed a lightweight thematic grouping of comments to extract recurring issues and actionable directions. Table 6 shows the themes and representative excerpts.

These suggestions motivate concrete design revisions for the next iteration: (i) readability improvements (larger fonts and higher contrast for time/interval indicators), (ii) frequency controls (e.g., a minimum cool down and a user-accessible snooze option), and (iii) improved cue interpretability (a simplified three-state indicator with explicit action labels, supported by a brief onboarding tutorial). Together, the subjective ratings and formative comments provide additional context for interpreting the behavioral effects observed in Sects. 4.2 and 4.3.

Because subjective measures were collected only for the Adaptive condition, the questionnaire results and open-ended feedback should be interpreted descriptively and should not be used to infer comparative user-experience differences across conditions.

4.5 Comparison with SOTA and design rationale

To evaluate the unique contribution of EyeWise 1.1, we compared its technical profile with three established SOTA blink intervention systems: Air-Puff Eyewear,[21] RhythmBlink,[22] and DualBlink.[23] As detailed in Table 7, while physical induction methods like Air-Puff Eyewear

Table 6
Formative feedback from Adaptive condition participants (n = 5).

Category	Key points	Representative comments
Positive feedback	System perceived as simple and purposeful	"None of the features are unnecessary".
	Features viewed as useful	"Helped me realize when I wasn't blinking enough".
	Reminders increased awareness of under-blinking	"None".
	Some users reported no concerns	—
Suggested improvements	Improve font readability/legibility	"Selected-seconds font is hard to read".
	Reduce perceived notification frequency in some cases	"Notifications still triggered every X seconds—distracting".
	Improve cue interpretability and intuitiveness	"Maybe a better UI."
	General UI refinement	"Visual cue shows too much info in short time".
	—	"Assumes users understand cues; should be more intuitive".

Table 7
Comparison of EyeWise 1.1 with SOTA Blink Interventions

System	Hardware	Modality	Adaptation logic
Air-Puff Eyewear [21]	Specialized Eyewear	Physical (Air-puff)	Reflexive induction
RhythmBlink [22]	Smart Glasses	Visual (On-lens)	Periodic prompting
DualBlink [23]	Head-mounted	Multi-modal	Static/Nudge-based
EyeWise 1.1	Standard Webcam	Visual and/or auditory	Adaptive timing (Backoff)

utilize direct airflow to trigger reflexive blinking, they require specialized and often intrusive wearable hardware. Similarly, RhythmBlink and DualBlink offer sophisticated prompting logic but remain dependent on specific external sensors or hardware-modified glasses.

In contrast, EyeWise 1.1 distinguishes itself as a purely software-based, multimodal approach that utilizes a standard notebook webcam for real-time monitoring. By employing a randomized exponential backoff logic to regulate feedback, the system maximizes accessibility through both visual (gauge) and auditory (sound) prompts. This design allows for a non-intrusive intervention that can be deployed on existing consumer hardware without the need for additional equipment.

We chose a between-subjects design based on how the different interventions work (Table 2). Unlike basic reminders, the adaptive "nudge" in EyeWise 1.1 is meant to help users build stable habits. A within-subjects design would create a substantial risk of learning effects.[24,25] If a participant learned better blinking habits during the adaptive session, they would likely keep those habits in later sessions, which would skew the baseline data.

To understand the reasons behind user behavior, we combined blink rate data with deep qualitative observations and post-experiment interviews. Doing this level of detailed observation with a large group would have lowered the quality of the feedback. Also, a within-subjects design would require about 90 min of continuous webcam monitoring per person, which could make participants tired and unnaturally change how they blink. Because of this, we chose a sample size of n = 5 per condition for this exploratory pilot study. We know that this sample is very small for definitive statistical testing. Instead, it was chosen to check the system's basic feasibility and gather rich user feedback.

While a small sample limits statistical power, Rossi[26] notes that genuinely large effects can still be found in small groups. Following Lakens'[27] standard classification of effect sizes as small (δ = 0.2), medium (δ = 0.5), and large (δ = 0.8), our results showed large estimates across all active conditions ($|\delta| \geq 0.84$). However, we treat these numbers carefully as preliminary indications of the system's potential, recognizing that effect size estimates from small samples can be highly unstable and sensitive to individual variability. Ultimately, these findings act as a functional proof-of-concept to help guide larger future studies.

5. Discussion

In this study, we examined how adaptive feedback helps users maintain healthy blinking within a target range of 15–30 BPM. It is important to clarify that blink rates exceeding 30 BPM are generally not viewed as a cause of eye strain and are often linked to medical or psychological factors rather than screen use. Therefore, we treat this range as a behavioral guide for habit regulation rather than a medical diagnostic boundary.

While a simpler fixed-interval method may seem more practical due to its lower complexity, our results highlight a key drawback: it lacks behavioral awareness. During our tests, fixed-interval reminders often triggered "unnecessary" blinks even when the user was already within the healthy range. In contrast, the adaptive approach is uniquely effective at preventing this excessive "over-blinking." By avoiding redundant notifications, the adaptive system provides a more natural and less intrusive user experience than a rigid schedule.

We recognize that the performance of EyeWise 1.1 is an integrated effect of both the smart timing logic and the improved semicircular interface. To provide a realistic comparison, the Fixed-Interval group used a simpler Dual-Bar interface and a standardized configuration. This setup represents the standard, non-adaptive reminder tools that are commonly available to users today. While this adds more variables to the study, it allows for a realistic comparison between common "standard" tools and our new integrated approach. Future studies could isolate these factors by evaluating the adaptive algorithm on a simplified interface to measure the algorithm's independent impact.

EyeWise 1.1 fills a critical gap by providing behavioral support without requiring specialized equipment. Many existing SOTA systems depend on expensive or intrusive hardware such as airflow sensors or specialized glasses. Our system is purely software-based, utilizing a standard notebook webcam to monitor blinks in real time, making it significantly more accessible for everyday users.

The reliability of this system depends on the specific detection parameters used to ensure reproducibility. We chose an T_{ear} of 0.2 because it is a proven benchmark for robust blink detection, providing gaze-drop immunity to ensure that the system does not make mistakes looking down at a notebook for a real blink. Blink confirmation was set to 3 consecutive frames to reduce noise from ocular micro-movements and jitters. The 60 s sliding window ensures that the system responds to real behavioral trends rather than one-time fluctuations, as a shorter window would make feedback erratic, while a longer window would delay necessary interventions. The update rate of 20 s balances system responsiveness with data consistency. For the adaptive notification logic, the backoff base of 4 s prevents notification overcrowding and user annoyance, while the max interval of 60 s guarantees that reminders are still delivered during periods of intense focus.

The Adaptive group's blink rates moved closer to the healthy range during evaluation. However, the difference between EyeWise 1.1 and fixed reminders did not reach statistical significance under the Bonferroni correction. This is expected, as a sample size of $n = 5$ per condition was sufficient to detect large effect sizes ($|\delta| \geq 0.84$), but not subtle differences between two active interventions. A between-subjects design was chosen to prevent learning effects, where habits formed during one session could carry over and distort results in the next. While this sample size was appropriate for a preliminary pilot study, future research with a larger and more diverse sample is needed to confirm the comparative effectiveness of EyeWise 1.1.

Finally, we must acknowledge the statistical limitations of this exploratory pilot study. Because of the small sample size ($n = 5$ per condition) and non-normal data distribution, we report uncertainty using the interquartile range (Q1 to Q3) rather than standard confidence intervals. The wide ranges observed—such as the 11 BPM gap between Q1 (22.0) and Q3 (33.0) for the Adaptive condition—reflect the high individual variability that naturally occurs in small groups. As a result, the large effect sizes observed ($|\delta| \geq 0.84$) are highly unstable. These numbers should not be viewed as definitive proof of comparative superiority, but rather as preliminary markers that highlight the need for larger, future studies.

6. Conclusion

This study introduced EyeWise 1.1, a lightweight adaptive blink-monitoring system intended to support blink regulation during screen use. EyeWise 1.1 combines real-time EAR-based blink detection with a sliding window estimator and an adaptive reminder policy that delivers feedback primarily when blinking deviates from a practical operational threshold. In a controlled reading task, both reminder strategies increased blinking relative to baseline; however, EyeWise 1.1 produced a more conservative distributional shift than fixed-interval prompting, suggesting that behavior-sensitive timing may encourage regulation while reducing over-correction. Participants in the adaptive condition also reported positive usability and perceived effectiveness, indicating that the approach is acceptable in principle and worth advancing.

These conclusions should be interpreted as preliminary given the pilot scale, the between-subjects design, and the use of window-level observations that may not be independent. Future work should evaluate EyeWise in longer-term, naturalistic deployments across diverse activities and incorporate repeated-measures analyses (e.g., aggregation or mixed-effects models). More broadly, the findings motivate an HCI perspective in which closed-loop, blink-aware timing functions as a practical mechanism for low-disruption micro-interventions, while deployment-ready implementations must explicitly address transparency, consent, and user control to sustain trust in webcam-based wellness tools.

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About the Authors

Muhammad Furqan Rasyid received his B.S. degree from Dipa Makassar University, Indonesia, in 2016, and his M.S. degree from Hasanuddin University, Indonesia, in 2019. He is currently pursuing his Ph.D. degree at Nara Institute of Science and Technology, Japan. His research interests include computer vision, machine learning, and human–computer interaction.
(rasyid.muhammad_furqan.ri4@naist.ac.jp)

Tomokazu Matsui received his M.S. and Ph.D. degrees from Nara Institute of Science and Technology, Japan, in 2019 and 2021, respectively. Since 2023, he has been an assistant professor at Nara Institute of Science and Technology, Japan. His research interests are in ubiquitous computing, daily living actions, IoT, smart home, machine learning, and action awareness.
(m.tomokazu@is.naist.jp)

Yuki Matsuda received his B.E. degree in advanced course of mechanical and electronic system engineering from the National Institute of Technology, Akashi College, Japan, in 2015, and his M.E. and Ph.D. degrees from the Graduate School of Information Science, Nara Institute of Science and Technology, Japan, in 2016 and 2019, respectively. Since 2024, he has been a lecturer at the Convivial Computing Laboratory, Faculty of Environmental, Life, Natural Science, and Technology of Okayama University. His current research interests include participatory sensing, location-based information systems, wearable computing, and affective computing.
(yukimat@okayama-u.ac.jp)

Hirohiko Suwa received his B.E. and M.E. degrees from Gunma University, in 1998 and 2000, respectively, and his Ph.D. degree from the University of Electro-Communications, Japan, in 2006. He was an assistant professor with the University of Electro-Communications from 2006 to 2014, and Nara Institute of Science and Technology (NAIST) from 2014 to 2018, where he has been an associate professor since 2019. His research interests include social informatics, real data mining, and ubiquitous computing systems.
(h-suwa@is.naist.jp)

Keiichi Yasumoto received his B.E., M.E., and Ph.D. degrees in information and computer sciences from Osaka University, Osaka, Japan, in 1991, 1993, and 1996, respectively. He is currently a professor at the Graduate School of Science and Technology at Nara Institute of Science and Technology. His research interests include distributed systems, mobile computing, and ubiquitous computing. (yasumoto@is.naist.jp)