Making Regular Eyeglasses Smart

Software apps running on smart eyeglasses offer unobtrusive universal assistance systems that can support wearers in their daily lives. The authors describe a blueprint of the embedded architecture of smart eyeglasses and discuss findings from using smart eyeglass prototypes.

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Most of our senses, vital signs, and actions involve the head, making the human skull one of the most interesting body locations for the simultaneous sensing and interaction of assistance applications. Although hearing aids and mobile headsets have become widely accepted as head-worn devices, users in public spaces often consider novel head-attached sensors and devices to be uncomfortable, irritating, or stigmatizing. Nevertheless, numerous wearable computing studies have shown that head-worn sensors and adequate signal processing could reveal cognition-related behavior and essential vital parameters (such as heartbeat and breathing rates). Behavior and vital data is the key component for many assistance applications in daily life, from those that offer memory augmentation to those advising chronically ill patients. Assistance applications thus require continuous measurements and context estimation.

Today's regular eyeglasses could fill the gap between sensing and assistance in daily life. Most eyeglasses are publicly accepted accessories, often worn continuously throughout the day, rendering them an ideal platform for additional assistive functions. In contrast to Google Glass and early wearable system approaches that just attached devices to standard glasses, we envision exploiting smart eyeglasses for assistance applications through fully integrated sensing, processing, and interaction functions in the regular spectacles design, thus maximizing unobtrusiveness. We also envision embedded software apps that let wearers dynamically alter assistance functionality depending on momentary needs. With a rich set of software apps that can be selectively run on smart eyeglasses, one pair of smart eyeglasses could serve various purposes in daily life and provide novel assistance applications in continuous monitoring, augmentation, and therapy, beyond what smartphones and smart watches can achieve today. They would offer much more than short-term interaction and quick information access.

Although the first steps toward commercial smart eyeglasses are currently being made (with J!NS MEME; www.jins-jp.com/jinsmeme/en), scientific analyses and studies of variable assistive functions in smart eyeglasses are lacking. Consequently, opportunities and requirements for smart eyeglasses and assistance applications are unclear. Following from commercial examples, smart eyeglasses seem to be primarily useful in sensing and processing tasks, given that eyeglasses provide access to unique sensor locations near the head. Here, we present an architecture for integrating technology into traditional eyeglass designs, discuss ergonomic design requirements, and derive recommendations for further smart eyeglasses developments. In three case studies, we observed the potential of using smart eyeglasses for assistive functions.

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(a) (b) (c)

Figure 1. Sensing in eyeglasses varies from (a) attaching devices to glasses (Google Glass) to initial attempts at integrated smart eyeglasses, such as the (b) J!NS MEME electrooculography (EOG) glasses, which measure eye movements and head motion, paired with several applications. (c) EnWake eyeglasses provide blue light therapy to help wearers manage their sleep-wake cycle, providing visualizations using a smartphone. (The EnWake images are courtesy of EnWake Holding BV; used with permission.)

Sensing in Everyday Eyeglasses

Humans receive approximately 87 percent of all sensory input via the head,[1] spurring the recent development of interaction and notification approaches involving head-mounted displays (see Figure 1). For example, Google Glass builds on the concept of micro-interactions to timely accomplish information search and feedback lasting only a few seconds (see Figure 1a). In contrast, many assistance applications require continuous sensing, processing, and interaction.

For such continuous operations, clinical measurement practices indicate that the head is a good place to sense and monitor body functions. For example, blood oxygen saturation, heart rate, and respiration are measured at the ear lobe. Core body temperature can be estimated from head-attached sensors. Similarly, human behavior assessments—related to diet, stress, concentration levels, and so on—often involve direct or indirect measurements taken near the head. For example, acoustic sensors and strain gauges have been used to monitor chewing and swallowing, both of which can indicate dieting habits and stress levels.[2] Pupil dilation and blink rate have been used to estimate concentration.[3] Abnormal walking patterns, which can indicate osteoarthritis and past knee- or hip-replacement surgery, were identified from head-worn motion sensors.[4] Recently proposed devices incorporate biopotential electrodes and acceleration sensors to support wellness and sports applications that encourage meditation and relaxation or detect the user's heart rate or count his or her steps. Examples of these devices include intelligent headbands, such as Muse (www.choosemuse.com) and Melon (www.thinkmelon.com), and sensor earplugs, such as those from PEARSports (www.pearsports.com). Although none of these approaches use eyeglasses, and most focus on individual applications, their sensing, processing, and interaction components are compatible with our architecture for smart eyeglasses.

When it comes to exploiting glasses for augmented and virtual reality applications, however, there has been substantial research. Such work has focused on improving see-through or look-around optics for information display—examples include the Oculus Rift (www.oculus.com/rift) and Sony smart glasses (https://developer.sony.com/develop/wearables/smarteyeglass-sdk). Furthermore, Oakley's sunglasses with an embedded music player and headphones illustrate the wider market potential of technology in eyewear (http://en.wikipedia.org/wiki/Oakley_THUMP). However, bulky frame-attached processing devices or otherwise cumbersome layouts make many existing eyewear designs impractical for everyday use. Technology miniaturization and power optimization will eventually make augmented reality functions smaller, but even today, assistive smart eyeglasses could be realized.

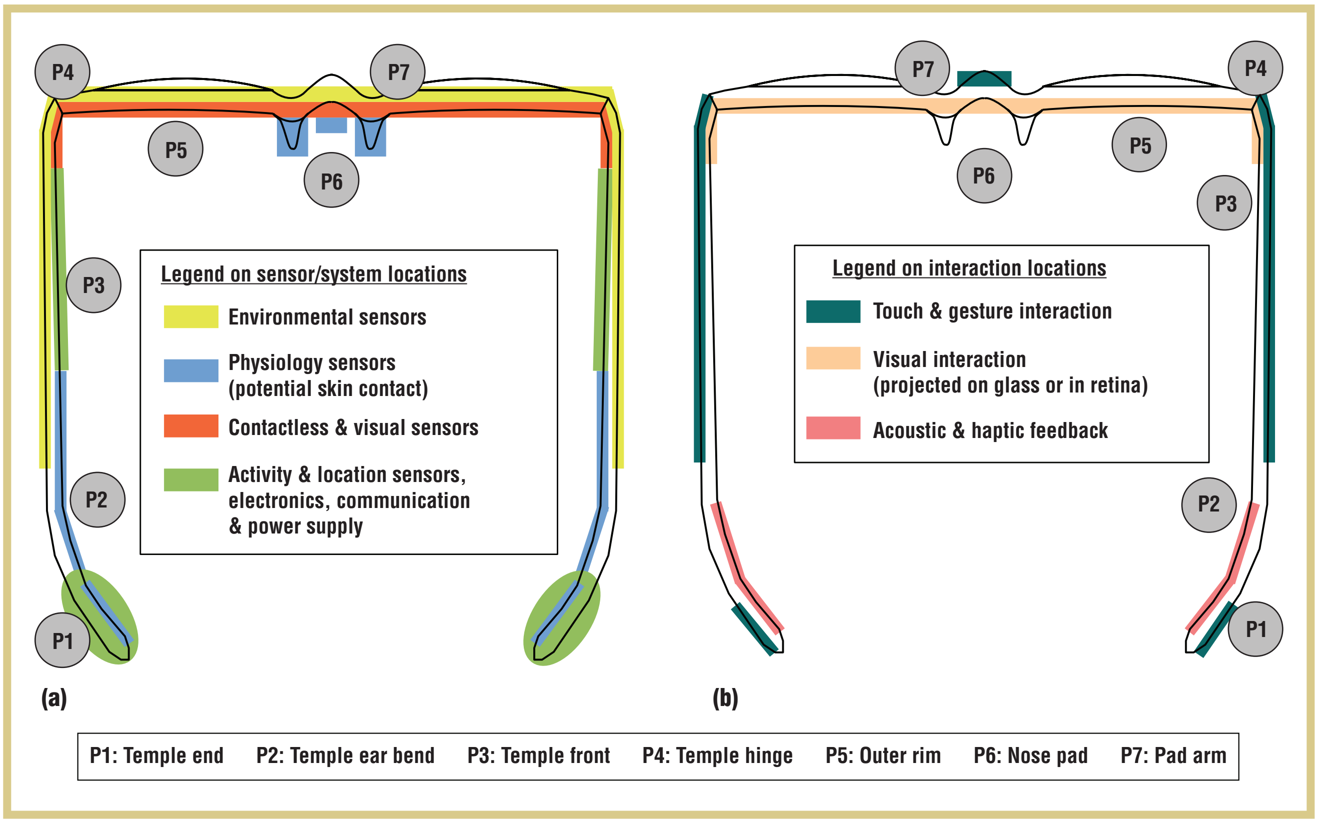

Figure 2. An illustration of smart eyeglasses architecture and device positioning: (a) sensor/system locations and (b) interaction locations. Positions on eyeglasses: temple ends/earpiece (P1); ear bends, which can be used as support over the ears (P2); temple sides and fronts, near the visible region of temples above the cheek (P3); the hinge connecting the lens frame and temple end piece ("butt-strap") (P4); the frame rim, which carries the lenses (P5); the nose pads (P6); and the pad arm/bar, connecting symmetric frame parts (P7).

Toward everyday settings, few attempts have been made to embed technology directly into the standard eyeglasses form factor. In addition to a motion sensor, the J!NS MEME (see Figure 1b) integrates electrodes in the nose pads of a traditional eyeglasses form factor. Electronics are placed behind the ears in the temple ends (see Figure 2a for an illustration of this and other terms related to eyewear frames). Nose-pad, pad-arm, and temple electrodes are used to capture biopotential, used in electrooculography (EOG) analysis to determine eye movement. In combination with head motion, the eyeglasses aim to detect tiredness, concentration, sleepiness, and energy expenditure during physical activity. The Optalert Fatigue Management Glasses use an LED and a photodetector to monitor drowsiness during driving (http://optalert.com). Optalert monitors the eyelid and derives amplitude-velocity rates of blinks. The EnWake eyeglasses (see Figure 1c) target light therapy and feature blue light LEDs diffused by a prism to stimulate the human circadian system through the eyes (http://ece.nl/enwake-minimizing-jetlags). Although EnWake eyeglasses are intended for noncontinuous stimulation only, their approach indicates potential for care and therapy applications integrated into eyeglasses.

Whereas Optalert and EnWake were designed for one function only, the J!NS MEME glasses illustrate the trend toward integrated multipurpose smart eyeglasses that could be used in different monitoring and assistance applications in everyday life. Beyond current eyeglasses designs, we envision many other assistive functions on smart eyeglasses—from software apps running on smart eyeglasses to functions exploiting dedicated hardware.

Smart Eyeglasses Architecture

A smart eyeglass design essentially depends on the form factor of the supporting eyeglass frame. Sensing and interaction modalities, the positioning of functions on eyeglasses, as well as the integration of processing electronics and powering are determined by the supporting frame (see Table 1 for more information).

Ergonomic Design

Smart eyeglasses provide a unique approach to ergonomic sensor placement

Table 1. An overview of smart eyeglass components and integration options. The location indicators (P1–P7) are illustrated in Figure 2.

Component	Possible location	Device examples	Integration considerations
Environmental sensors	Temple fronts (P3), temple hinges (P4), outer rims (P5), and pad arms (P7), because they are most exposed to the outside world	Devices that monitor environmental temperatures, humidity, sounds, and so on	The sensors weigh only a few grams Sensor appearance should minimize obtrusiveness
Physiological sensors	Nose pads (P6), pad arms (P7), and temple ear bends (P2), so the sensors can maintain constant contact with the skin and controlled contact pressure (given by the weight of the eyeglasses) For sports glasses, the skin-contacted regions of the inner rims and temple fronts	Devices that monitor skin temperature or that measure eye movement or heart activity (for example, using biopotential electrodes)	The electrode weight is typically negligible, and the size can be adjusted to eyeglass dimensions for nose pads and temples
Contactless and visual sensors	Inner rims (P5) and the inner side of a pad arm (P7), so the sensors can directly measure the face and eyes to monitor blinks or pupils	Low resolution cameras or LED-based detectors	The weight and size are critical (especially for optical sensors) Weight balance can be reached when placing components that weigh more than ~10 g at the pad arm (P7) rather than temple edges (P4)
Activity and location sensors	Temple ends (P1) provide a space for sensors that do not require exposed position or skin contact	Orientation sensors or GPS	Temple ends (P1) are least constrained in weight, size, and weight balance Sensors can be integrated into the main electronics
Touch interaction	Temple fronts (P3) are well suited for touch micro-interaction (for less than two seconds) and can support multiple touch commands along the temples The pad arm (P7) can be used for a button-like interface	Touch pads	Touch sensors are planar and weigh in the milligram range
Visual interaction	Temple fronts (P3) and rims (P5) can carry optical feedback or assistive devices	Projection optics or LEDs	Optical devices can be large and heavy (25 g or more), and single-eye optical devices should be avoided due to uneven weight balance
Acoustic and haptic interaction	Temple ear bends (P2), optionally with attached headphones.	Headphones or buzzers	Additional weight ($\sim$ 10g) can be supported at the rear side of temples (P1 and P2)
Electronics, communication, and power supply	Temple ends (P1) are the best-suited location, with temple fronts (P3) as an alternative Electronics, communication, and the power supply (battery) can be distributed onto both temples and interconnected via the temples and rim	Microcontrollers, wireless modules, antennas, batteries, and so on	Although size and weight at temple ends are the least constrained, weight balance must be achieved between both temples

at important head locations. Nevertheless, key ergonomic design constraints including size, weight, and weight balance around the pad arm must be respected. We consider that the basic shape and dimensions of spectacles should be maintained for smart eyeglasses, which limits component selection. In particular, for many assistance applications, smart eyeglasses will likely integrate sensing, data processing, and communication functions in addition to the power supply. Interaction functions must be used selectively, due to the displays' relatively large size and weight requirements.

Finally, imbalances—due to devices attached at one temple side, for example—result in wearer discomfort and irritation. In contrast, eyeglasses can carry balanced weight at the temple ends. For example, the main electronics and battery can be placed on respective temple ends to balance weight.

Size

Our comparison of dimensions among regular eyeglasses showed that the distance between the temple hinges and skin, as well as rim size, are important measures. Smart eyeglasses thus should use rim and temple designs similar to regular eyeglasses. In contrast, the vertical size of temple sides and ends is less limited, as J!NS MEME and En-Wake illustrate.

Weight

For everyday continuous use, weight appears to be a critical constraint. In a user study on spectacles, participants rated the total weight, giving eyeglasses that weighed 100 grams an average score of 8 out of 10 points, where 10 indicated high wearing comfort.[5] For eyeglasses that weighed 75g, the average score improved to 9 out of 10 points. Frame and sight-correcting plastic lenses typically require approximately 50g, thus leaving a practically useful weight budget of 25 to 50g for additional smart eyeglasses components. Our personal discussions with J!NS researchers confirmed this weight budget.

Power Consumption

Runtime requirements of smart eyeglasses will be similar to smart watches and smartphones today—that is, smart eyeglasses need to operate for at least one day without needing to be recharged. The temple ends support a rechargeable battery with approximately 250 mAh total capacity, similar to batteries in a small smart watch.

Many sensors considered in our architecture are available in low-power designs, and related processing strategies are well documented. For example, inertial sensors and Photoplethysmography (PPG) sensors could be continuously operated, because only few milliamperes are needed to sample and process sensor data. Nevertheless, components including cameras, GPS, and displays for visual interaction typically require several 10 mA or more. High-power components thus are not well suited for continuous operation and need appropriate sampling strategies.

Skin Contact

Sensors in contact with the skin are central for many behavior and physiological monitoring tasks, including EOG and heart rate. Eyeglass ergonomics provide useful spots for skin contact, such as nose pads, the pad arm, and temple ear bends (see Figure 2). In addition, tight-fitting sports glasses could use temple fronts for sensors that require skin contact (at P3 in Figure 2). Most skin contact locations for eyeglasses provide constant contact pressure due to the eyeglass weight, supporting reliable measurements.

Placement Invariability

Eyeglass designs support correct placement on the head, and large misalignment is less likely than with other wearable devices. However, eyeglasses tend to be repositioned during daylong wear, and for smart eyeglasses that include sensors and interaction functions, repositioning and motion-intensive activity could lead to sensor and input artifacts that require corrective processing. In motion-intensive applications, specific tight-fitting sports-eyeglass designs might be needed to reduce artifacts.

Component Priorities

Several locations could be used for different components, such as temples, hinge, rims, and pad arms, providing flexibility for designers. Placement conflicts are unlikely for most environmental, activity, and location sensors, because their placement does not depend on an exact position and the components are small. In contrast, physiological sensors are usually location-dependent—for example, EOG electrodes on nose pads (P6). Similarly, many interaction modalities will require specific locations, such as acoustics at P2 or touch at P3. Due to the relevance of sensing in assistance applications, interaction in smart eyeglasses might thus provide limited functionality or could be omitted. Instead, external interaction options, such as a Web portal, display, or smartphone, might be used.

Apps for Smart Eyeglasses

Among the wide range of potential software apps that can be executed on smart eyeglasses, we investigated examples that leverage earlier work using head-attached assistive technology (see Table 2).[4,6–16] For all apps, smart eyeglasses require programmable processing and communication components to provide processed information to feedback services (such as Web portals) or to interact with surrounding devices (such as smartphones). Consequently, running smart eyeglass apps requires only that app-specific sensors and interaction modalities be available.

Application domains of previous head-attached systems span a wide range of fields, from health and fitness to tourism to interaction and cognitive aids. Nevertheless, the required sensor and interaction modalities overlap, suggesting that smart eyeglasses could indeed serve multiple purposes.

App Clusters

Here, we group apps into clusters that use common smart eyeglasses hardware and cover related assistance applications (see Table 2).

Health and interaction. This cluster addresses everyday apps in health monitoring, the quantified self, and interaction. Activity and physiological information is processed and communicated to external feedback devices. Smart eyeglasses might provide limited notification interfaces, such as indicator LEDs. All functions have low size, weight, and power requirements and thus could operate continuously throughout the day.

Location and cognition. This cluster emphasizes location tracking and remembering applications, with hardware requirements similar to the health and interaction cluster. We view this as a separate cluster, because cameras can be considered intrusive in public settings and raise power requirements.

Gaze control. The apps in this cluster are suitable for touchless interaction and hands-free control using eye gestures.

Table 2. Potential software apps that can be executed on smart eyeglasses to assist in different situations. Apps were clustered according to common smart eyeglasses hardware requirements. The location indicators (P1–P7) are illustrated in Figure 2.

Hardware configuration	Smart eyeglass apps and reference to details	Sensors, interaction, and location
Health and interaction	Energy expenditure estimation[6] Detecting gait abnormalities[4] Monitoring heart activity and respiration[7] Managing subtle/private notifications via indicator LED[8] Monitoring light exposure to adjust the sleep-wake cycle (in this work)	Acceleration sensor (P1), light sensor (P7), heart rate and respiration rate via Photoplethysmography (PPG) at the ear (P1 and P2) Indicator LED in a visual space (P5) Additional feedback/interaction via Web portal, computer/tablet, and smartphone
Location and cognition	Locating in indoor environments, such as offices[9] Locating via pictured points of interests in unknown environments[10] Remembering people from camera images[11]	Inertial sensors (P1) Laser range sensors and camera in viewing direction (P3, P4) Feedback/interaction via Web portal and smartphone
Gaze interaction	Detecting eye gestures relative to the head during reading[12] for touchless display control Eye gaze as hands-free control of a music player[13] Quantifying reading habits (in this work)	Inertial sensors (P1) Electrooculography (EOG) electrodes around eyes (P5 and P6) Interaction via a controllable device, such as a display
Therapy	Acoustic monitoring of chewing microstructure parameters and food consumption patterns[14]	Microphone at ear (P2) Feedback/interaction via Web portal and smartphone
Cognitive aid and control	General memory augmentation[15] Monitoring driver vigilance[16] Cognitive workload monitoring to pace learning (in this work)	Camera and optical eye tracking in visual space (P5) EOG electrodes around eyes (P5 and P6) Interaction via feedback device, such as a car dashboard, display, or computer

Output is realized via external devices, such as displays. Eye-based interaction requires specific sensors (such as EOG). As J!NS MEME demonstrates, a combination of a few biopotential electrodes and inertial sensors is sufficient for monitoring tiredness, concentration, sleepiness, or energy expenditure. EOG sensors add to the size, weight, and power requirements, but they can be operated continuously throughout the day.

Therapy. This cluster exemplifies a lifestyle therapy application using application-dedicated sensors and actuators. Here, dietary advice is generated based on acoustic data processed on the smart eyeglasses. Other therapy applications might require different dedicated sensors or actuators (such as blue LEDs for EnWake). Cumulative feedback and interaction options, such as goal setting, could be realized via Web portals and smartphones. Even small wearable systems can process continuous audio data and potentially forward intermediate information to a cloud service, thus providing monitoring throughout the day.

Cognitive aid and control. This cluster uses an eye-facing camera, optical eye-tracking, and EOG sensors to analyze a perceived or actual cognitive load. Due to the complex monitoring components (eye-facing camera), smart eyeglasses in this cluster might serve in focused control tasks and cognitive assistance applications, such as for cognitive training apps.

Design Considerations

In our architecture and ergonomic design considerations, we found that integrating sensing, data processing, and communication functions is essential for smart eyeglasses. However, eyeglasses-integrated interaction is often limited to simple indicators, such as an LED for subtle notifications, due to size, weight, and power consumption requirements, and none of the apps envisioned in Table 2 offer a glasses-attached display. Moreover, none of the commercial smart eyeglasses (J!NS MEME, EnWake, or Optalert) provide interaction functions. Although interaction is essential for assistance applications, notifications could be perceived as highly disruptive in smart eyeglasses. Similarly, due to resource limitations, input modalities often only provide micro-indications.

Our analysis, however, indicates that various external interaction options can be used with smart eyeglasses in assistance applications, such as Web portals, external displays, and smartphones.

Case Studies

We highlight three promising assistive applications, where smart eyeglasses provide cognitive and health assistance functions. To track basic cognitive functions, we explored recognizing the cognitive load; to support learning, we quantified reading habits; and to track health and circadian rhythm, we monitored light exposure behavior.

Recognizing Cognitive Workload

Real-time tracking of changes in cognitive workload while users perform tasks could lead to a paradigm shift in education, because we could give learners challenging problems without asking too much from them. Workload estimation can help judge the likelihood of a user successfully completing a task.

Current measurement practice. From psychology research, a correlation between eye motion features and cognitive workload is well known.[3] Yet most studies still use questionnaires to detect workload level and focus on basic experimental setups using medical monitoring equipment. Functional near-infrared spectroscopy (NIRS) is often considered as a reference for detecting changes in brain activation related to cognitive workload. NIRS measures changes in oxyhemoglobin in a particular brain area. However, NIRS requires wearing a headband or similar bulky device. Based on earlier work,[3] we are confident that smart eyeglasses could estimate both perceived and actual cognitive workload using blink frequency and pupil diameter measurements, respectively.

Smart eyeglasses use cases. A smart eyeglasses app can easily assess blink frequency and estimates perceived workload using two-electrode EOG sensors or an infrared distance measurement integrated in frames and the nose pad (P5 and P6 in Figure 2). In contrast, an app running on smart eyeglasses to estimate actual workload must determine pupil diameter and track pupils. Because pupil tracking typically requires an eye-facing camera, the battery runtime is constrained to few hours. Due to camera size, smart eyeglasses specifically intended for reading and actual workload estimation ("reading glasses") are conceivable.

Learning tasks are usually displayed on a computing system, such as a tablet for grammar learning. The smart eyeglasses app could thus forward workload estimates to the display, where the optimal difficulty level could be continuously adjusted.

Another use case is tracking cognitive workload over a day—for air-traffic controllers, for example. A smart eyeglasses app could connect to a computer or smartphone, so when a user loses focus (as evidenced by a detected decline in cognitive load), warnings could be displayed or the interface could change to recapture the user's attention.

Initial analysis. Using NIRS as a reference, we investigated the relationship between cognitive load and eye motion using features from EOG glasses. Eight participants (three females and five males, between ages 19 and 32) performed a dual n-back memory task ($n = 1, 2, 3, 4$), where the difficulty level increases with n. We used alphabet letters as acoustic stimuli and single highlighted squares in a grid of eight squares as visual stimuli. The n-back task is well explored using NIRS and aims at a linear increase in brain activation for increasing difficulty level. Participants performed each difficulty level for one minute with eight repetitions, resting for one minute between repetitions. We interviewed participants after each repetition to determine if they were "giving up" prematurely during the game. Assigned tasks were performed using a Latin square method to swap task type and difficulty level.

We recorded data from a stationary eye-tracker (SMI RED) at 250 Hz, a 42-channel NIRS device (Shimadzu LabNIRS) at 6 Hz, and five-point EOG eyeglasses (J!NS MEME) at 100 Hz. Figure 3 illustrates the experimental setup. We applied all 42 NIRS channels to the prefrontal cortex responsible for most complex planning, learning, decision making, and action during demanding cognitive tasks. For our NIRS analysis, we applied a standard methodology to assess brain activation by selecting the NIRS channel with the highest activation and then we averaged changes in this channel. We measured pupil diameter using the eye tracker and changes in blink frequency using the J!NS MEME EOG signal.

Figure 3 shows that with increasing task difficulty, change in pupil diameter increases and blink frequency decreases. We confirmed task difficulty in participant interviews and by analyzing NIRS brain activation. Some task recordings from higher difficulty levels were not available, because participants gave up or could no longer perform the task. We identified "giving up" as drop in the overall NIRS brain activation and as a drop in the participant's performance (getting no or very few correct answers compared to other participants). The "giving up" state was also confirmed in participant interviews. Our ANOVA tests confirmed a relationship between the task difficulty as an independent variable and the change in pupil diameter, $p < 0.05$, with $F = 6.89$, $F_{crit}(3, 4) = 6.59$ (where denotes the F-distribution cumulative distribution function); and normalized blink frequency $p < 0.05$, $F = 6.63$, $F_{crit}(3, 4) = 6.59$, both separately considered as dependent variables. The Pearson product-moment correlation revealed good positive correlation for task difficulty and change in pupil diameter ($r = 0.71$), and decent negative correlation for task difficulty and normalized blink frequency ($r = -0.53$).

The results have yet to be verified, as the overall blink frequency and the pupil diameter are crude measurements and we used only a small user sample. Greg J. Siegle and his colleagues show that the relation of blink frequency and pupil diameter over time could provide more insights regarding cognitive workload.[3] Analyzing the time series of brain activity, blinks, and pupil changes is a promising direction, where smart eyeglasses might provide long-term assistance.

Quantifying Reading Habits

Increasing reading volume is in line with cognitive merits, including larger vocabulary and higher general knowledge.[17] Reading is entertaining and has social value too. Higher reading volumes in adolescents are correlated with higher self-esteem and improved cognitive and emotional well-being.[18]

Current measurement practice. Most work focuses on reading detection only.[12] A few online reading services, such as Goodreads (www.goodreads.com), enable readers to track their habits manually. So far, automatic reading habit recognition and recording has not been implemented or used to improve reading habits.

Smart eyeglasses use cases. Smart eyeglasses are ideally suited for exploring and improving reading habits, because many people already wear eyeglasses for reading. In the most basic scenario, a smart eyeglasses app could quantify a wearer's reading—for example, by counting words. For simple reading tracking using glasses, EOG is a viable choice, because electrodes can be integrated into the eyeglass frame. Estimated reading performance can be forwarded to a smartphone and shared on a Web portal. Users could compare their performance to that of their friends. We expect that tracking word count will have a similar effect as tracking step counts using a pedometer—increasing the overall reading volume of users. For this purpose, we implemented a Web portal to test a quantified feedback approach.

A smart eyeglasses app could detect document type and how documents are read—determining, for example, concentration and attention levels related to certain sections—providing insight into healthy reading habits and helping users revisit vital information that they might have missed. Moreover, associating a comprehension level with text sections could help authors improve their writing or could provide feedback about readers' progress.

Initial analysis. Initially, we used mobile optical eye tracking (see Figure 4a) to implement a word count system and detected reading using simple saccade features (average saccade length, direction, horizontal/vertical element of saccades). Details can be found elsewhere.[19] We counted line breaks by recognizing long saccades (eye movements) against the dominant reading direction and approximated word count, either by assuming a fixed word count per line or by estimating word count from the average saccade number and length in a line (see Figure 4b). Our analysis showed an error rate of 6 to 11 percent when reading 20 to 30 minutes from different display sizes.[19] There were 10 participants, including university students and staff (four female and six male, between ages 20 and 36), who were screened for potential reading disabilities before the study. Although eyeglasses were not used here, we considered features that could be derived from EOG-enabled smart eyeglasses too. Therefore, we believe that the approach could be transferred to smart eyeglasses.

Furthermore, saccade features are well suited for classifying whether a user is reading a textbook (Figure 4c), comic (Figure 4d), fashion magazine, or newspaper.[20] Our document type classification is based on eye movement features too (saccade direction, slope, length, and general reading direction, summarizing saccade direction over longer times). We evaluated our approach in a study with eight participants (three females and five males with a mean age of 24) on the five document types listed above. Recognition performance was 74 percent for user-independent training and 98 percent for user-dependent training, as long as document layouts

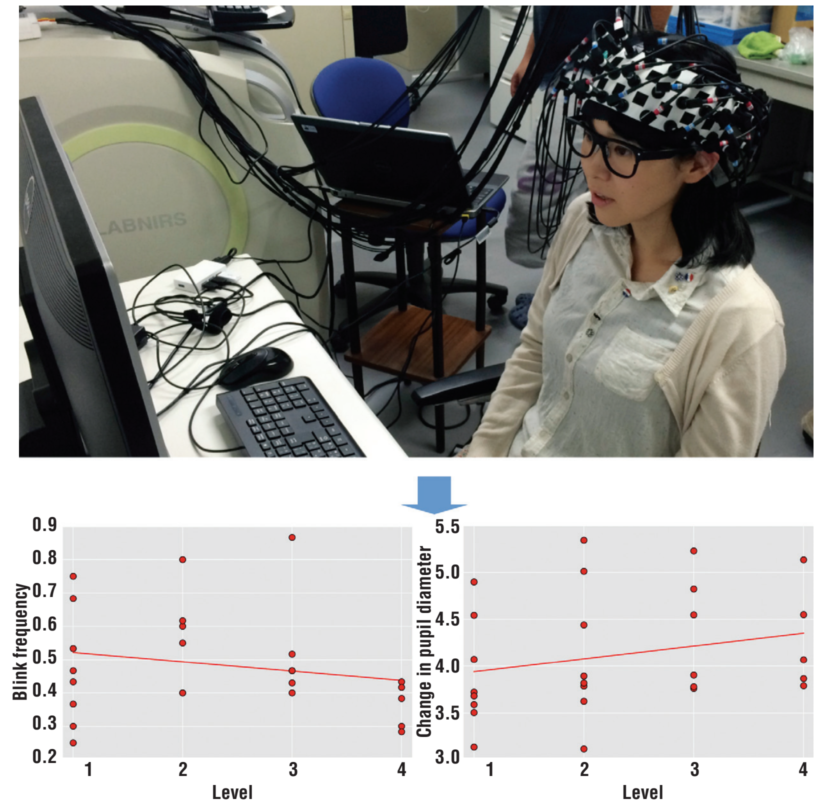

Figure 3. Recognizing cognitive workload. Increasing task difficulty (from L1 to L4) also increases changes in normalized blink frequency (measured by J!NS MEME EOG) and decreases pupil diameter (measured by a stationary eye tracker). Average results over eight repetitions per participant are shown. Correlations with cognitive workload were observed.

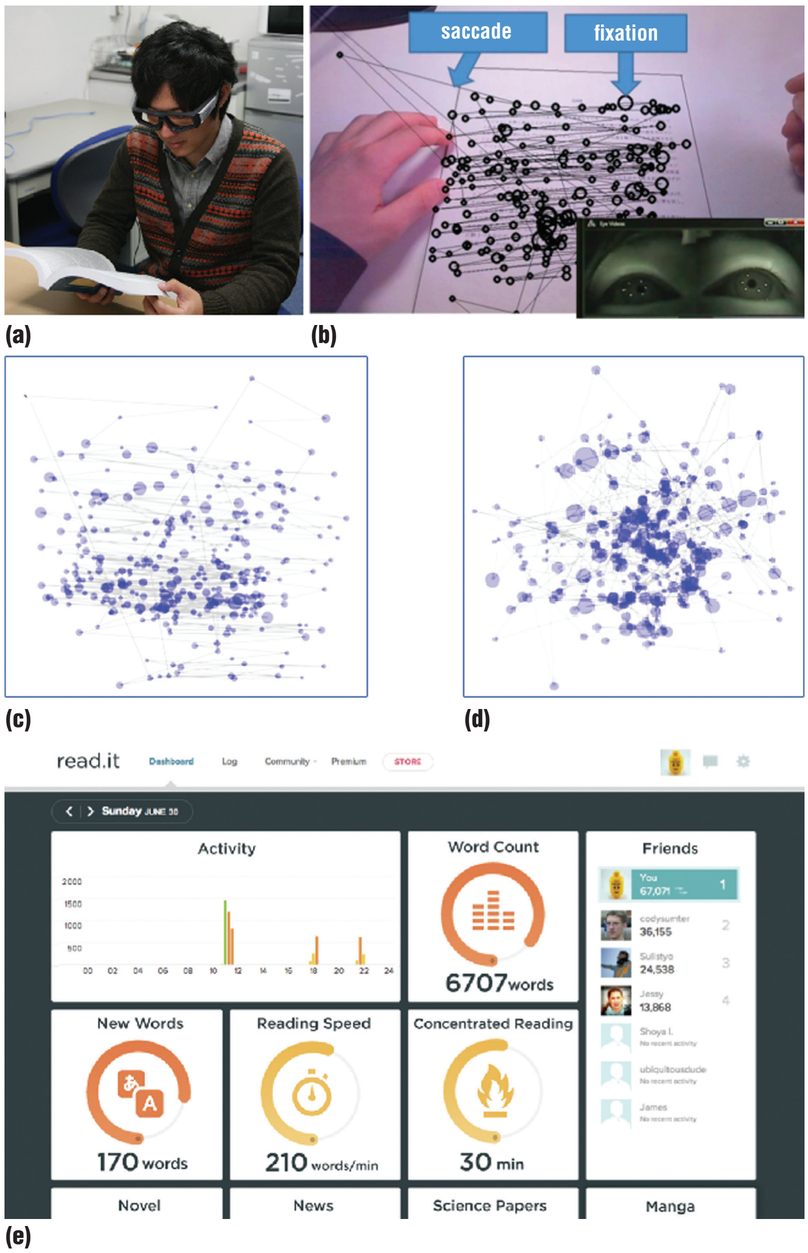

Figure 4. Quantifying reading habits. (a) A participant wearing an SMI mobile eye tracker while reading. (b) The camera view of the eye tracker with fixations and saccades. The visual behavior recorded by the eye tracker for reading (c) a textbook and (d) a comic. (e) A mock-up of a reading assistance service, providing quantified feedback on reading habits (on a Web portal).

differed sufficiently (page size, relationship of words to images, two column versus one column layouts, and so on).[20] Figure 4e shows a mock-up of a reading assistance service, implemented a Web portal.

Monitoring Light Exposure Behavior

Light entering through the eyes cues our circadian phase and controls the human sleep-wake cycle.[21] For example, in shift workers, research found that a misalignment between sleep-wake and day-night cycles led to lower performance, memory, alertness, and gastrointestinal function. In various studies, light exposure was found to be key in adjusting sleep-wake times. Light in the morning increased daytime alertness, and light during evening hours postponed sleep.[22] Moreover, blue light has a stronger awakening effect than other wavelengths.

Current measurement practice. In free-living circadian clock studies, light exposure is currently measured using wrist-worn sensor devices, necklaces, or specialized head-mounted light sensors. We found that wrist-worn sensors are often occluded by cloths, leading to substantial underestimation of the actual light exposure.[23] Necklace devices might similarly be hidden under garments, and thus incur measurement errors. Measuring light exposure directly at the eyes is thus preferred by experts.

Smart eyeglasses use cases. Smart eyeglasses could measure light exposure in daily life using a light sensor integrated in rims or pad arm, hence close to the eyes but minimally occluded by hair or head. A smart eyeglasses app could derive light-related behavior indicators and recommendations for efficient sleep based on light measurement throughout a day. For example, to fall asleep earlier at night, morning light exposure should be increased. Consequently, the app could recommend cycling to work or taking a longer walk outside during an early lunch break. Moreover, blue light exposure during late evenings, due to TV or PC screen use, could be identified by the app.

Although smart eyeglasses serve here as platform for sensors and processing, a smart eyeglasses app would forward processed data to the Web portal, computer display, or smartphone for instant or regular user feedback. Consequently, smart eyeglasses require communication functions (such as Wi-Fi or Bluetooth), but no visual user interface.

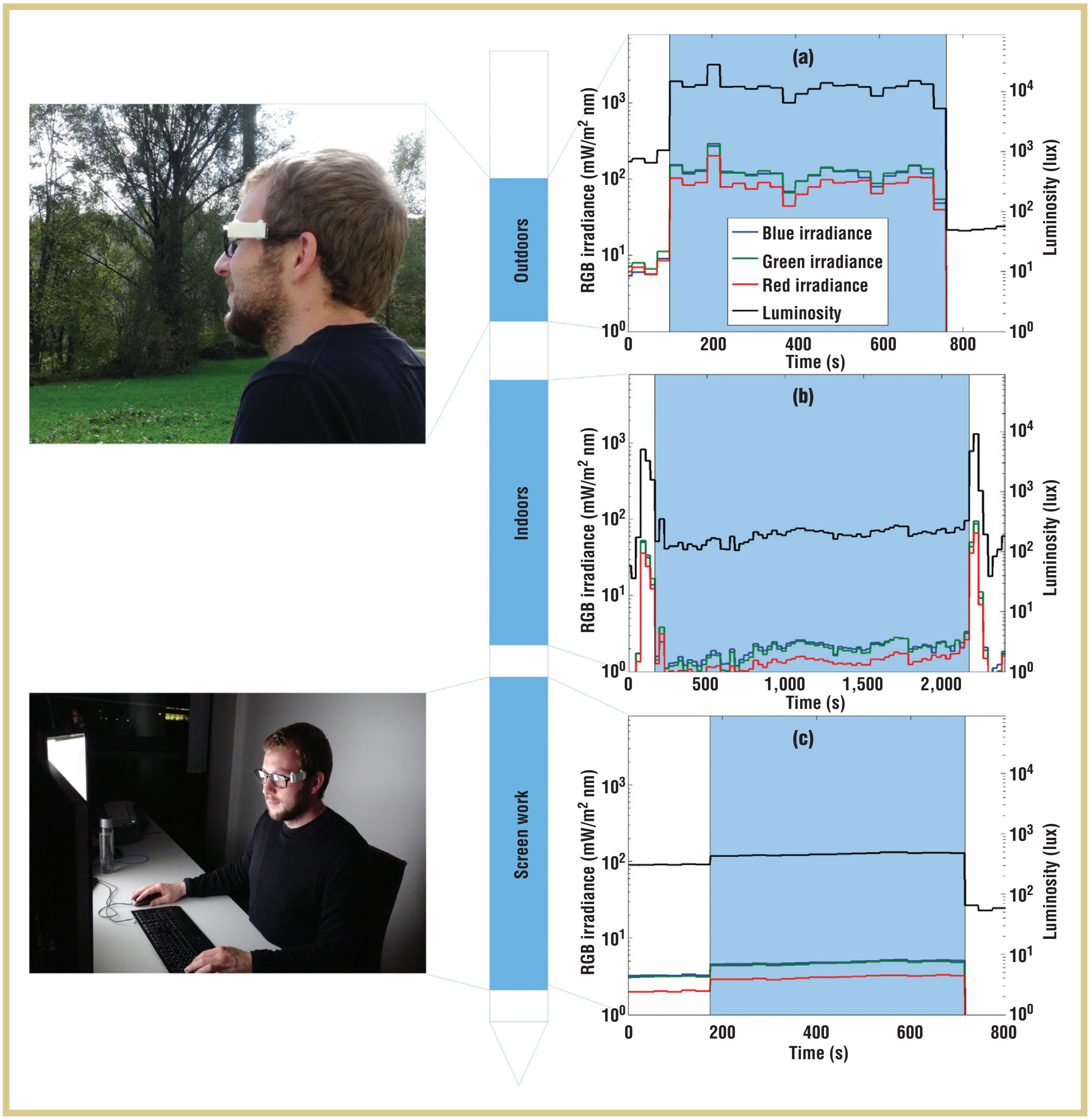

Figure 5. Monitoring light exposure behavior via eyeglasses over a regular day. Activities and locations are illustrated in irradiance/luminosity waveforms as colored areas: (a) Outdoors, luminosity is typically very high (≥ 5000 lux). (b) Indoors, luminosity is much smaller than outdoors. (c) When viewing a screen work, luminosity and blue irradiance is elevated compared to typical indoor conditions.

Initial analysis. We conducted a free-living study with 12 university students (five female and seven male, all between ages 18 and 28). Participants continuously wore a custom light measurement device attached to regular eyeglasses for six consecutive days and annotated whether they were indoors or outdoors.[23] Glasses were detached only when sleeping or showering. Participants who did not normally wear eyeglasses were given dioptre-free eyeglasses, individually adapted by an optician. Light measurements were taken continuously every 30 seconds.

Figure 5 shows wearing conditions and example irradiance measurements in RGB components from our study

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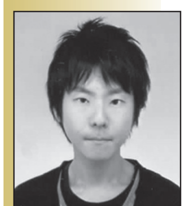

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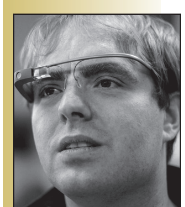

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data. As the waveforms illustrate, outdoor light intensity can be 100 times higher than indoors. TVs or computer screens increase blue light components and luminosity at the head to approximately 300 lux or more, thus much higher luminosity than otherwise found after sunset. A Wilcoxen ranksum test across all study participants showed highly significant differences ($\alpha = 0.01$, $p = 0$) between indoor and outdoor luminosity in daytime. We expect that smart eyeglasses will become a monitoring accessory to align the sleep-wake cycle in regular daily life. In particular, users with varying work schedules, such as airline flight staff, will benefit from light accounting and could use smart eyeglasses to adjust their circadian phase ahead of time for their next destination's time zone.

With a catalogue of software apps to select from, integrated multipurpose smart eyeglasses could be used in different applications and move from niche to mainstream markets. Yet several technical challenges must be further explored to realize the vision of smart eyeglasses, including sensor design and integration, low-power processing, overall ergonomic design, and devising adequate interaction approaches. Unobtrusiveness will be key to user adoption. Size, weight, weight balance, and power consumption constraints will prevent designers from integrating too many functional components in one eyeglass device—especially if the glasses are intended for continuous use daily. Considering the identified hardware clusters, we rarely expect existing interaction modalities to be integrated in smart eyeglasses. Instead, novel lightweight and low-power interaction approaches for smart eyeglasses need to be developed, such as audio and vibration feedback. Given suitable communication interfaces and interoperability, smart eyeglasses will also exploit use external interaction devices.

Furthermore, smart eyeglasses need to overcome psychological and social hurdles. The examples of J!NS MEME, Optalert, and EnWake smart eyeglasses suggest that wearers accept continuous sensing when they identify clear benefits from using the device. Nevertheless, qualitative studies are needed to investigate wearer opinions when using smart eyeglasses. Social hurdles include both the wearer's fear of being stigmatized and privacy concerns of those around them. In part, social hurdles might be overcome if more smart eyeglasses become available, minimizing privacy concerns by not including cameras.

It is interesting to note that when we informally asked our nontech colleagues about the idea of continuously worn smart eyeglasses, those who do not normally wear eyeglasses reacted negatively. However, after explaining the potential uses and assistance functions, people often agreed that the benefits were convincing. We nevertheless believe that initial integrated multipurpose smart eyeglasses will best serve select application fields, including health and interaction—particularly as related to sports—and cognitive aid.

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