PrivacEye: Privacy-Preserving Head-Mounted Eye Tracking Using Egocentric Scene Image and Eye Movement Features

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ABSTRACT

Eyewear devices, such as augmented reality displays, increasingly integrate eye tracking but the first-person camera required to map a user's gaze to the visual scene can pose a significant threat to user and bystander privacy. We present *PrivacEye*, a method to detect privacy-sensitive everyday situations and automatically enable and disable the eye tracker's first-person camera using a mechanical shutter. To close the shutter in privacy-sensitive situations, the method uses a deep representation of the first-person video combined with rich features that encode users' eye movements. To open the shutter without visual input, PrivacEye detects changes in users' eye movements alone to gauge changes in the "privacy level" of the current situation. We evaluate our method on a first-person video dataset recorded in daily life situations of 17 participants, annotated by themselves for privacy sensitivity, and show that our method is effective in preserving privacy in this challenging setting.

CCS CONCEPTS

• **Human-centered computing** → **Interactive systems and tools**; **Ubiquitous and mobile computing**; **Ubiquitous and mobile devices**; **Human computer interaction (HCI)**;

KEYWORDS

Egocentric Vision; Eye Tracking; Gaze Behaviour

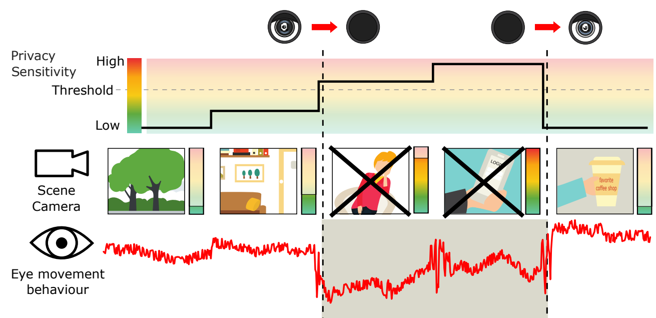


Figure 1: Our method uses a mechanical camera shutter (top) to preserve users' and bystanders' privacy with head-mounted eye trackers. Privacy-sensitive situations are detected by combining deep scene image and eye movement features (middle) while changes in eye movement behaviour alone trigger the reopening of the camera shutter (bottom).

1 INTRODUCTION

Eyewear devices, such as head-mounted displays or augmented reality glasses, have recently emerged as a new research platform in fields such as human-computer interaction, computer vision, or the behavioural and social sciences [5]. An ever-increasing number of these devices integrate eye tracking capabilities given their significant potential for analysing and better understanding users' attention allocation [15, 50], for computational user modelling [17, 25], and as a versatile means for interaction [19, 55]. Head-mounted eye tracking typically requires two cameras: An eye camera that records a close-up video of the eye and a high-resolution first-person (scene) camera to map gaze estimates to the real-world scene [26]. The scene camera poses a serious privacy risk given that it may record highly sensitive personal information, such as login credentials, banking information, or personal text messages, and it may potentially allow individuals to be identified, thus also infringing on the privacy of bystanders [37]. This privacy risk will become even more pervasive and severe with the unnoticeable integration of eye tracking in ordinary glasses frames [53].

In the area of first-person vision, prior work proposed self-censorship [27] but this approach is prone to misinterpretation of situations, may neglect social norms and legal regulations, or may result in forgetting to de-activate or re-activate the camera altogether. This approach may not only reduce user experience and comfort or increase a user's mental and emotional load, but also potentially captures and leaks sensitive personal information. Other works therefore investigated alternative solutions, such as communicating a bystander's privacy preferences using short-range wireless radio [1], visual markers [44], or techniques to compromise recordings [21, 54]. However, all of these methods require bystanders to take action themselves to protect their privacy. None of these works addressed the problem at its source, i.e. the scene camera, nor did they offer a means to protect the privacy of both the wearer and potential bystanders.

To address this limitation, we propose *PrivacEye*, the first method for privacy-preserving head-mounted eye tracking (see Figure 1). The key idea and core novelty of our method is to detect users' transitions into and out of privacy-sensitive everyday situations by leveraging both cameras available on these trackers. More specifically, to detect privacy-sensitive situations, our method combines a deep (learning) image representation obtained from the eye tracker's egocentric scene camera with features that encode users' eye movements observed with the eye camera. If a privacy-sensitive situation is detected, the scene camera is occluded by a physical shutter. Our design choice to use a non-spoofable physical shutter, which closes for some time and therefore provides feedback to bystanders, is substantiated by [29], who showed increased trustworthiness over LED lights on the camera or pure software solutions. While this approach is secure and visible to bystanders, it completely disables visual input from the camera. Thus, our method analyses changes in a user's eye movement behaviour alone to detect if s/he moves out of a privacy-sensitive situation and reopens the camera shutter. A naive, vision-only system could reopen the shutter at regular intervals, e.g. every 30 seconds, to detect whether the current situation is still privacy-sensitive. However, this approach may negatively affect perceived reliability and increase mistrust in the system. Therefore, our eye-tracking approach promises significant advantages over a purely interval-based approach in terms of user experience and perceived trustworthiness.

Our approach is motivated by prior works demonstrating that eye movements are a rich source of information on a user's everyday activities [7, 47], social interactions and current environment [8], or even a user's personality traits [22]. In addition, prior work showed that perceived privacy sensitivity is related to a user's location and activity [23]. We therefore hypothesized a transitive relationship where *privacy sensitivity* links to the current *activity and environment*, which inform – transitively – a user's *eye movements*. We are the first to confirm this transitivity, which results as a reasoned deduction from prior work.

The specific contributions of this work are three-fold: First, we present *PrivacEye*, the first method that combines the analysis of egocentric scene image features with eye movement analysis to enable context-specific, privacy-preserving de-activation and re-activation of a head-mounted eye tracker's scene camera. As such, we show a previously unconfirmed transitive relationship between a user's eye movements, his/her current activity and environment, as well as the perceived privacy sensitivity of the situation s/he is in. Second, we evaluate our method on a dataset of real-world mobile interactions and eye movement data, fully annotated with locations, activities, and privacy sensitivity levels of 17 participants. Third, we provide qualitative insights on the perceived social acceptability, trustworthiness, and desirability of *PrivacEye*, based on semi-structured interviews, using a fully functional prototype.

2 RELATED WORK

As research on privacy is relatively sparse in eye tracking research, our work is most closely related to previous works on (1) privacy concerns with first-person cameras and (2) methods to enhance the privacy of such cameras.

2.1 Privacy Concerns - First-Person Cameras

First-person cameras are well-suited for continuous and unobtrusive recordings, which causes them to be perceived as more unsettling by bystanders [12]. Both users' and bystanders' privacy concerns and attitudes towards head-mounted devices with integrated cameras were found to be affected by context, situation, usage intentions [28], and user group [42]. Hoyle et al. showed that the presence and the number of people in a picture, specific objects (e.g., computer displays, ATM cards, physical documents), location, and activity affected whether lifeloggers deemed an image "shareable" [24]. They also highlighted the need for automatic privacy-preserving mechanisms to detect those elements, as individual sharing decisions are likely to be context-dependent and subjective. Their results were partly confirmed by Price et al., who, however, found no significant differences in sharing when a screen was present [41]. Chowdhury et al. [11] found that whether lifelogging imagery is suitable for sharing is (in addition to content, scenario, and location) mainly determined by its sensitivity. Ferdous et al. proposed a set of guidelines that, among others, include semi-automatic procedures to determine the sensitivity of captured images according to user-provided preferences [16]. All of these works underline the privacy-sensitive nature of first-person cameras and the importance of protecting the privacy of users and bystanders.

2.2 Enhancing Privacy of First-Person Cameras

To increase the privacy of first-person cameras for bystanders, researchers have suggested communicating their privacy preferences to nearby capture devices using wireless connections as well as mobile or wearable interfaces [32]. Others have suggested preventing unauthorised recordings by compromising the recorded imagery, e.g., using infra-red light signals [20, 57] or disturbing face recognition [21]. In contrast to our approach, these techniques all require the bystander to take action, which might be impractical due to costs and efforts [12].

Methods to increase the privacy of the user typically require active user involvement. For example, Templeman et al. introduced *PlaceAvoider*, a technique that allowed users to "blacklist" sensitive spaces, such as the bedroom or bathroom [52]. Similarly, Erickson et al. proposed a method to identify security risks, such as ATMs, keyboards, and credit cards, in images captured by first-person wearable devices [14]. However, instead of assessing the whole scene in terms of privacy sensitivity, their systems only detected individual sensitive objects. Raval et al. presented *MarkIt*, a computer vision-based privacy marker framework that allowed users to use self-defined bounding boxes and hand-gestures to restrict visibility of content on two dimensional surfaces (e.g. white boards) or sensitive real-world objects [43]. Similarly, *ScreenAvoider* allowed users to control the disclosure of images of computer screens showing potentially private content [31]. *iPrivacy* automatically detects privacy-sensitive objects from social images users are willing to share using deep multi-task learning [58]. It warns the image owners what objects in the images need to be protected before sharing and recommends privacy settings.

While all of these methods improved privacy, they either only did so post-hoc, i.e. after images had already been captured, or they required active user input. In contrast, our approach aims to prevent potentially sensitive imagery from being recorded at all, automatically in the background, i.e. without engaging the user. Unlike current computer vision based approaches that work in image space, e.g. by masking objects or faces [43, 46, 57], restricting access [31], or deleting recorded images post-hoc [52], we de-activate the camera completely using a mechanical shutter and also signal this to bystanders. Our approach is the first to employ eye movement analysis for camera re-activation that, unlike other sensing techniques (e.g., microphones, infra-red cameras), does not compromise the privacy of potential bystanders.

3 DESIGN RATIONALE

PrivacEye's design rationale is based on user and bystander goals and expectations. In this section, we outline how PrivacEye's design contributes to avoiding misclosures (User Goal 1), and social friction (User Goal 2), and detail on three resultant design requirements.

3.1 Goals and Expectations

Avoid Misclosure of Sensitive Data. A user wearing smart glasses with an integrated camera would typically do so to make use of a particular functionality, e.g., visual navigation. However, the device's "always-on" characteristic causes it to capture more than originally intended. A navigation aid would require capturing certain landmarks for tracking and localisation. In addition, unintended imagery and potentially sensitive data is captured. Ideally, to prevent misclosures [9], sensitive data should not be captured. However, requiring the user to constantly monitor her actions and environment for potential sensitive information (and then deactivate the camera manually) might increase the workload and cause stress. As users might be forgetful, misinterpret situations, or overlook privacy-sensitive items, automatic support from the system would be desirable from a user's perspective.

Avoid Social Friction. The smart glasses recording capabilities may cause social friction if they do not provide a clear indication whether the camera is on or off: Bystanders might even perceive device usage as a privacy threat when the camera is turned off [28, 29]. In consequence, they feel uncomfortable around such devices [4, 12, 13, 28]. Similarly, user experience is impaired when device users feel a need for justification as they could be accused of taking surreptitious pictures [18, 29].

3.2 Design Requirements

As a consequence of these user goals there are three essential design requirements that PrivacEye addresses: (1) The user can make use of the camera-based functionality without the risk of misclosures or leakage of sensitive information. (2) The system pro-actively reacts to the presence or absence of potentially privacy-sensitive situations and objects. (3) The camera device communicates the recording status clearly to both user and bystander.

4 PRIVACEYE PROTOTYPE

Our fully functional PrivacEye prototype, shown in Figure 2, is based on the PUPIL head-mounted eye tracker [26] and features one 640×480 pixel camera (the so-called "eye camera") that records the right eye from close proximity (30 fps), and a second camera (1280×720 pixels, 24 fps) to record a user's environment (the so-called "scene camera"). The first-person camera is equipped with a fish eye lens with a 175° field of view and can be closed with

Figure 2: PrivacEye prototype with labelled components (B) and worn by a user with a USB-connected laptop in a backpack (A). Detection of privacy-sensitive situations using computer vision closes the camera shutter (C), which is reopened based on a change in the privacy detected level in a user's eye movements (D).

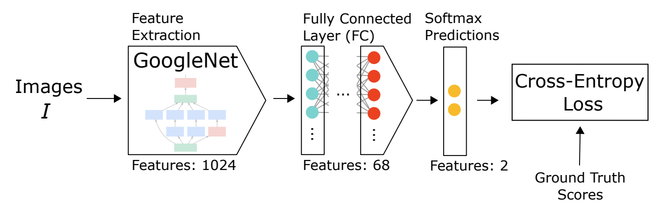


Figure 3: Our method for detecting privacy-sensitive situations is based on a pre-trained GoogleNet model that we adapted with a fully connected (FC) and a Softmax layer. Cross-entropy loss is used for training the model.

a mechanical shutter. The shutter comprises a servo motor and a custom-made 3D-printed casing, including a mechanical lid to occlude the camera's lens. The motor and the lid are operated via a micro controller, namely a Feather M0 Proto. Both cameras and the micro controller were connected to a laptop via USB. PrivacEye further consists of two main software components: (1) detection of privacy-sensitive situations to close the mechanical camera shutter and (2) detection of changes in user's eye movements that are likely to indicate suitable points in time for reopening the camera shutter.

4.1 Detection of Privacy-Sensitive Situations

The approaches for detecting privacy-sensitive situations we evaluated are (1) *CNN-Direct*, (2) *SVM-Eye*, and (3) *SVM-Combined*.

4.1.1 CNN-Direct. Inspired by prior work on predicting privacy-sensitive pictures posted in social networks [36], we used a pre-trained GoogleNet, a 22-layer deep convolutional neural network [51]. We adapted the original GoogleNet model for our specific prediction task by adding two additional fully connected (FC) layers. The first layer was used to reduce the feature dimensionality from 1024 to 68 and the second one, a Softmax layer, to calculate the prediction scores. Output of our model was a score for each first-person image indicating whether the situation visible in that image was privacy-sensitive or not. The cross-entropy loss was used to train the model. The full network architecture is shown in Figure 3.

4.1.2 SVM-Eye. Given that eye movements are independent from the scene camera's shutter status, they can be used to (1) detect

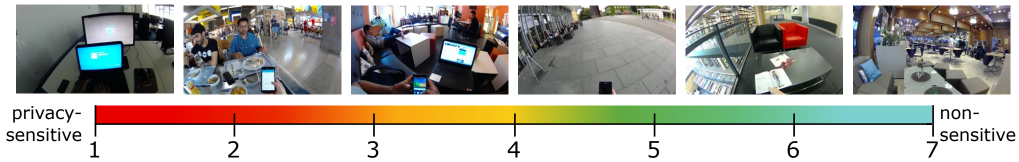


Figure 4: Sample images showing daily situations ranging from "privacy-sensitive", such as password entry or social interactions, to "non-sensitive", such as walking down a road or sitting in a café.

Fixation (8)	rate, mean, max, var of durations, mean/var of mean/var pupil position within one fixation
Saccades (12)	rate/ratio of (small/large/right/left) saccades, mean, max, variance of amplitudes
Combined (1)	ratio saccades to fixations
Wordbooks (24)	number of non-zero entries, maximum and minimum entries as well as their difference for n-grams with $n <= 4$
Blinks (3)	rate, mean/var blink duration
Pupil Diameter (4)	mean/variance of mean/variance during fixations

Table 1: We extracted a total of 52 eye movement features to describe a user's visual behaviour. The number of features per category is given in parentheses.

privacy-sensitive situations while the camera shutter is open and (2) detect changes in the subjective privacy level while the camera shutter is closed.

The goal of this second component is to instead detect changes in a user's eye movements that are likely linked to changes in the privacy sensitivity of the current situation and thereby to reduce the number of shutter reopenings as much as possible. To detect privacy-sensitive situations and changes, we trained SVM classifiers (kernel=rbf, C=1) with characteristic eye movement features, which we extracted using only the eye camera video data. Table 1 summarises the features that we extracted from fixations, saccades, blinks, pupil diameter, and a user's scan paths. Similar to [7], each saccade is encoded as a character forming words of length n (wordbook). We extracted these features on a sliding window of 30 seconds (step size of 1 second).

4.1.3 SVM-Combined. A third approach for the detection of privacy-sensitive situations is a hybrid method. We trained SVM classifiers using the extracted eye movement features (52) and combined them with CNN features (68) from the scene image, which we extracted from the first fully connected layer of our trained CNN model (see Figure 3), creating 120 feature large samples. With the concatenation of eye movement and scene features, we are able to extend the information from the two previous approaches during recording phases where the camera shutter is open.

5 EXPERIMENTS

We evaluated the different approaches on their own and in combination in a realistic temporal sequential analysis trained in a person-specific (leave-one-recording-out) and person-independent (leave-one-person-out) manner. We assume in the beginning that the camera shutter is open. If no privacy-sensitive situation is detected, the camera shutter remains open and the current situation is rated "non-sensitive", otherwise, the camera shutter is closed and the current situation is rated "privacy-sensitive". Finally, we analysed error cases and investigated the performance of PrivacEye in different environments and activities.

5.1 Dataset

While an ever-increasing number of eye movement datasets have been published in recent years (see [6, 7, 22, 47–49] for examples), none of them has been recorded in the context of privacy. We therefore recorded our own dataset. The dataset contains more than 90 hours of data recorded continuously from 20 participants (six females, ages 22-31) over more than four hours each. Participants were students with different backgrounds and subjects with normal or corrected-to-normal vision. During the recordings, participants roamed a university campus and performed their everyday activities, such as meeting people, eating, or working as they normally would on any day at the university. To obtain some data from multiple, and thus also "privacy-sensitive", places on the university campus, participants were asked to not stay in one place for more than 30 minutes. Participants were further asked to stop the recording after about one and a half hours so that the laptop's battery packs could be changed and the eye tracker re-calibrated. This yielded three recordings of about 1.5 hours per participant. Participants regularly interacted with a mobile phone provided to them and were also encouraged to use their own laptop, desktop computer, or music player if desired. The dataset thus covers a rich set of representative real-world situations, including sensitive environments and tasks (see Figure 4). The data collection was performed with the same equipment as shown in Figure 2 excluding the camera shutter.

5.2 Data Annotation

The dataset was fully annotated by the participants themselves with continuous annotations of location, activity, scene content, and subjective privacy sensitivity level. 17 out of the 20 participants finished the annotation of their own recording resulting in about 70 hours of annotated video data. They again gave informed consent and completed a questionnaire on demographics, social media experience and sharing behaviour (based on Hoyle et al. [24]), general privacy attitudes, as well as other-contingent privacy [3] and respect for bystander privacy [41]. General privacy attitudes were assessed using the *Privacy Attitudes Questionnaire* (PAQ), a modified Westin Scale [56] as used by [9, 41].

Annotations were performed using Advene [2]. Participants were asked to annotate continuous video segments showing the same situation, environment, or activity. They could also introduce new

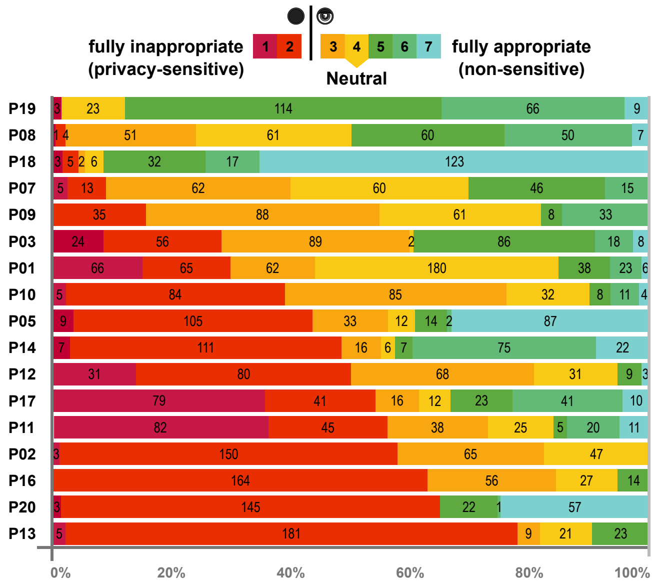


Figure 5: Privacy sensitivity levels rated on a 7-pt Likert scale from 1: fully inappropriate (i.e., privacy-sensitive imagery) to 7: fully appropriate (i.e., non-sensitive). Distributions in labelled minutes per level per participant, sorted according to the “cut-off” between closed shutter (lvl 1-2) and open shutter (lvl 3-7), resulting in “privacy pragmatist” [top] to “privacy fundamentalist” [bottom] (c.f., [56]).

segments in case a privacy-relevant feature in the scene changed, e.g., when a participant switched to a sensitive app on the mobile phone. Participants were asked to annotate each of these segments according to the annotation scheme (see supplementary material). Privacy sensitivity was rated on a 7-point Likert scale (see Figure 4) ranging from 1 (fully inappropriate) to 7 (fully appropriate). As we expected our participants to have difficulties understanding the concept of “privacy sensitivity”, we rephrased it for the annotation to “How appropriate is it that a camera is in the scene?”. Figure 5 visualises the labelled privacy sensitivity levels for each participant. Based on the latter distribution, we pooled ratings of 1 and 2 in the class “privacy-sensitive”, and all others in the class “non-sensitive”. A final product would provide the option to choose this “cut-off”. We will use these two classes for all evaluations and discussions that follow in order to show the effectiveness of our proof-of-concept system.

5.3 Sequential Analysis

To evaluate PrivacEye, we applied the three proposed approaches separately as well as in combination in a realistic temporal sequential analysis, evaluating the system as a whole within person-specific (leave-one-recording-out) and person-independent (leave-one-person-out) cross validation schemes. Independent of CNN or SVM approaches, we first trained and then tested in a person-specific fashion. That is, we trained on two of the three recordings of each participant and tested on the remaining one – iteratively over all combinations and averaging the performance results in the end. For the leave-one-person-out cross validation, we trained on the data of 16 participants and tested on the remaining one.

SVM-Eye is the only one of the three proposed approaches that allows PrivacEye to be functional when no scene imagery is available, i.e., when the shutter is closed. Additionally, it can be applied when the shutter is open thus serving both software components of PrivacEye. While the camera shutter is not closed, i.e., scene imagery is available, *CNN-Direct* or *SVM-Combined* can be applied. To provide a comprehensive picture, we then analysed the combinations *CNN-Direct* + *SVM-Eye* (*CNN/SVM*) and *SVM-Combined* + *SVM-Eye* (*SVM/SVM*). The first approach is applied when the camera shutter is open and *SVM-Eye* only when the shutter is closed. For the sake of completeness, we also evaluated *SVM-Combined* and *CNN-Direct* on the whole dataset. However, these two methods represent hypothetical best-case scenarios in which eye and scene features are always available. As this is in practice not possible, they have to be viewed as an upper-bound baseline. For evaluation purposes, we apply the proposed approaches within a step size of one second in a sequential manner. The previously predicted camera shutter position (open or close) decides which approach is applied for the prediction of the current state to achieve realistic results. We use $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$, where TP, FP, TN, and FN represent sample-based true positive, false positive, true negative, and false negative counts, respectively, to measure the performance of our system.

5.3.1 *CNN-Direct.*

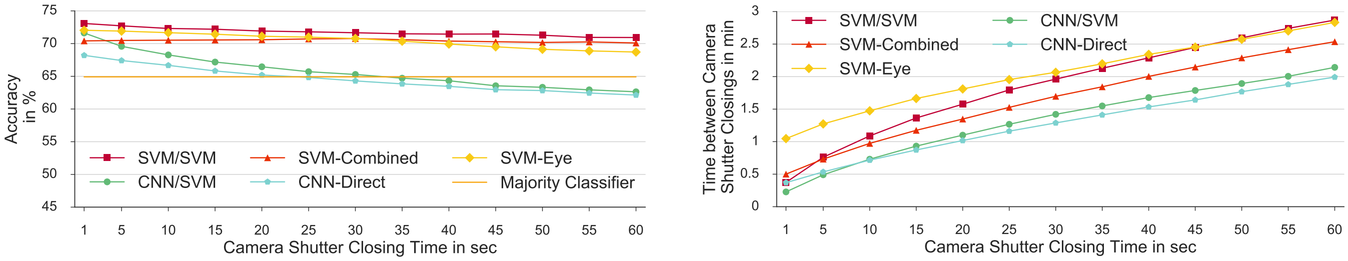
For training the CNN classifier, which classifies a given scene image directly as privacy-sensitive or non-sensitive, we split the data from each participant into segments. Every time the environment, activity, or the annotated privacy sensitivity level changed, a new segment started. From each segment, we extracted one random image to train our model.

5.3.2 *SVM-Eye and SVM-Combined.*

For the SVM classifiers using only eye movement features (*SVM-Eye*) or the combination of eye movement and CNN features (*SVM-Combined*), we standardised the training data (zero mean, unit variance) for the person-specific and leave-one-person-out cross validation before training the classifiers. The test data was standardised with the same parameters as the training data.

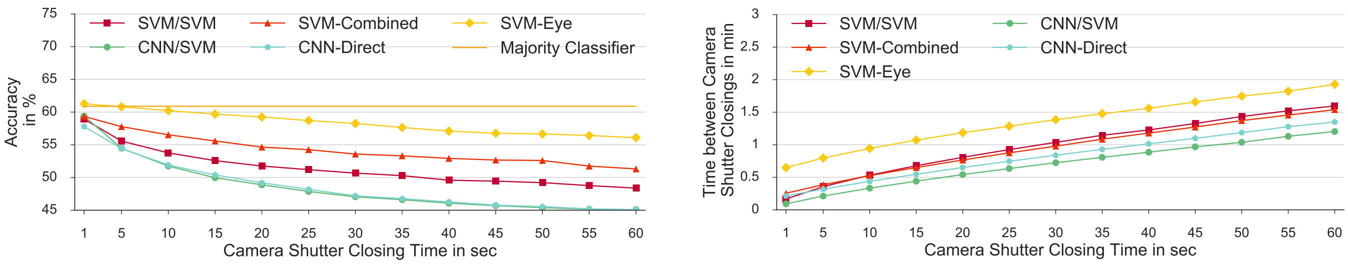
5.4 Results

With potential usability implications in mind, we evaluate performance over a range of camera shutter closing times. If a privacy-sensitive situation is detected from the *CNN-Direct* or *SVM-Combined* approach, the camera shutter is kept closed for an interval between 1 and 60 seconds. If *SVM-Eye* is applied and no privacy change is detected, the shutter remains closed. In a practical application, users gain more trustworthiness when the camera shutter remains closed, at least for a sufficient amount of time, to guarantee the protection of privacy-sensitive scene content when such a situation is detected [29]. We also evaluated *CNN-Direct* and *SVM-Combined* on the whole recording as hypothetical best-case scenarios. However, comparing their performance against the combinations *SVM/SVM* and *CNN/SVM* illustrate the performance improvement using *SVM-Eye* when the camera shutter is closed.



(a) **(b)**

Figure 6: Person-specific leave-one-recording-out evaluation showing the achieved accuracy (a) and the time between camera shutter closings (b) across different camera shutter closing times.



(a) **(b)**

Figure 7: Person-independent leave-one-person-out evaluation showing the accuracy results (a) and the time between camera shutter closings (b) across different camera shutter closing times.

5.4.1 Person-specific (leave-one-recording-out) evaluation. Figure 6a shows the person-specific accuracy performance of PrivacEye against increasing camera shutter closing time for two combinations *CNN/SVM* and *SVM/SVM*, and *SVM-Eye*, which can be applied independent of the camera shutter status. Besides *CNN-Direct* and *SVM-Combined*, the majority class classifier serves as a baseline, predicting the majority class from the training set. The results reveal that all trained approaches and combinations perform above the majority class classifier. However, we can see that *CNN-Direct* and its combination with *SVM-Eye* (*CNN/SVM*) perform below the other approaches and below the majority class classifier for longer camera shutter closing times. *SVM-Eye* and *SVM-Combined* perform quite robustly, around 70% accuracy, while *SVM-Eye* performs better for shorter closing times and *SVM-Combined* for longer closing durations. The interplay approach *SVM/SVM*, which we would include in our prototype, exceeds 73% with a camera shutter closing time of one second and outperforms all other combinations in terms of accuracy in all other closing times. One reason for the performance improvement of *SVM/SVM* in comparison to its single components is that *SVM-Combined* performs better for the detection of privacy-sensitive situations when the camera shutter is open while *SVM-Eye* performs better for preserving privacy-sensitive situations so that the camera shutter remains closed. Another aim of our proposed approach is the reduction of opening and closing events during a recording to build the sense of reliability and trustworthiness. From Figure 6b and in comparison with Figure 6a, we can see that there is a clear trade-off between accuracy performance and time between camera shutter closing instances. For very short camera shutter closing times the *SVM-Eye* approach, which only relies on eye movement features from the eye camera, shows the best performance, whereas for longer camera shutter closing times, the combination *SVM/SVM* shows better accuracy with a comparable amount of time between camera shutter closing instances. However, the current approaches are actually not able to reach the averaged ground truth of about 8.2 minutes between camera shutter closings.

5.4.2 Person-independent (leave-one-person-out) evaluation. The more challenging task, which assumes that privacy-sensitivity could generalise over multiple participants, is given in the person-independent leave-one-person-out cross validation of Figure 7a. Similar to the person-specific evaluation, *CNN-Direct* and *CNN/SVM* perform worse than the other approaches. Here, *SVM-Eye* outperforms *SVM-Combined* and *SVM/SVM*. However, none of the approaches are able to outperform the majority classifier. These results show that eye movement features generalise better over multiple participants to detect privacy-sensitive situations than scene image information. Comparing the number of minutes between camera shutter closing events of person-specific and leave-one-person-out in Figure 6b and Figure 7b, the person-specific approach outperforms the person-independent leave-one-person-out evaluation scheme for each approach. It thus becomes apparent that privacy sensitivity is difficult to generalise, and a final real-world system would need a person-specific calibration to detect privacy-sensitive-situations in a robust manner.

5.4.3 Error Case Analysis. Our results suggest that the combination *SVM/SVM* performs best for the person-specific case. In the supplementary material we investigate its performance on data recorded in different environments and during different activities within a detailed error case analysis.

6 USER FEEDBACK

Collecting initial subjective feedback during early stages of system development allows us to put research concepts in a broader context and helps to shape hypotheses for future quantitative user studies. In this section, we report on a set of semi-structured one-to-one interviews on the use of head-worn augmented reality displays in general, and our interaction design and prototype in particular. To obtain the user feedback, we recruited 12 new and distinct participants (six females), ages 21 to 31 years (M=24, SD=3) from the local student population. They were enrolled in seven highly diverse majors, ranging from computer science and biology to special needs education. We decided to recruit students, given that we believe they and their peers are potential users of a future implementation of our prototype. We acknowledge that this sample, consisting of rather well educated young adults (with six of them having obtained a Bachelor's degree), is not representative for the general population. Interviews lasted about half an hour and participants received a 5 Euro Amazon voucher. We provide a detailed interview protocol with the supplementary material. The semi-structured interviews were audio recorded and transcribed for later analysis. Subsequently, qualitative analysis was performed following inductive category development [34]. Key motives and reoccurring themes were extracted and are presented in this section. Subsequently, we link the interviews back to PrivacEye's design and discuss implications for future work.

6.1 User Views on Transparency

Making it transparent (using the 3D-printed shutter), whether the camera was turned on or off, was valued by all participants. Seven participants found the integrated shutter increased perceived safety in contrast to current smart glasses; only few participants stated that they made no difference between the shutter and other visual feedback mechanisms, e.g. LEDs (n=2). Several participants noted that the physical coverage increased trustworthiness because it made the system more robust against hackers (*concerns:hacking*, n=3) than LEDs. Concluding, the usage of physical occlusion could increase perceived safety and, thus, could be considered an option for future designs. Participants even noted that the usage of the shutter as reassuring as pasting up a laptop camera (*laptop comparison*, n=4), which is common practice.

6.2 User Views on Trustworthiness

In contrast, participants also expressed technology scepticism, particularly that the system might secretly record audio (*concerns:audio*, n=5) or malfunction (*concerns:malfunction*, n=4). With the increasing power of deep neural networks malfunctions, system failures, or inaccuracies will be addressable in the future, interaction designers will have to address this fear of "being invisibly audio-recorded". A lack of knowledge about eye tracking on both the user's and the bystander's side might even back this misconception. Therefore, future systems using eye tracking for context recognition will have to clearly communicate their modus operandi.

6.3 Perceived Privacy of Eye Tracking

The majority of participants claimed to have no privacy concerns about smart glasses with integrated eye tracking functionality: *"I do see no threat to my privacy or the like from tracking my eye movements; this [the eye tracking] would rather be something which could offer a certain comfort."* (P11) Only two participants expressed concerns about their privacy, e.g., due to fearing eye-based emotion recognition (P3). One was uncodeable. This underlines our assumption that eye tracking promises privacy-preserving and socially acceptable sensing in head-mounted augmented reality devices and, thus, should be further explored.

6.4 Desired Level of Control

Participants were encouraged to elaborate on whether the recording status should be user-controlled or system-controlled. P10 notes: *"I'd prefer if it was automatic, because if it is not automatic, then the wearer can forget to do that [de-activating the camera]. Or maybe he will say 'Oh, I do not want to do that' and then [...] that leads to a conflict. So better is automatic, to avoid questions."* Four other participants also preferred the camera to be solely controlled by the system (*control:automatic*, n=4). Their preference is motivated by user forgetfulness (n=5), and potential non-compliance of users (in the bystander use case, n=1). Only two participants expressed a preference for sole (*control:manual*) control, due to an expected lack of system reliability, and technical feasibility. Two responses were uncodable. All other participants requested to implement manual confirmation of camera de-activation/re-activation or manual operation as alternative modes (*control:mixed*, n=4), i.e., they like to feel in control. To meet these user expectations, future interaction designs would have to find an adequate mix of user control and automatic support through the system; for example, by enabling users to explicitly record sensitive information (e.g. in cases of emergency) or label seemingly non-sensitive situations "confidential".

7 DISCUSSION

7.1 Privacy Preserving Device Behaviour

Design Requirements 1 and *2* demand privacy-preserving device behaviour. With PrivacEye, we have presented a computer vision routine that analyses all imagery obtained from the scene camera, combined with eye movement features with regard to privacy sensitivity and, in case a situation requires protection, the ability to de-activate the scene camera and close the system's camera shutter. This approach prevents both accidental misclosure and malicious procurance (e.g. hacking) of sensitive data, as has been positively highlighted by our interview participants. However, closing the shutter comes at the cost of having the scene camera unavailable for sensing after it has been de-activated. PrivacEye solves this problem by using a second eye camera that allows us, in contrast to prior work, to locate all required sensing hardware on the user's side. With PrivacEye we have provided a proof-of-concept that context-dependent re-activation of a first-person scene camera is feasible using only eye movement data. Future work will be able to build upon these findings and further explore eye tracking as a sensor for privacy-enhancing technologies.

7.2 Defining Privacy Sensitivity

An analysis of related work has shown that the presence of a camera may be perceived appropriate or inappropriate depending on social context, location, or activity [23, 24, 41]. However, related work does, to the best of our knowledge, not provide any insights on eye tracking data in this context. For this reason, we run a dedicated data collection and ground truth annotation. Designing a practicable data collection experiment requires the overall time spent by a participant for data recording and annotation to be reduced to a reasonable amount. Hence, we made use of an already collected data set, and re-invited the participants only for the annotation task. While the pre-existing data set provided a rich diversity of privacy-sensitive locations and objects, including smart phone interaction, and realistically depicts everyday student life, it is most likely not applicable to other contexts, e.g., industrial work or medical scenarios.

For PrivacEye, we rely on a 17-participant-large, ground truth annotated dataset with highly realistic training data. Thus, the collected training data cannot be fully generalised, e.g., to other regions or age groups. On the plus side, however, this data already demonstrates that in a future real-world application, sensitivity ratings may vary largely between otherwise similar participants. This might also be affected by their (supposedly) highly individual definition of "privacy". Consequently, a future consumer system should be pre-trained and then adapted online, based on personalised re-training after user feedback. In addition, users should be enabled to select their individual "cut-off", i.e., the level from which a recording is blocked, which was set to "2" for PrivacEye. Real-life users might choose more rigorous or relaxed "cut-off" levels depending on their personal preference. Initial user feedback also indicated that an interaction design that combines automatic, software-controlled de- and re-activation, with conscious control of the camera by the user, could be beneficial.

7.3 Eye Tracking for Privacy-Enhancement

Eye tracking is advantageous for bystander privacy given that it only senses users and their eye movements. In contrast to, e.g., microphones or infra-red sensing, it senses a bystander and/or an environment only indirectly via the user's eye motion or reflections. Furthermore, eye tracking allows for implicit interaction and is non-invasive, and we expect it to become integrated into commercially available smart glasses in the near future. On the other hand, as noted by Liebling and Preibusch [33, 40], eye tracking data is a scare resource, which can be used to identify user attributes like age, gender, health, or user's current task. For this reason, the collection and use of eye tracking data could be perceived as a potential threat to user privacy. However, our interviews showed that eye tracking was not perceived as problematic by a large majority of our participants. Nevertheless, eye tracking data must be protected by appropriate privacy policies and data hygiene.

To use our proposed hardware prototype in a real-world scenario, data sampling and analysis need to run on a mobile phone. The CNN feature extraction is the biggest computational bottleneck at the moment but could be implemented in hardware to allow for real-time operation (c.f., QualcomâĂŹs Snapdragon 845). Further, we believe that a market-ready product should provide an accuracy >90% which could be achieved using additional sensors such as GPS or inertial tracking. However, presenting the first approach for automatic de- and re-activation of a first-person camera that achieves ~73% with competitive performance to *ScreenAvoider* (54.2 - 77.7%) [30] and *iPrivacy* (~75%) [58], which are restricted to scene content protection and post-hoc privacy protection, we build the basis for follow up work. We still aim for a generalized person-independent model for privacy sensitivity protection. For this work only the participants themselves labelled their own data. Aggregated labels of multiple annotators would result in a more consistent and generalizable "consensus" model and improve test accuracy, but would dilute the fact that actually perceived privacy sensitivity is highly subjective [41]. Specifically, similar activities and environments were judged differently by the individual participants. Figure 5 illustrates this with the underlying time sequence pattern of privacy-sensitive periods. We actually see the availability of this information as an advantage of our dataset.

7.4 Communicating Privacy Protection

The interaction design of PrivacEye tackles *Design Requirement 3* using a non-transparent shutter. Ens et al. [13] reported that the majority of their participants expected to feel more comfortable around a wearable camera device if it clearly indicated whether the camera was turned on or off. Hence, our proposed interaction design aims to improve a bystander's awareness of the recording status by employing an *eye metaphor*. For our prototype, we opted to implement the "eye lid" as a retractable shutter made from non-transparent material: open when the camera is active, closed when the camera is de-active. Thus, the metaphor mimics "being watched" by the camera. The "eye lid" shutter ensures that bystanders can comprehend the recording status without prior knowledge, as eye metaphors have been widely employed for interaction design, e.g., to distinguish visibility or information disclosure [35, 39, 45] or to signal user attention [10]. Furthermore, in contrast to visual status indicators, such as point lights (LEDs), physical occlusion is non-spoofable (c.f., [12, 38]). This concept has been highly appreciated during our interviews, which is why we would recommend adopting it for future hardware designs.

8 CONCLUSION

In this work, we have proposed PrivacEye, a method that combines first-person computer vision with eye movement analysis to enable context-specific, privacy-preserving de-activation and re-activation of a head-mounted eye tracker's scene camera. We have evaluated our method quantitatively on a 17-participant dataset of fully annotated everyday behaviour as well as qualitatively, by collecting subjective user feedback from 12 potential future users. To the best of our knowledge, our method is the first of its kind and prevents potentially sensitive imagery from being recorded at all, without the need for active user input. As such, we believe the method opens up a new and promising direction for future work in head-mounted eye tracking, the importance of which will only increase with further miniaturisation and integration of eye tracking in head-worn devices or even in normal glasses frames.

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Supplementary Material

PrivacEye: Privacy-Preserving Head-Mounted Eye Tracking Using Egocentric Scene Image and Eye Movement Features

This supplementary document contains a detailed data annotation scheme description, an error case analysis, and the interview protocol analysing users' feedback towards PrivacEye.

1 DATA ANNOTATION SCHEME

Annotations were performed using Advene [Aubert et al. 2012]. Participants were asked to annotate continuous video segments showing the same situation, environment, or activity. They could also introduce new segments in case a privacy-relevant feature in the scene changed, e.g., when a participant switched to a sensitive app on the mobile phone. Participants were asked to annotate each of these segments according to the annotation scheme shown in Table 1, specifically scene content (Q1-7) and privacy sensitivity ratings (Q8). Privacy sensitivity was rated on a 7-point Likert scale (see Figure 1) ranging from 1 (fully inappropriate) to 7 (fully appropriate). As we expected our participants to have difficulties understanding the concept of "privacy sensitivity", we rephrased it for the annotation to "How appropriate is it that a camera is in the scene?".

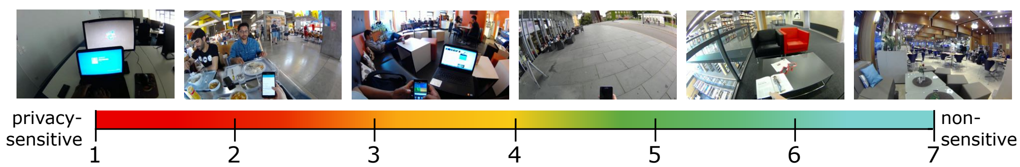


Figure 1: Sample images showing daily situations ranging from "privacy-sensitive", such as password entry or social interactions, to "non-sensitive", such as walking down a road or sitting in a café.

# Question	Example Annotation
1. What is the current environment you are in?	office, library, street, canteen
2. Is this an indoor or outdoor environment?	indoor, outdoor
3. What is your current activity in the video segment?	talking, texting, walking
4. Are private objects present in the scene?	schedule, notes, wallet
5. Are devices with potentially sensitive content present in the scene?	laptop, mobile phone
6. Is a person present that you personally know?	yes, no
7. Is the scene a public or a private place?	private, public, mixed
8. How appropriate is it that a camera is in the scene?	Likert scale (1: fully inappropriate – 7: fully appropriate)

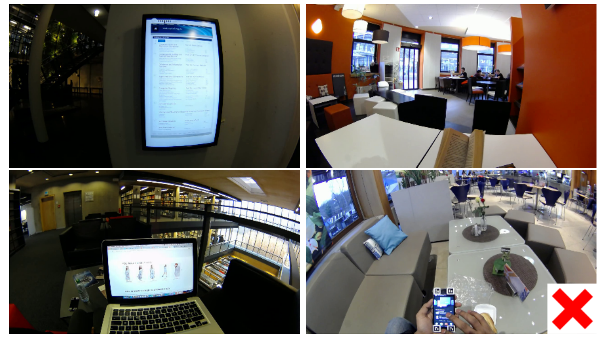
Table 1: Annotation scheme used by the participants to annotate their recordings.

2 ERROR CASE ANALYSIS

For our system, it is not only important to detect the privacy-sensitive situations (TP), but equally important to detect non-sensitive situations (TN), which we are interested in recording while avoiding error cases.

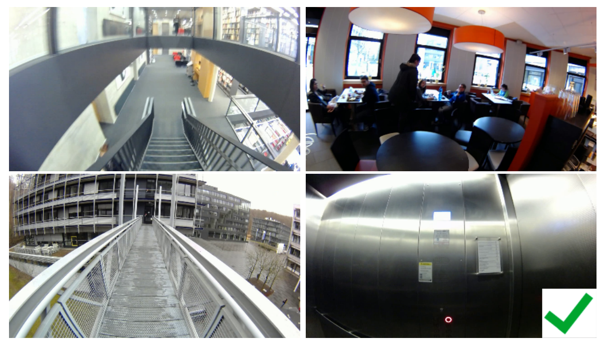
Our results suggest that the combination *SVM/SVM* performs best for the person-specific case. In the following, we detail its performance on data recorded in different environments and during different activities. We detail on the occurrence of false positives, i.e., cases where the camera is de-activated in a non-sensitive situation, as well as false negatives, i.e., cases where the camera remains active although the scene is privacy-sensitive. Examples such as in Figure 2 show that, while false positives would be rather unproblematic in a realistic usage

(a) True positives



(b) False positives

(c) False negatives



(d) True negatives

Figure 2: Examples for (a) correct detection of "privacy-sensitive" situations, (b) incorrect detection of "non-sensitive" situations, (c) incorrect detection of "privacy-sensitive" situations, and (d) correct detection of "non-sensitive" situations.

scenario, false negatives are critical and might lead to misclosures. Thus, our argumentation focuses on eliminating false negatives. While PrivacEye correctly identifies signing a document, social interactions, and screen interactions as privacy-sensitive, false positives contain reading a book or standing in front of a public display. In these cases PrivacEye would act too restrictively in cases where de-activating the camera would lead to a loss of functionality (e.g. tracking). False negative cases include, e.g., reflections (when standing in front of a window), self-luminous screens, or cases that are under-represented in our data set (e.g. entering a pin at the ATM).

Figure 3 provides a detailed overview of true positives and false negatives with respect to the labelled environments (3, left) and activities (3, right). For each label two stacked bars are shown: PrivacEye's prediction (top row) and the ground truth annotation (GT, bottom row). The prediction's result defines the "cut-off" between closed shutter (left, privacy-sensitive) and open shutter (right, non-sensitive), which is displayed as vertical bar. Segments that were predicted to be privacy-sensitive, include both true positives (TP, red) and false positives (FP, orange) are shown left of the "cut-off". Similarly, those segments that were predicted to be non-sensitive, including true negatives (TN, yellow-green) and false negatives (FN, red), are displayed right of the "cut-off". While false positives (FP) (i.e., non-sensitive situations classified as sensitive) are not problematic, as they to not create the risk of misclosures, false negatives (FN) are critical. Thus, we focus our discussion on the false negatives (red, top, right). A comparison of true positives (TP) and false negatives (FN) shows that PrivacEye performs well within most environments, e.g., offices or corridors. In these environments true positives outweigh false negatives. However, in the computer room environment, where a lot of screens with potentially problematic content (which the wearer might not even be aware of at recording time) are present, performance drops. Misclassifications between personal displays, e.g., laptops and public displays (e.g. room occupancy plans) are a likely reason for the larger amount of false negatives (FN). Future work might aim to combine PrivacEye with an image-based classifier trained for screen contents (c.f., [Korayem et al. 2016]), which, however, would come at the cost of excluding also non-sensitive screens from the footage. Future work might specifically target these situations to increase accuracy. For the activities outlined in Figure 3 (left), PrivacEye works best while eating/drinking and in media interactions. Also, the results are promising for detecting social interactions. The performance for password entry, however, is still limited. Although the results show that it is possible to detect password entry, the amount of true negatives (TN) is comparatively high. This is likely caused by the under-representation of this activity, which typically lasts only a few seconds in our data set. Future work might be able to eliminate this by specifically training for password and PIN entry, possibly enabling the classifier to better distinguish between PIN entry and, e.g., reading.

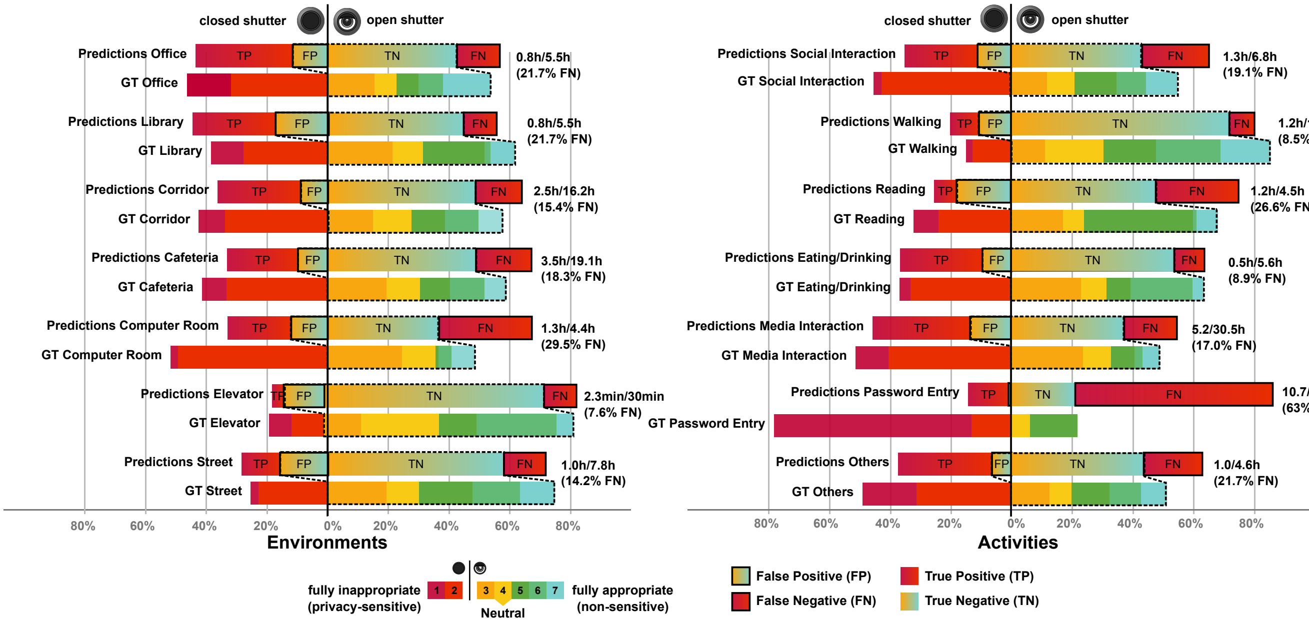


Figure 3: Error case analysis for different environments (left) and activities (right) showing the "cut-off" between closed shutter (left, *privacy-sensitive*) and open shutter (right, *non-sensitive*) with PrivacEye prediction and the corresponding ground truth (GT). False positives (FP) are *non-sensitive* but protected (closed shutter), false negatives (FN) are *privacy-sensitive* but unprotected (open shutter).

3 INTERVIEW PROTOCOL

During the interviews, participants were encouraged to interact with state-of-the-art head-mounted displays (Vuzix M300 and Sony SmartEyeglass) and our prototype. Participants were presented with the fully functional PrivacEye prototype, which was used to illustrate three scenarios: 1) interpersonal conversations, 2) sensitive objects (a credit card and a passport), and 3) sensitive contents on a device screen. Due to the time required to gather person-specific training data for each interviewee as well as runtime restrictions, the scenarios were presented using the Wizard-of-Oz method. This is also advantageous, as the laboratory-style study environment – with white walls, an interviewer and no distractors present – might have induced different eye movement patterns than a natural environment. Also, potential errors of the system, caused by its prototypical implementation, might have caused participant bias toward the concept. To prevent these issues, the shutter was controlled remotely by an experimental assistant. This way, the interviewees commented on the concept and vision of PrivacEye and not on the actual proof-of-concept implementation, which – complementing the afore-described evaluation – provides a more comprehensive and universal set of results altogether. The semi-structured interview was based on the following questions:

Q1 *Would you be willing to wear something that would block someone from being able to record you?*
Q2 *If technically feasible, would you expect the devices themselves, instead of their user, to protect your privacy automatically?*
Q3 *Would you feel different about being around someone who is wearing those kinds of intelligent glasses than about those commercially available today? Why?*
Q4 *If you were using AR glasses, would you be concerned about accidentally recording any sensitive information belonging to you?*
Q5 *How would you feel about (such) a system automatically taking care that you do not capture any sensitive information?*
Q6 *How do you think the eye tracking works? What can the system infer from your eye data?*
Q7 *How would you feel about having your eye movements tracked by augmented reality glasses?*

The questions were designed following a "funnel principle", with increasing specificity towards the end of the interview. We started with four more general questions (not listed above), such as "Do you think recording with those glasses is similar or different to recording with a cell phone? Why?", based on [Denning et al. 2014]. This provided the participant with some time to familiarize herself with the topic before being presented with the proof-of-concept prototype (use case "bystander privacy") after Q1 and the use cases "sensitive objects" (e.g., credit card, passport) and "sensitive data" (e.g. login data) after Q4. Eye tracking functionality was demonstrated after Q5. While acquiescence and other forms of interviewer effects cannot be ruled out completely, this step-by-step presentation of the prototype and its scenarios ensured that the participants voiced their own ideas first, before being directed towards discussing the actual concept of the PrivacEye prototype. Each participant was asked for his/her perspectives on the PrivacEye's concept (Q2-Q5) and eye tracking (Q6 and Q7). The interviews were audio recorded and transcribed for later analysis. Subsequently, qualitative analysis was performed following inductive category development [Mayring 2014]. Key motives and reoccurring themes were extracted and are presented in this section.

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