Gaze3P: Gaze-Based Prediction of User-Perceived Privacy

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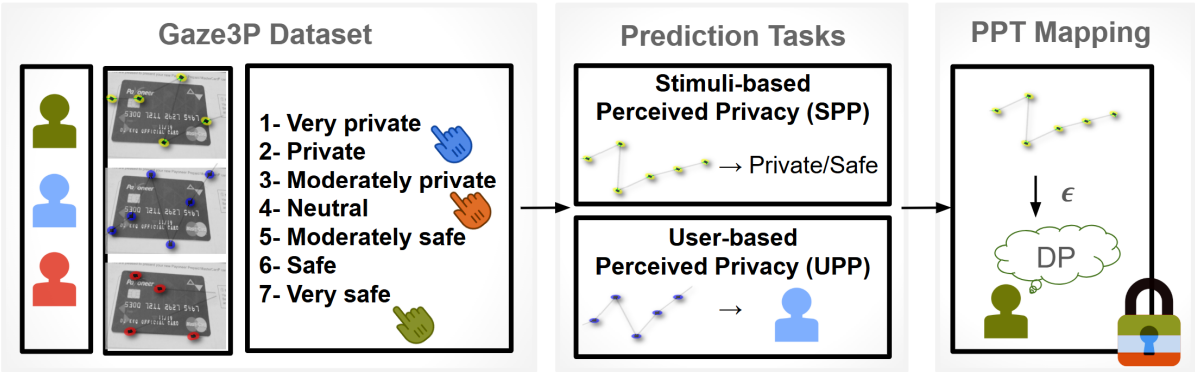

Figure 1: Users deal with various types of information in daily life that can have vastly different privacy requirements, e.g., personal photographs, passwords, or social media posts. Gaze3P is the first large-scale dataset that allows for the systematic study of user-perceived privacy. We report extensive experiments demonstrating the feasibility of predicting perceived privacy from human eye gaze. We also show how predicted privacy can be used to optimise the parameters of privacy-preserving techniques for data analysis and learning, such as Differential Privacy (DP), to better align them with user expectations.

Abstract

Privacy is a highly subjective concept and perceived variably by different individuals. Previous research on quantifying user-perceived privacy has primarily relied on questionnaires. Furthermore, applying user-perceived privacy to optimise the parameters of privacy-preserving techniques (PPT) remains insufficiently explored. To address these limitations, we introduce Gaze3P – the first dataset specifically designed to facilitate systematic investigations into user-perceived privacy. Our dataset comprises gaze data from 100 participants and 1,000 stimuli, encompassing a range of private and safe attributes. With Gaze3P we train a machine learning model to implicitly and dynamically predict perceived privacy from human eye gaze. Through comprehensive experiments, we show that the resulting models achieve high accuracy. Finally, we illustrate how predicted privacy can be used to optimise the parameters of differentially private mechanisms, thereby enhancing their alignment with user expectations.

Keywords

Gaze, Eye Tracking, Perceived Privacy, Privacy Quantification, Differential Privacy

1 Introduction

Privacy, particularly as it is perceived by individuals, is a complex and deeply subjective construct that varies significantly across contexts, cultures, and personal experiences [16, 20, 65]. Unlike technical privacy, which can be quantified through cryptographic guarantees or formal metrics, perceived privacy refers to an individual's internal judgment about the sensitivity or appropriateness of data sharing [8, 51]. Understanding and quantifying user-perceived privacy is essential because it directly influences users' willingness to engage with digital systems, share information, or consent to data sharing requests [10, 43, 65]. Therefore, accurately quantifying perceived privacy helps designers create user-aligned privacy mechanisms, improve transparency, and ultimately enhance user satisfaction and system usability [10, 39, 44, 54].

The ability to quantify user-perceived privacy levels also has significant potential for optimising the parameters of security protocols, such as Differential Privacy (DP) [23]. However, despite continuing discussions, the problem of how to map users' privacy perception to protocol parameters remains unsolved [16, 16, 20, 20, 48, 65, 76]. A key reason for this failure is the large number of factors that affect privacy perception, such as (i) oversight of the situational diversity [63], (ii) neglect of within- vs. between-subject

variations [65], (iii) effects of biases, heuristics, or impulsivity on online user behaviour [48, 76], and, most importantly, (iv) the scarcity of the available behavioural data that encapsulates all relevant aspects. Previous work mainly relied on explicit feedback, such as questionnaires, which has been shown to not align well with users' satisfaction [75, 89], especially since user judgement dynamically changes depending on context, behaviour, or knowledge [38].

In this work, we explore a novel approach: The use of *human eye gaze as an implicit source of information on user-perceived privacy*. Prior research has shown that eye gaze contains rich information about the user, such as identifiers [14], quasi-identifiers [85], confidential attributes (e.g. user activities [88], attentive [28, 90] and cognitive states [12, 41], or information about private situations [89]). Consequently, we hypothesise that gaze data also provides insights into users' perceived privacy levels. To this end, we present Gaze3P – the first large-scale dataset for studying user-perceived privacy from the perspective of human eye gaze. Gaze3P includes gaze data (i.e. where, when, and how a person looks) of 100 participants viewing 1,000 natural images showing different objects, some with private attributes (e.g. credit cards and medical history) as shown in Fig. 2. The dataset also provides user ratings of perceived privacy on a scale from 1 (very private) to 7 (very safe) for each image. The full dataset, including all annotations, will be made publicly available upon acceptance (cf. [7] for the implementation).

Using our new dataset, we then explore different learning tasks, focusing on the automatic prediction of users' perceived privacy solely from gaze behaviour using machine learning. These tasks include: **Stimuli-based Perceived Privacy (SPP)** tasks to infer how private a stimulus (e.g. image) is and **User-based Perceived Privacy (UPP)** tasks to infer informtion about the user (e.g. privacy expertise or identity). Our models demonstrate that human eye gaze provides accurate predictions of perceived privacy.

We use the Gaze3P predictions of user-perceived privacy to optimise the parameters of differentially private mechanisms. Differentially private mechanisms obfuscate sensitive data samples such that only a limited amount of information about the private data can still be deduced from the obfuscated output of the mechanism. The exact amount of acceptable leakage depends on a privacy budget parameter $\varepsilon > 0$, which determines the obfuscating noise added by the mechanism. If ε is small, the privacy guarantee becomes stronger, but usually, the output of the mechanism is less accurate, and usability decreases. It is therefore important to not choose the privacy budget ε too small, i.e. to only add the minimal amount of noise that guarantees a target privacy level. The optimisation of DP-parameters has therefore seen much attention in recent years [10, 39, 44, 54].

Our new dataset Gaze3P and the resulting ML model predictions provide a new way to determine ε which reflects a user's perceived privacy. Depending on the actual use case we propose different mappings from perceived privacy levels to ε-values. We evaluate how each mapping affects the utility of the obfuscated output dataset and show that our gaze-based approach outperforms previous work.

Contributions. In summary, our work makes the following contributions:

(1) We present Gaze3P – the first large-scale dataset for studying user-perceived privacy using human eye gaze[1].
(2) We propose several novel learning tasks focusing on predicting user-perceived privacy from human eye gaze. These tasks cover different aspects of privacy and also allow us to explore potential applications and limitations of gaze-based privacy perception.
(3) We demonstrate how gaze-based predictions can be used to optimise parameters of privacy-preserving techniques. Specifically, we introduce a novel approach that maps predicted privacy levels to DP's privacy parameter ε and show that aligning DP with user expectations improves the data utility in data analysis and learning.

2 Preliminaries

Eye Tracking. Gaze data is typically collected using eye-tracking devices that record the position and movement of a user's eyes relative to a visual stimulus or screen. Modern eye trackers employ infrared light to detect corneal reflection and pupil centre, enabling accurate estimation of gaze coordinates at high temporal resolutions. The raw gaze signal is then processed into interpretable features such as fixations, saccades, and pupil dilation:

- *Fixations* refer to time periods where the eye remains focused on a specific location, typically lasting 100–400 ms. They are indicative of visual attention and cognitive processing of that region.
- *Saccades* are rapid eye movements between fixations used to reposition the fovea to new visual targets, lasting 20–80 ms. These movements are ballistic, and their patterns can inform about scanning behaviour and search strategies.
- *Pupil dilation* is a physiological response modulated, amongst others, by both environmental lighting and cognitive load. Increased dilation was linked to heightened mental effort, emotional arousal, or attentional demand.

Together, these gaze features provide a rich, temporally fine-grained source of implicit user feedback (i.e. without requiring direct input or explicit interaction). We refer the reader to [36, 37, 69, 74] for details about eye tracking and gaze behaviour analysis.

Differential Privacy (DP). DP is a mathematical framework that ensures privacy by limiting the impact of any single data point on the output of a computation. A randomised algorithm M satisfies ε-DP if, for all datasets D and D' differing by at most one element, and for all measurable subsets S of the output space:

$$\Pr[M(D) \in S] \leq e^{\varepsilon} \cdot \Pr[M(D') \in S], \tag{1}$$

where $\varepsilon \geq 0$ is the privacy budget, controlling the privacy loss. A small ε means that D and D' are (almost) not distinguishable given a set of outputs S. From an adversarial perspective, an adversary $\mathcal{A}$ challenged to distinguish D and D' given an output set S will output the dataset which is more likely, e.g. D if $\Pr(D|S) \geq \frac{1}{2} \geq Pr(D'|S)$. In the most extreme case of Eq. (1) we have $\Pr(M(D) \in S) = e^{\varepsilon} \Pr(M(D') \in S)$ and hence $\Pr(D|S) = e^{\varepsilon} \Pr(D'|S) = e^{\varepsilon}(1 - \Pr(D|S)) \Rightarrow \Pr(D|S) = \frac{e^{\varepsilon}}{1+e^{\varepsilon}}$. Thus, the (absolute) advantage of an

[1] Gaze3P is available at https://collaborative-ai.org/research/datasets/Gaze3P/

adversary is bounded by $\text{adv}_{\mathcal{A}} \leq 2\frac{e^{\varepsilon}}{1+e^{\varepsilon}} - 1 = \frac{e^{\varepsilon}-1}{e^{\varepsilon}+1}$ (cf. Appendix C for more details).

3 Related Work

User Perceived Privacy. As more data is being collected, shared, and processed, sensitive insights about the user's personality, intentions, and preferences are being leaked [46, 65]. Hence, to better protect user privacy, prior works have investigated the psychological mechanisms of privacy decision-making [65], self-disclosure [20], and the related cost-benefit analysis [16]. They showed that the user-perceived privacy dynamically changes according to the user's context, behaviour, and knowledge. Other works focused on privacy-in-context (i.e. contextual integrity) [71, 92] and further showed that user-perceived privacy is affected by culture, activities (e.g., online shopping vs. online banking), and platforms (desktop vs. mobile). Prior works [46, 57, 89] often used generic privacy mechanisms that remain static throughout the interaction. These mechanisms are typically predefined at the onset of a session (e.g., at the initiation of a protocol) and fail to account for the dynamic nature and context-dependent fluctuations of the users' privacy judgments [38].

Eye Gaze and Privacy. The results of the aforementioned works usually rely on user questionnaires. However, when using questionnaires, users often fail to follow their own privacy preferences [67, 75, 81]. In this paper, we propose to use human eye gaze (instead of questionnaires) to implicitly capture the dynamics of user-specific privacy perception. Eye-tracking data is already widely used to study human behaviour and cognition [27] and hypothesise that it can also be used as an indicator of user-perceived privacy. The idea to use gaze to detect privacy-sensitive situations is not completly new and has been explored in [89] where the users' eye movements and first-person video were recorded using an egocentric (head-mounted) camera. However, [89] focuses on detecting privacy-sensitive situations rather than quantifying privacy perception. It also only features a small set of 17 participants in a free-viewing task and relies on recording and processing the scene imagery, which might break privacy [75]. In this paper, we instead focus on the implicit and dynamic privacy perception feedback solely through gaze, without using the visual stimulus.

Personalised Differential Privacy. In classical differential privacy (DP), the privacy parameter ε is chosen independently of the subjective privacy perception of an individual user but instead provides the same privacy guarantees to all users [44]. This is despite the fact that users have varying expectations about acceptable privacy levels. As a result, a certain DP-privacy level ε might not offer enough protection for some users while overprotecting others [30, 44]. Personalised Differential Privacy (PDP) [2, 4, 10, 19, 26, 44, 72] is an extension of standard DP that introduces flexibility by tailoring privacy protections based on individual preferences, allowing for a more nuanced balance between privacy and utility. Alaggan et al. [4] first introduced the theoretical concept of PDP through linear pre-processing (a.k.a stretching) of the input data. In their approach, the input data is scaled according to each individual's privacy preference before applying a differentially private mechanism. Cummings and Durfee [18] generalised the PDP framework to a broader class of mechanisms. They proposed a constructive method for implementing personalised privacy guarantees directly within the mechanism design. However, they demonstrated that computing an optimal personalised mechanism under these conditions is NP-hard. Later works [17, 29] used weighted moment estimation of each data point according to the privacy level. In these approaches, the privacy level specified by each user was used to assign a weight to their corresponding data contribution during the statistical estimation process. This weighting strategy ensured that data from users requiring stronger privacy protections (i.e., lower ε values) exert less influence on the aggregate statistics, while users with looser privacy requirements (higher ε values) contribute more significantly. Other works [9, 55] proposed partitioning the data into separate groups and then assigning different privacy levels. Jorgensen et al. [44], followed by Niu et al. [72] and Ebadi et al. [26], relied on excluding or sub-sampling some data samples according to their privacy levels. While all of these methods were designed for data analysis, Boesnisch et al. designed a privacy-preserving training mechanism for machine learning models that integrated individual privacy levels directly into the optimisation process [9, 10]. They adapted the gradient computation and noise addition to reflect user-specific privacy budgets.

Similarly, we determine a suitable privacy budget ε based on behavioural data rather than assigning it arbitrarily or using assumptions. Our work is the first to do so using human gaze data. This approach ensures that the privacy budgets more accurately reflect users' actual perceptions and expectations of privacy. Grounding ε in observed user behaviour not only improves the practical relevance and usability of privacy-preserving systems but also helps bridge the gap between formal privacy theory and human-centred privacy concerns, ultimately leading to more trustworthy and adaptive data handling practices.

4 Gaze3P Dataset

Due to the lack of available datasets, in this section, we present our new gaze-based dataset Gaze3P. Our large-scale data collection is essential for deriving statistically significant insights into users' perceptions of privacy and for empirically validating the use of gaze as a reliable indicator of perceived privacy. By offering a standardized dataset, Gaze3Paims to facilitate reproducible research and enable the development and evaluation of models that infer perceived privacy dynamically and without explicit feedback through gaze patterns.

Eye tracker. For gaze data collection, we used an Eyelink eye tracker that provides binocular gaze data at a sampling rate of 2 kHz. As is common practice in laboratory eye tracking studies, we used a chin rest to stabilise participants' heads. Images were shown on a computer screen with a resolution of 1920x1080 pixels and a size of 545 mm x 303 mm. The eye-to-screen distance was 700 mm. The proportion of the calibrated area was set to 0.63 x 0.88 to stay within the trackable range of the system with an HV13-13 (horizontal/vertical 13 targets) calibration type for better spatial accuracy across the entire screen. The recorded gaze data was then

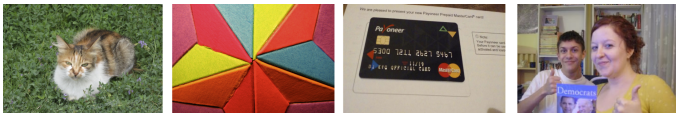

Figure 2: Sample images from the VISPR dataset with safe (e.g. cat, colours) and private (e.g. credit card, political opinion) attributes

processed into fixations, saccades, and pupil information (cf. Section 2). More details and visualisations can be found in Appendix A.

Stimuli. We used a subset of the VISPR dataset [75] as our stimuli. Our dataset includes 1,000 images with corresponding private and safe (i.e. non-private) attributes. See Fig. 2 for sample images. The dataset contains 68 attributes categorised into nine attribute groups. The attributes were compiled according to the guidelines for the EU Data Protection Directive (GDPR) 95/46/EC, the US Privacy Act of 1974, and the data sharing rules in online social networks. The attribute categories are:

- **Personal information:** e.g. age, gender, race, fingerprint, signature.
- **Documents:** e.g. credit card, passport, national ID, driver's license.
- **Medical:** e.g. medical history, hospital tickets, physical disability.
- **Employment:** e.g. occupation, work occasion.
- **Life:** e.g. culture, religion, political opinion, sexual orientation.
- **Relationship:** e.g. personal, social, professional.
- **Whereabouts:** e.g. landmark, home address.
- **Online activity:** e.g. date/time of activity, username, password, email, online conversations.
- **Automobile:** e.g. license plate, vehicle ownership.

Participants. We initially recruited 103 participants through university mailing lists and notice boards. We had to exclude three participants due to calibration failures [52]. This resulted in a final group of 100 participants (37 females and 63 males). Participants were aged between 18 and 35 years, had different nationalities (25) and different (self-reported) privacy knowledge (12 experts). All participants had normal or corrected-to-normal vision. We refer to Appendix A for more demographic details.

Experiment design. After arriving in the lab, participants were first informed about the general purpose and procedures of the study. Following [86], we explicitly asked participants to consider the data as their own, e.g. their phone gallery. The experiment consisted of four blocks with 25 participants each. Each block included two tasks: free-viewing and a search task. In the former, participants were shown a stimulus (e.g. an image of a credit card) for five seconds and asked to rate its privacy-sensitivity for sharing on a scale from 1 (very private) to 7 (very safe) following [89]. Similarly, for the search task, participants were asked to search for a specific image (by a category, e.g. *document*) in a 2 x 2 image collage, and click the mouse and rate its sensitivity once found, following [86]. The same attributes were presented in both tasks, but each task featured different sets of images within those attributes. Each task included three practice trials and 50 recorded trials with randomized order of (non)private stimuli (50 %-50 % ratio). The resulting dataset includes a set of triplets of {stimulus, gaze patterns (timestamped coordinates), and privacy rating} for each participant in each task. Refer to Appendix A for more details on the dataset structure and data collection software.

Compliance with the privacy and ethics guidelines. The data was collected and processed according to the standards and guidelines of the ethical committee of the authors' institution, with participants' consent, remuneration, and pseudo-anonymisation procedures. In particular, the privacy and ethical guidelines of the Menlo Report [21] were satisfied.

5 Gaze3P Tasks

Our Gaze3P dataset enables new analyses that shed light on how users cognitively and behaviourally respond to privacy-relevant stimuli. More specifically, in this section we explore how well our gaze-based dataset Gaze3P is suited for two groups of learning tasks: (i) *stimuli-based perceived privacy* (SPP) tasks that infer how private a stimulus (e.g. image) is in Section 5.1 and (ii) *user-based perceived privacy (UPP)* tasks that infer informtion about the user (e.g. privacy expertise or identity) in Section 5.2. Each task entails learning a distinct mapping or pattern within the gaze data, such as predicting privacy ratings from gaze, classifying stimuli as private or non-private, or identifying user-specific privacy preferences based on demographic or behavioural features. We remark that we train all our models on annotated gaze data (i.e. with user-specified privacy ratings), such that they generalise to unseen users or stimuli. This not only facilitates the development of scalable and user-adaptive privacy-aware systems, but also provides empirical insights into the underlying mechanisms of perceived privacy.

In the following, we describe the two training tasks in detail and evaluate the performance of our trained models w.r.t standard baselines, namely decision tree (DT), support vector machine (SVM), logistic regression (LR), random forest (RF), K-nearest neighbour (KNN), convolutional neural networks (CNN), recurrent neural networks (RNN), and transformer (TF) models (cf. Table 1). To study individual stimuli, we focused on the free-viewing data of our dataset.

5.1 Stimuli-based Perceived Privacy (SPP)

Quantifying perceived privacy levels helps understand how users feel about their privacy protections. Privacy perception is mainly influenced by the nature of the stimuli, e.g. their type (e.g. images) and the content being shared or observed (e.g. a credit card). A quantitative relation between the stimuli and the corresponding privacy perception can help in designing more context-aware and effective privacy-preserving mechanisms. We, therefore, propose four main SPP tasks:

(1) Binary Privacy Perception. Given solely the gaze data, the binary privacy perception task [89] aims to determine whether a user is exposed to or interacts with potentially sensitive information. In addition to the pioneering work of Steil et al. [89], we also want to determine how the different setups affect the binary perception, e.g. how the perception of a specific user (intra-user setting) varies

for different stimuli in comparison to how the perception of many users (inter-user setting) varies.

(2) Privacy Level Perception. This task aims to map the gaze data as inputs to a privacy level as output. The dataset includes a ground truth of 7 different privacy levels, following Steil et al. [89], indicated by participants for each stimulus. Note that, unlike Steil et al. [89], we process all classes instead of combining them into two.

(3) Contextual Privacy Perception. Integrating contextual information such as demographics or user expertise can potentially improve predictions of user-perceived privacy levels[2] Contextual information is provided as additional features to the model, capturing the user's age, gender, nationality, and privacy expertise.

(4) Private Attribute Recognition. Prior works [14, 85] showed that gaze is a good predictor of the user's private attributes, such as age and gender. Other works [75, 89] recognise the private attribute directly from images as inputs to their models. Here, we focus on predicting what private attribute the user is looking at, given the gaze data alone. The task becomes more challenging as semantics become more complex and diverse.

SPP applications. Before we discuss our results on tasks (1)–(4), we want to outline how stimuli-based perceived privacy results can be used in applications. For example, the quantified values in Tasks 1-3 (classified per attribute in Task 4, if needed) can be mapped to the corresponding parameters in privacy-preserving protocols. Such parameters can include ε values in DP [23, 24], model update perturbation or gradient clipping thresholds in federated learning [46, 64], and similar hand-picked parameters in K-anonymity [84], L-diversity [61], T-closeness [56], privacy auctions [32, 93], synthetic data generation [58], etc. Other stimuli-specific insights are important for multiple applications, such as access control models (to define who can access which piece of information, e.g. attribute-based access control (ABAC) [40] which uses attributes for dynamic access control and human-in-the-loop privacy controls (e.g. Instagram's 'Restrict' feature [78] for controlling interactions, e-mail spam filters that allow manual corrections [5], and marketing campaigns that respect the user's perceived privacy preferences [62]). We refer to Section 6 for sample applications.

SPP Baselines and Evaluation. As baselines, we ran the aforementioned basic models. We evaluate the accuracy of the models with cross-validation and test sets to ensure that the model generalises well to unseen data. We also perform statistical hypothesis testing on the extracted eye-tracking features to examine whether the observed differences across experimental conditions or participant groups are statistically significant. These tests assess whether variations in metrics such as fixation duration, saccade amplitude, or pupil dilation are likely to reflect systematic effects rather than random noise or individual variability. To quantify the strength of evidence against the null hypothesis (i.e., that there is no meaningful difference between groups or conditions), we compute p-values. These values represent the probability of observing the given data, or something more extreme, under the assumption that the null hypothesis is true. A p-value below a conventional threshold (typically 0.05) is considered indicative of a statistically significant effect. Hence, we made the following key observations in relation to SPP Tasks 1-4:

[2]Other contextual information like the type of application, time of the day, and the type of platform, has been shown to influence the user privacy perception too (cf. Section 3). To simplify the setup, we did not include this information in our dataset; however, our approach naturally extends to more detailed datasets.

Table 1: Accuracy of the SPP tasks Section 5.1.

	Binary Privacy Perception	Privacy Level Perception	Contextual Privacy Perception
		Person-independent	
DT	0.54	0.19	0.23
SVM	0.64	0.34	0.37
LR	0.63	0.34	0.36
RF	0.60	0.29	0.32
KNN	0.56	0.21	0.24
TF	0.52	0.34	0.37
		Person-specific	
DT	0.61	0.23	0.24
SVM	0.70	0.38	0.39
LR	0.75	0.40	0.40
RF	0.66	0.35	0.37
KNN	0.62	0.30	0.31
TF	0.81	0.52	0.54
		Down-sampling	
DT	0.48	0.15	0.16
SVM	**0.57**	0.30	0.33
LR	0.55	0.28	0.29
RF	0.52	0.24	0.26
KNN	0.45	0.20	0.20
TF	0.46	0.30	0.31
		Gaze + Stimuli (ours)	
DT	0.89	0.73	0.72
SVM	0.93	0.81	0.83
LR	0.92	0.80	0.81
RF	0.90	0.82	0.80
KNN	0.88	0.79	0.82
TF	0.97	0.87	0.90
		Gaze + Stimuli (PrivacEye)	
DT	0.58	-	-
SVM	0.67	-	-
LR	0.66	-	-
RF	0.70	-	-
KNN	0.58	-	-
TF	0.75	-	-

Inter- and intra-user variations. As shown in Table 1, our results demonstrate that gaze data can quantify perceived privacy since results exceed chance levels (0.5 for Task 1 and 0.14 for Tasks 2 and 3). We further analyse this in both person-specific and person-independent settings. In the person-specific setting, models are

Figure 3: Qualitative example of the inter- and intra-person differences: Each row corresponds to a different participant, where red dots depict the areas that participants attended to the most (i.e. more fixations). The user-selected privacy levels l are consistent for each participant but different across participants. For example, the *political opinion* attribute is private (l between 1 and 2 - the private levels) for one user -the first row- and not private for the second (l between 4 and 6 - the safe levels). The gaze fixations are also denser on the private regions of interest (e.g. faces and politicians) for the *private* levels.

tested on individual participants, accounting for personal gaze behaviours, whereas in the person-independent approach, a generalizable model is trained across all participants and tested on 20% of each participant's data. Results in Table 1 and Fig. 3 indicate significant variations in inter-user differences (person-independent, leading to lower accuracy), whereas intra-user features exhibit greater consistency (person-specific, leading to higher accuracy). This suggests that each user possesses a distinct and individualised perception of privacy.

Fixation-based attention allocation. In general, fixation duration increases on private cues with fewer fixations on less private regions (tested with Kruskal-Wallis H-test and Dunn's test with Bonferroni correction for multiple comparisons with the different privacy levels, with $p\text{-}value = 0.04 < 0.05$). This can also be seen in Fig. 3. It further suggests that less fine-grained tracking is sufficient (i.e. relying on fixations alone). This was further supported by downsampling the gaze data to 30 Hz (30 FPS) to simulate commodity-level standard webcams, as shown in Table 1-downsampling. The results, again, suggest that high-resolution gaze data (Table 1-person-independent) may not be necessary for effective privacy perception prediction, facilitating a more widespread implementation and enhancing accessibility and usability for a broader audience [3].

Social influence: Users' privacy perception may be guided by social influence (e.g. demographics), as shown in the *Contextual Privacy Perception* results and Fig. 4. Our results indicate that demographics play a significant role in shaping outcomes (i.e. increasing accuracy).

[3]As this study represents exploratory research, we employed a high-resolution, constrained experimental setup. This choice was motivated by the initial uncertainty regarding whether a lower-resolution configuration would yield significant results and to what extent fine-grained details in the data would be necessary to capture relevant effects. The high-resolution setup ensured maximal data fidelity, allowing for comprehensive observation of potentially subtle phenomena during the early stages of research.

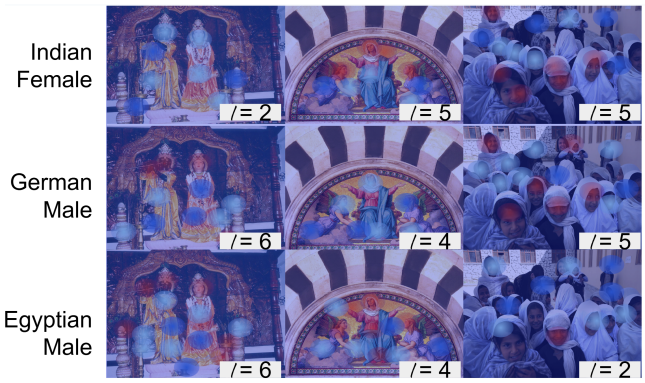

Figure 4: Qualitative example of social influence: By looking at the attribute *religion*, participants assign *private* ratings to stimuli that are more closely associated with or frequently encountered within their social background, probably due to their personal significance (c.f. Section 3).

This suggests that demographic factors and social background contribute to identifiable patterns that machine learning models can detect. Consequently, these factors enhance the predictive power of the models, highlighting their relevance in understanding variations in the data.[4]

Long-term learning and adaptive privacy behaviour. Repeated exposure to private attributes changes user behaviour over time. As shown in Fig. 5, while gaze fixations decrease on repeated attributes over time (i.e. desensitisation to privacy risks), the privacy ratings increase (i.e. learning effect and growing privacy awareness), and response time decreases.

Visual Privacy. For private attribute recognition, we compared our findings with the VISPR [75] evaluation. While they only input the stimuli, we replicated their models and metrics on our dataset and inputted the gaze data alone vs the gaze and stimuli. As shown in Table 2, when used in conjunction with stimuli, gaze data enhances the informational richness available to the model by providing additional features that complement the stimuli. However, even when gaze data is used in isolation, it remains beneficial while reducing the amount of shared data. Note that the models used are relatively basic for the sake of comparison with [75], and more advanced models could potentially enhance the results. Nonetheless, we observed that, as shown in Fig. 6 (left to right): (i) when using gaze as the only input, the models are able to identify objects that occupy a significant proportion of the image space while failing at identifying other subordinate attributes such as age or gender; (ii) when augmenting the stimulus with the gaze data, the models are able to identify more fine-grained details such as wedding rings and tattoos that the stimuli-alone version fails at (as long as the participants paid attention to such details), (iii) in all versions, models fail at

[4]It is important to note that our unbalanced demographics—an inherent consequence of the open and uncontrolled call for participation—limit our ability to make broad or generalizable claims about specific demographic groups or extrapolating results to a wider population. As a result, while our analysis may reveal meaningful trends, caution is required when interpreting demographic-specific conclusions using our dataset

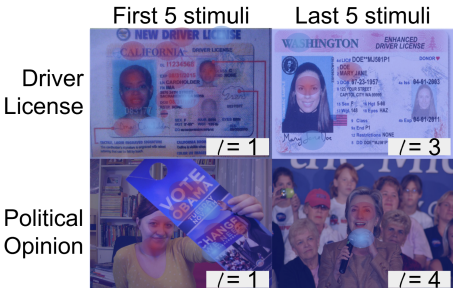

Figure 5: Qualitative example of learning effect: Examples belong to the same participants on images of two different attributes *driver license* and *political opinion*, sampled from the first and last 5 stimuli. When a specific attribute is presented (e.g. in the first 5 stimuli) and repeated multiple times, it increases the participant's familiarity with the attribute through repeated exposure. Hence, the number of fixations, response time, and privacy-sensitivity decrease.

Table 2: Evaluation of the private attribute recognition task as class-based mean average precision (C-MAP) (the average of the per-attribute average of the area under the Precision-Recall curve on all attributes), following [75]

Model	Feature	VISPR [75] (stimuli)	Ours (gaze)	Ours (gaze + stimuli)
SVM	CaffeNet	41.34	29.80	58.22
SVM	GoogleNet	43.77	30.07	60.43
SVM	Resnet-50	44.21	32.45	62.37
E2E	CaffeNet	47.56	35.98	65.85
E2E	GoogleNet	47.72	34.08	67.00
E2E	Resnet-50	56.13	35.32	69.13

Figure 6: Qualitative example for visual privacy observations: Example stimuli corresponding to the gaze data that were misclassified

identifying the relationship-based attributes (as also reported by [75]) since they require some reasoning capabilities that our basic models do not achieve.

Gaze as a supplementary input. When data minimisation constraints are not imposed, we assess model performance with the inclusion of stimulus data and compare it to PrivacEye [89]. Results in Table 1-gaze+stimuli show that the stimulus features significantly improve the performance.

5.2 User-based Perceived Privacy (UPP)

Even for the same stimuli, different users develop different privacy perceptions. Hence, perceived privacy is subjective and varies substantially among participants. Understanding the user-specific features of privacy allows researchers and policymakers to design more effective, personalised, and user-centric privacy solutions. We, therefore, propose three UPP-tasks:

(1) Privacy Expertise Prediction. Prior works [11, 53, 59] showed that distinctive eye movement behaviours and gaze strategies correlate with domain-specific expertise. This task aims to develop a model that can distinguish between privacy experts and non-experts based on their gaze patterns during interactions with digital content or privacy-related tasks. The gaze data was collected from participants with varying levels of privacy expertise, potentially revealing how different levels of knowledge influence visual attention and decision-making in privacy-sensitive contexts. We address this task, therefore, by training a classifier to distinguish between the two groups based on the gaze features.

(2) User Privacy Profiling. The privacy expertise prediction task can be further extended to capture the gaze behaviour profile, e.g. a summary of the key gaze features that characterise each group [75], such as differences in attention to specific elements or gaze strategies. This is commonly used to adapt privacy preferences according to different cohorts [33]. Hence, the task aims to cluster the different groups according to the gaze patterns.

(3) Privacy-aware Gaze Identification. Current gaze-based user identification methods often rely on specially designed visual stimuli or induced artificial gaze patterns. Prior works [1, 22] have investigated the feasibility of distinguishing individuals based on their natural gaze behaviour while freely viewing images and suggested that viewing different images, such as a personal vacation photo, elicits distinct emotional responses, which are reflected in gaze patterns and are unique to each individual. We extend this idea to privacy-aware gaze behaviour, proposing that individuals exhibit unique gaze patterns not only in response to personal relevance but also when assessing perceived privacy. Privacy perception is inherently subjective, shaped by personal experiences, cultural influences, and cognitive biases. By analysing how users visually explore and evaluate images with different privacy implications, we need to demonstrate in this task that privacy perception itself can serve as an implicit user identifier [25].

UPP applications. User-specific insights can, for example, be used for privacy nudges [42] (to encourage users to make privacy-conscious decisions according to their expertise or profiles, commonly used in social media platforms to prevent oversharing, e.g. Facebook's contextual privacy warnings [66] and Chrome browser-based security warnings [34]), adaptive two-factor-authentication (2FA) [22] (which requires extra authentication only in suspicious situations), privacy labels and transparency notices (to help users understand and control their privacy choices according to their profiles, e.g. Apple's App Store privacy labels [6]), and cohort-based recommendations (for group-based personalization, e.g. Google's Federated Learning of Cohorts (FLoC) [33] for ad targeting).

Table 3: Accuracy of the UPP tasks

	Privacy Expertise Prediction	Privacy-aware Gaze Identification
DT	0.78	0.05
SVM	0.45	0.04
LR	0.46	0.02
RF	0.87	0.04
KNN	0.85	0.03

UPP Baselines and Evaluation. To predict the privacy expertise of users and groups, we ran the same evaluation as in Section 5.1. The results are shown in Table 3, where results exceed the chance levels (0.5 and 0.01 accuracy for privacy expertise prediction and privacy-aware gaze identification, respectively). We observe the following key results:

Cognitive and Perceptual Adaptation. The difference in gaze behaviour between experts and non-experts arises due to cognitive and perceptual adaptations that develop with experience and training [11, 53, 59]. Our results show that privacy experts exhibit more focused attention on privacy-relevant information and quicker identification of potential privacy risks compared to non-experts. In other words, privacy experts have rapid gaze shifts, suggesting automatic heuristic-based decision-making, while non-experts have longer dwell time, indicating uncertainty and high cognitive load in privacy assessment (tested by a Mann-Whitney U-test with $p\text{-}value = 0.03 < 0.05$), leading to distinguishing features that ML models can identify with high accuracy (c.f. Table 3).

Distinct Profiles. We further evaluated the participants' profiles per attribute and found out that, following [75], K-means clustering yields the lowest silhouette score with 12 distinct gaze behaviour profiles (as opposed to 30 profiles when clustering images [75]).

Genuine significance. Previous studies on gaze behaviour indicate that viewing different images, such as personal photos, elicits distinct emotional responses that are reflected in gaze patterns and are unique to each individual [1, 22]. In our experimental setup, we tried to simulate this setup by instructing participants to conceptualise the stimuli as their own phone gallery without incorporating actual personal photos. Unfortunately, the previously observed personalised effect could not be replicated in our study and setup (cf. Table 3). We believe that this is due to the lack of genuine emotional attachment and/or lack of personal significance and familiarity.

6 Privacy-Preserving Applications

Our results so far showed how gaze can be used to predict the privacy perception of an individual or a group of users. There are many potential applications for this approach (we already hinted at some of them). Here, we concentrate on one important task, and study this in more detail, namely, finding good and tailored epsilon values for DP.

6.1 Privacy-Utility-Cognition Trade-Off

To use our results from Section 5 with a DP-mechanism, we first need to map user-perceived privacy levels $l \in \{1, \ldots, L\}$ with a function f to ε-values for Differential Privacy.[5]

Depending on the cognitive aspects behind the user-perceived privacy preference, which we discussed already in Section 3, we want to connect l with different privacy loss functions $g(l)$, e.g. such that the privacy loss depends linearly on l as in [50, 60].

To construct a suitable mapping f to DP-privacy levels ε, recall from Section 2 that a privacy-budget ε ensures that an adversary $\mathcal{A}$ can distinguish two data sets with advantage bounded by $\text{adv}_{\mathcal{A}}(\varepsilon) := \frac{e^{\varepsilon}-1}{e^{\varepsilon}+1}$. Hence, if we require the privacy loss (in terms of the success of a potential adversary) to have a certain behaviour g, we need $g(l) = \text{adv}_{\mathcal{A}}(f(l))$. Observe that we can compute $f(l) = \log\left(\frac{1+g(l)}{1-g(l)}\right)$ explicitly. In particular, we find a mapping function f for every positive loss function g with values smaller than 1.

Since users do not select privacy levels purely based on objective risks or technical parameters, but rather through subjective interpretations shaped by cognitive biases (cf. Appendix B), we now want to discuss the typical choices of g in cognitive science and how they affect the accuracy of a model obfuscated with ε-DP noise if $\varepsilon = f(l)$.

Note that for real-world applications, we can usually restrict the privacy budget to $\varepsilon_{min} \leq \varepsilon \leq \varepsilon_{max}$ where the minimum $\varepsilon_{min} \geq 0$ and maximum $\varepsilon_{max} < \infty$ are application-specific [68]. We therefore, use functions g depending on $\varepsilon_{min}, \varepsilon_{max}$.

It is important to note that users employ diverse rationales and cognitive strategies when forming their privacy perceptions, and these strategies are shaped by multiple interacting factors, such as the stimuli, background knowledge, and demographic (cf. Section 5). As a result, there is no universally correct mapping function, as these differences reflect valid subjective interpretations rooted in cognitive and contextual variability. Rather than assuming a single ground truth, such mappings should be empirically learned from user behaviour and validated through data-driven analysis. Hence, later in this section, we illustrate this point by providing a practical example based on our dataset.

6.1.1 Linear Mapping. A straightforward way to interpret perceived privacy is a function g linear in l [50, 60]. Namely, we choose for $l \in \{1, \ldots, L\}$:

$$g(l) = \text{adv}_{\mathcal{A}}(\varepsilon_{min}) + \frac{l-1}{L-1}(\text{adv}_{\mathcal{A}}(\varepsilon_{max}) - \text{adv}_{\mathcal{A}}(\varepsilon_{min}))$$

This mapping assumes equal intervals between privacy levels. Linear mappings are widely used in statistics, cognitive sciences, and machine learning for their mathematical simplicity, speed, and interoperability, and serve as good approximation functions. Nonetheless, they may potentially lead to inaccurate interpretations [13]. This is because, although privacy levels are numerically treated as equidistant, the psychological or cognitive perception of the distance between those points may not be equal [47, 91]. For example, the difference between 'very safe' and 'safe' may be much smaller in the user's mind than the difference between 'neutral' and 'moderately private'. Similarly, the midpoint ('neutral') may be

[5] In our evaluation, we use $L = 7$ (cf. Section 3).

seen not as a numerical centre but rather as a safe choice. Hence, we now longer have a linear relation.

6.1.2 Exponential Mapping. Alternatively, an exponential function could be used when users interpret privacy levels as a continuum, with thresholds separating the different privacy levels. In other words, in such cases, small variations in the privacy parameter may be perceived as insignificant at higher levels (e.g. 'very safe' and 'moderately safe'), while similar changes near specific lower thresholds elicit disproportionately larger responses (e.g.'neutral' and 'moderately private'). These thresholds may vary due to the user's cognitive processes, where users with less familiarity with privacy concepts may rely on intuitive or categorical decision-making or cases where specific features of the images (e.g., presence of identifiable faces or objects) might consistently evoke higher or lower ratings. An exponential mapping addresses this pattern and emphasises stronger privacy guarantees at lower ratings and captures a cognitive tendency where users may undervalue small privacy differences in higher ratings, improving utility. We get:

$$g(l) = \mathrm{adv}_{\mathcal{A}}(\varepsilon_{min})^{(L-l)/(L-1)}\,\mathrm{adv}_{\mathcal{A}}(\varepsilon_{max})^{(l-1)/(L-1)}$$

6.1.3 Sequential Mapping. Another alternative is a sequential mapping, where the choice of the privacy level is reached in steps. This models the probability of the selected privacy level being in a particular category, given that it has surpassed the previous category. In some cases, decision-making unfolds in steps [3, 31, 51, 70], such as deciding whether something is private and then determining the degree of privacy, e.g. "Is the stimulus sensitive/ does it violate a norm/should the information be shared? If yes, how private are the stimuli?/ How severe is the violation?/ How much information should be disclosed?". In these cases, automatic and heuristic-driven decisions (e.g., 'private or not') may precede more deliberative evaluations of privacy levels [3, 31]. In other cases, the stimuli's complexity may drive such behaviour, e.g. images with progressively more sensitive content may encourage stepwise evaluation (e.g., abstract shapes → objects → faces). Therefore, prior works [73, 80, 82] typically model this behaviour using step functions, incorporating heuristic-based decision-making as the primary mechanism to mitigate ambiguity aversion and prevent cognitive overload during deliberative evaluations.

Hence, a piecewise mapping (i.e. a step function) can be used to accommodate the different perceived privacy ranges to handle that different tiers of privacy ratings have different baseline ε values and slopes and allow more granularity within n ranges. Especially when certain ranges require higher privacy guarantees (e.g. handling extreme outliers). E.g. a look-up table where $n = 3$ (e.g. 'private', 'neutral', 'safe'):

$$g(l) = \begin{cases} \mathrm{adv}_{\mathcal{A}}(\varepsilon_{min}), & \text{if } l = 1 \text{ or } 2 \\ \frac{1}{2}(\mathrm{adv}_{\mathcal{A}}(\varepsilon_{max}) + \mathrm{adv}_{\mathcal{A}}(\varepsilon_{min})), & \text{if } 2 < l < L-1 \\ \mathrm{adv}_{\mathcal{A}}(\varepsilon_{max}), & \text{if } l = L \text{ or } L-1 \end{cases}$$

6.1.4 Sigmoid-based Mapping. Furthermore, adjacent-category models [13] are common in statistics and item response theory. They are usually used when thinking of a natural cognitive process is not possible and decisions may involve iterative, contextual, uncertain, or unstructured processes. In these cases, users can make fragmented decisions or skip steps due to limited information. In other cases, similar stimuli with only slight changes in features (e.g., cropped vs. full image) require users to make nuanced decisions. Commonly in machine learning and statistics, sigmoid (logistic) functions are used to describe the probability of selecting one option over another under uncertainty. It naturally models probabilistic decisions that become more deterministic as the evidence or difference between choices increases.

This behaviour aligns well with empirical findings in psychology, economics, and cognitive science, where decision-making often follows a logistic-like pattern. That is, in stochastic cases, for highly private images where the perceived privacy is greater (i.e. lower ratings), the sigmoid function outputs a lower ε value, accentuating privacy protection. Conversely, for images considered safe, the function assigns a higher ε, allowing less noise and thus better utility of the data.

Hence, a sigmoid mapping function can be expressed as the smooth continuation of

$$g(l) = \mathrm{adv}_{\mathcal{A}}(\varepsilon_{max}) + \frac{\mathrm{adv}_{\mathcal{A}}(\varepsilon_{min}) - \mathrm{adv}_{\mathcal{A}}(\varepsilon_{max})}{1 + \left(\frac{L-1}{l-1} - 1\right)^{-k}}$$

where k controls the steepness of the curve (higher values make the transition sharper, e.g. $k = 1.5$ represents moderate steepness). As shown in Fig. 7, such smooth transitions ensure that ε values transition gradually instead of changing too sharply with diminishing effects at the extremes, allowing to smoothly handle uncertainty or borderline cases without abrupt changes in behaviour.

6.2 Empirical Evaluation

We now show how our results from Section 5 could be used in combination with mappings to epsilon values proposed in Section 6.1. To illustrate the applicability of our approach, we adopt a representative example from the *privacy level perception* task. This example serves to show how our method can be operationalized in practice. Importantly, the proposed framework is not limited to this specific task; it can be extended to other tasks by incorporating stimuli- or user-based information, thereby enhancing its generalizability across various privacy-sensitive applications.

We apply the state-of-the-art personalised differential privacy (PDP) mechanisms from [44] for privacy budgets ε determined with our mapping functions from Section 6.1. Recall that [44] is originally used with randomly chosen ε. For our comparison, we use different common tasks from data analysis and machine learning tasks, which we want to describe briefly next.

Benchmarks. Our evaluation uses the same benchmarks as Jorgensen et al. [44] to evaluate PDP mechanisms for search analytics, e.g. count query for the number of documents that participants searched for, median and minimum queries for attention allocation (number of fixations) per stimulus. Once a ε-value is determined, either randomly by [44] or by applying our method on the user's gaze data, a trusted data analyst receives the data and the ε values, then adds suitable noise to query results and publishes the aggregate statistics.

In addition to these classical data analysis benchmarks, we also evaluate PDP mechanisms for machine learning tasks, namely,

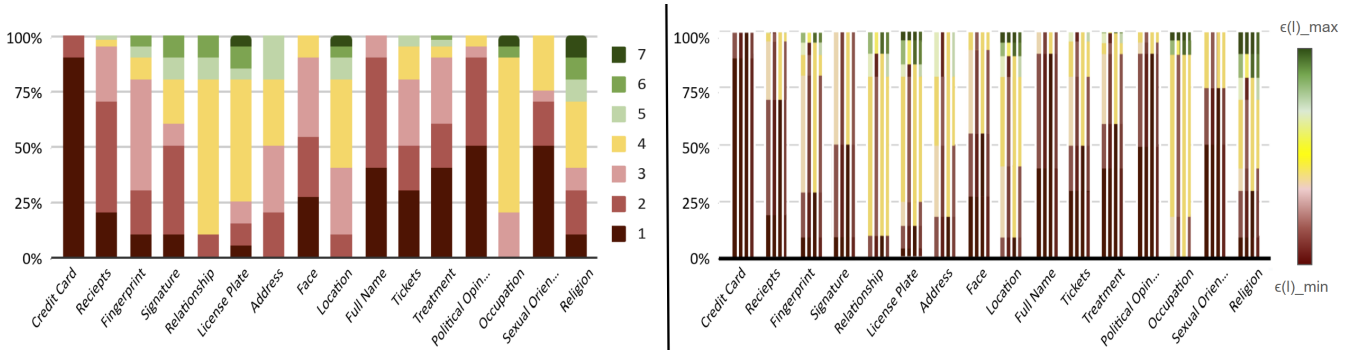

Figure 7: The left figure shows the distribution of the perceived privacy levels $l \in$ {1 (very private),...,7 (very safe)} selected by the participants per attribute. The right figure shows an example of mapping the perceived privacy level l to the corresponding $\varepsilon(l) = f(l)$ using the different mapping functions for $\varepsilon_{min} = 0.1, \varepsilon_{max} = 5$ and $k = 1.5$. The results are applied to the l distribution where, for each attribute, the mapping functions (linear, exponential, sequential, and sigmoid) are depicted from left to right.

search intention prediction, using the default models and parameters of [9, 10, 44] (cf. Section 3).

Results. As shown in Table 4, PDP approaches significantly improve over the static DP approaches (i.e. worst-case ε, the common approach in DP) and are significantly closer to the plain approaches (i.e. without noise addition). In addition, our proposed mapping functions yield better utility than the random benchmark (i.e. the random ε values generated by the existing benchmarks).
To further analyse the effect of the different mapping functions, Fig. 7 shows the resulting ϵ values for different image attributes. The amount of added noise (according to the ε values) differs according to the mapping function (i.e. more noise is introduced to the private levels represented in red, whereas less noise is applied to those depicted in green), hence improving utility compared to static worst-case approaches. Our results indicate that:

- **The linear mapping** is particularly appealing in scenarios where exact precision is not critical, and approximate representations are sufficient for the intended application, e.g. when ratings are equally distributed, unlike our dataset, where the number of classes is skewed toward the private ratings. In former cases, linear functions offer a simpler and more computationally efficient mapping. However, the trade-off lies in the potential loss of granularity or accuracy.
- **The exponential mapping** is mostly suitable for applications where strong privacy is paramount and small changes in high ratings imply steep privacy needs. This is true for clearly sensitive attributes, i.e. attributes with an l range ≤ 2, such as credit cards. This could also be seen in the higher performance for weighting algorithms in Table 4 where less private data contributes more (given the skewed data distribution as shown in Fig. 7) with less noise to the final learning outcome.
- **The sequential mapping** demonstrates superior performance for attributes with deliberative privacy sensitivity ($2 < range(l) < 5$), such as political opinions, where participants' gaze shifts between the privacy levels before selection, suggesting an initial classification of the attribute as private, followed by a secondary assessment of its degree of privacy.
- **The sigmoid mapping** is most effective for attributes where participants either make arbitrary choices (can also be seen in minimal rating time) or are uncertain (can be seen in extended rating time), resulting in attributes with $range(l) > 5$, e.g., license plates that some participants did not pay attention to (i.e., no fixations) or fingerprints with long fixations. This could also be seen in the better performance of the sigmoid mapping for sampling algorithms in Table 4 where neutral samples are sampled more, balancing the data distribution and the added noise, hence improving utility.

Therefore, given the absence of a universal solution, we recommend selecting the appropriate mapping function based on the specific application and the characteristics of its stimuli.

7 Discussion

Our dataset showed that eye gaze reliably reflects user privacy perceptions across privacy-related tasks. It further revealed user- and stimulus-based insights that could be used across a variety of applications.

By modelling perceived privacy alongside formal guarantees, we improved data utility while (cognitively) aligning with individual privacy expectations. Although a single universal mapping between perception and privacy budgets is unlikely to exist due to inter-individual variability, we propose a set of adaptable mapping functions that can be selected contextually based on application needs and behavioural insights.

Our proposed datasets include further information that we encourage the community to develop upon. This can include (i) additional tasks, such as multi-attribute and multi-user correlation analyses (i.e. each group of stimuli was shown to various participants, with each stimulus containing several attributes), (ii) more advanced models to capture more patterns and enhance our baseline performance, and (iii) other DP and privacy-preserving protocols (i.e. adding noise to different privacy units, the fundamental entity whose privacy is protected, user-, label-, feature- or pixel-level DP) that would benefit from the user (cognitive) privacy perceptions without explicit interaction.

Table 4: Evaluation of the PDP benchmarks. The table shows results for data analysis and machine learning tasks where (i) plain is the non-private computation and, hence, the best utility, (ii) static is the worst-case privacy loss and the most commonly used in standard DP protocols, (iii) random is a random distribution of ϵ values that are commonly used in PDP protocols, and (iv) our four proposed mapping functions.

		Plain	Static	Random	Linear	Exponential	Sequential	Sigmoid
Analysis	Count [44]	100	76	84	87	90	86	87
	Median [44]	16	12	19	14	18	19	19
	Min [44]	5	8	7	7	4	7	6
Learning	Linear regression [44]	0.57	0.31	0.43	0.46	0.50	0.49	0.47
	Weighting [10]	0.68	0.38	0.52	0.53	0.57	0.56	0.55
	Weighting [9]	0.49	0.32	0.43	0.44	0.46	0.45	0.42
	Sampling [10]	0.68	0.38	0.55	0.58	0.60	0.61	0.63
	Sampling [9]	0.49	0.32	0.43	0.43	0.44	0.44	0.46

8 Conclusion

Given its inherently subjective nature, which varies substantially across individuals, we presented the first large-scale dataset for studying user-perceived privacy. The dataset encompasses a diverse range of participants, demographic profiles, and visual stimuli. Using this novel dataset, we demonstrated that eye gaze can serve as a rich source of information on user-perceived privacy across multiple privacy-related tasks. Gaze behaviour, by providing implicit and dynamic feedback, offers a powerful and promising avenue for enhancing user interaction and overall system usability. Moreover, by modelling users' perceived privacy and applying our findings to PDP protocols – complementing the underlying mathematical and technical privacy guarantees – we were able to improve data utility while better aligning with users' expectations of privacy. As such, our work bridges the gap between technical and usable privacy by aligning theoretical privacy models with user perceptions.

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Appendix

A Eye Tracking Data

Here, we present a detailed breakdown of the process of data collection with an eye tracker (EyeLink 1000), starting from participant recruitment to creating a public dataset:

A.1 Participant Recruitment

As shown in Figure 8, we aimed to recruit a diverse set of participants with different demographics, e.g. age, gender, nationalities, and AI/Security expertise. The call for participation was sent out on different channels, e.g. online platforms, university participant pools, and social media, with clear information about the study, duration, and incentives (e.g., monetary compensation or credits).

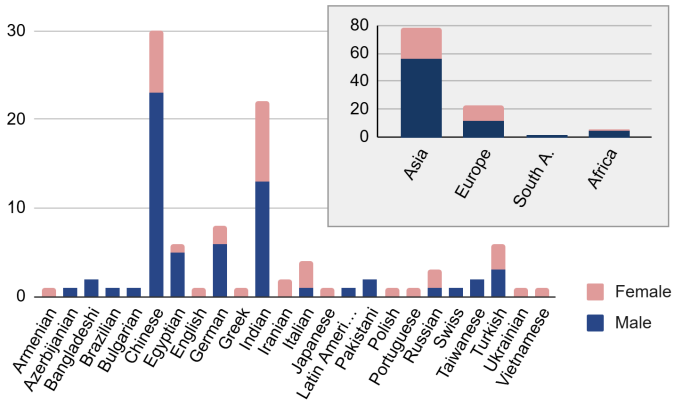


Figure 8: Demographics' distribution of the number of male and female participants per nationality and continent

Informed consent was obtained following ethical guidelines of the author's institution while ensuring that participants can withdraw at any time. We excluded participants with specific conditions like eye disorders that may affect tracking accuracy (e.g., nystagmus, extremely poor vision).

A.2 Eye Tracker Configuration

We used the EyeLink-1000 eye tracker, the current state-of-the-art in terms of precision and accuracy for video-based eye tracking. We created an in-lab setup as shown in Figure 9.

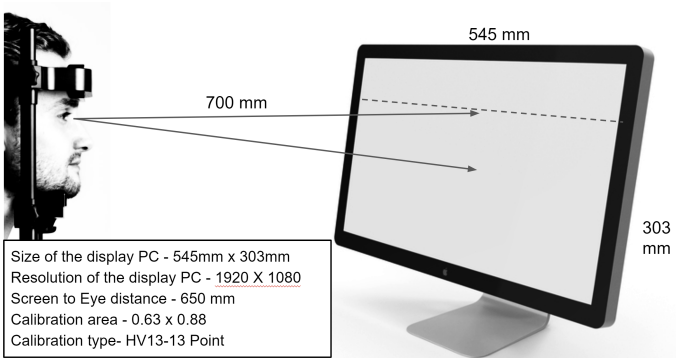


Figure 9: The eye-tracker setup

A.3 Experiment Design

A sample trial is conducted as shown in Figure 10.

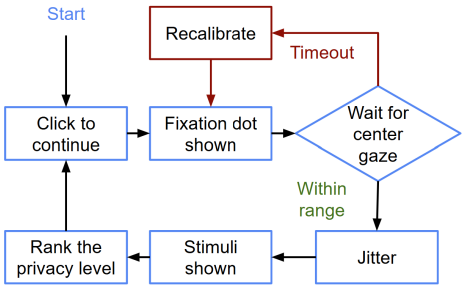


Figure 10: A sample trial flow-chart

The stimuli were gathered from the validation and test sets of the VISPR dataset [75]. Every block contained writing-based and human stimuli to avoid bias, with a distribution of private attributes as shown in Table 5.

Table 5: Stimuli distribution over blocks

Block	Attribute	Category
1	Fingerprint, Receipts, Occupation, Sexual Orientation, Political Opinion	Personal Description, Documents, Employment, Personal Life, Personal Life
2	Signature, Tickets, Medical Treatment, Personal Occasion, Home address	Personal Information, Documents, Health, Personal Life, Whereabouts
3	Face Complete, Credit Card, Medical History, Email Content, Religion	Personal Description, Documents, Health, Internet, Personal Life
4	Full Name, Mail, License Plate Complete, Personal Relationship, Visited Location	Personal Information, Documents, Automobile, Personal Life, Whereabouts

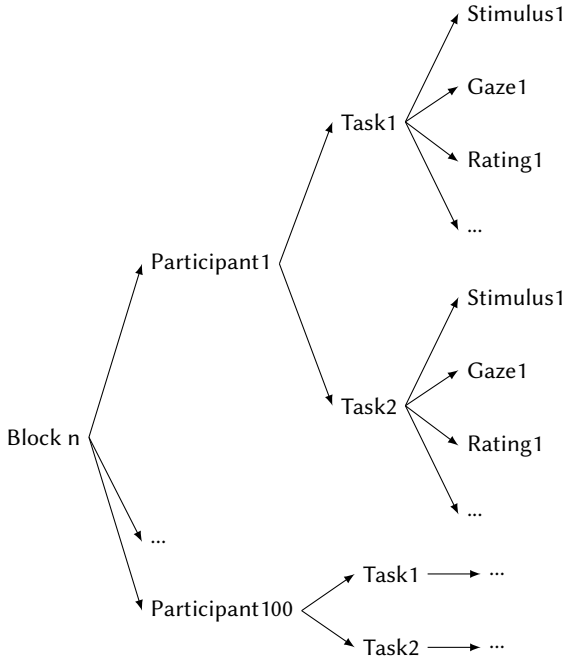
A.4 Data Collection

To accurately track participants' gaze and record eye movement data during the experiment, we first conduct a 13-point calibration to ensure the eye tracker is accurately mapping gaze coordinates to the screen, followed by a validation check to confirm that gaze accuracy is within acceptable error limits (e.g., <0.5°). We further recalibrate if drift or errors occur during the session. The stimuli are then presented and data streams are recorded.

A.5 Data Processing

We cleaned and processed raw eye-tracking data for further analysis. The raw data is extracted from the EyeLink Data Viewer as .edf files, including the timestamped gaze coordinates (X, Y), fixation and saccade metrics (e.g., duration, amplitude, velocity), and pupil size. We then used the stimulus metadata to map gaze coordinates to specific ROIs, categorised gaze events into relevant regions for analysis, and merged eye-tracking data with task-specific inputs (e.g., participant ratings and mouse clicks).

We structured the processed data into a usable dataset for analysis, by organizing data into rows and columns (.csv format), including information such as participant demographics, stimuli details, and task condition. Finally, we formatted the data for statistical or machine learning tools (e.g., Python) in the following structure:



B Cognitive Theories and Privacy

Here, we give more details about some cognitive theories that further support our mapping functions.

The Exponential Mapping. captures a perception that escalates rapidly with small increases in privacy risk or sensitivity. The related theories include:
(i) The prospect theory [15, 45] where people weigh potential losses and gains and can provide a direct assessment of privacy levels based on their perception of risks and benefits. Individuals may perceive increasing risk with diminishing marginal tolerance—well captured by an exponential curve. The exponential shape models the non-linear, often risk-averse valuation of privacy losses.
(ii) The risk-reward trade-off theory [77] where individuals balance risks and rewards in a unified decision, leading to a cumulative rating of privacy. This model implies that perception accumulates as users weigh these aspects, with increasingly steep aversion to risk—supporting an exponential model for mapping ratings to privacy budgets.
(iii) The communication privacy management (CPM) theory [79] frames privacy as the control of boundary permeability based on accumulated context and sensitivity. The control intensifies sharply as users assess perceived violations, again suggesting an exponential increase in perceived privacy sensitivity.
(iv) The theory of planned behaviour [83] where attitudes, norms, and perceived control influence a single privacy decision, often resulting in a direct rating. The interaction of these variables can

collectively lead to a compounded privacy concern that builds up non-linearly, fitting an exponential growth in privacy valuation.

The Sequential Mapping. corresponds to decision-making that unfolds in discrete steps. The following theories underpin this logic:
(i) Contextual integrity [70] sequentially considers factors like actors, attributes, and transmission principles. For example, a user might first decide if a context violates norms, then determine the severity of the violation, resulting in a layered decision path consistent with step-wise or rule-based mappings.
(ii) The privacy paradox [51] suggests that users might decide in one step whether to share information and then, based on cognitive dissonance, adjust how much information they disclose or rate its privacy (i.e. a post-hoc justification). This aligns with a sequential structure where decisions are refined over time.
(iii) The dual-process theory [3] assumes that automatic, heuristic-driven decisions (e.g., 'private or not') may precede more deliberative evaluations of privacy levels.
(iv) The heuristic-systematic model [31] suggest that a heuristic (i.e. quick judgment) may guide the first decision, followed by a deeper systematic analysis to refine privacy preferences.

The Sigmoid Mapping. reflects bounded sensitivity at both extremes: users are easily decide on very safe or very private data, but become highly sensitive in an intermediate uncertainty zone. The following theories justify this mapping:
(i) The bounded rationality theory [87] suggests that decisions are made with limited information, often leading to "good enough" rather than systematically cumulative or sequential outcomes. Users might skip steps or make fragmented decisions. The sigmoid captures this minimal sensitivity at low and high certainty, with steep reactivity in ambiguous cases.
(ii) The uncertainty reduction theory [49] suggests that decisions aim to reduce uncertainty and may involve multiple rounds of information gathering and refinement.
(iii) The cognitive dissonance theory [35] suggests that users adjust decisions retroactively to reduce dissonance. This retroactive calibration results in smooth but non-linear adjustments over time—reflected in the sigmoid's gentle asymptotes and steep central slope.

C Adverserial Perspective on Differential Privacy

We want to briefly motivate the definition of the adversarial advantage for differential private mechanism we use in Section 2 and Section 6.

We use the following security game for a DP-mechanism M, an adversary $\mathcal{A}$ and a challenger C.

(1) The adversary $\mathcal{A}$ chooses two valid adjacent inputs sets D_0, D_1 for M and sends them to the challenger.
(2) The challenger samples a bit b. It runs $M(D_b)$ a random number of times and stores the outputs in a set S.
(3) Upon receiving S, $\mathcal{A}$ outputs a bit b'.

The adversary wins the security game if $b' = b$. The advantage of $\mathcal{A}$ is defined as $\mathrm{adv}_{\mathcal{A}} := 2p - 1$, where p is the maximal probability that $\mathcal{A}$ wins for *any* S. Note that the adversary in this game is exceptionally strong since it only needs to win the game for one specific output set S (no matter how unlikely S itself is). The setup is nevertheless relevant, since in real-world use cased unlikely outputs might nevertheless occur and even then the privacy of the input data should be preserved.

In slight abuse of notation we also denote by $\mathrm{adv}_{\mathcal{A}}$ the maximal advantage achieved by a ppt. adversary $\mathcal{A}$. We want to determine an upper bound on the advantage. Given the limited information available the most successful adversary $\mathcal{A}$ outputs $b' = 0$ if $\Pr(0|S) \geq \Pr(1|S)$ and $b' = 1$ otherwise. Let w.l.o.g. $\Pr(0|S) \geq \Pr(1|S)$. Hence this adversary has advantage $\mathrm{adv}_{\mathcal{A}} = 2\Pr(b = 0|S) - 1$. If the mechanism satisfies ε-differential privacy, Eq. (1) implies $\Pr(S|b = 0) \leq e^{\varepsilon}\Pr(S|b = 1)$. But $\Pr(S|b = i) = \frac{\Pr(S,b=i)}{\Pr(b=i)} = 2\Pr(S, b = i) = 2\Pr(S)\Pr(b = i|S)$ for $i = 0, 1$. Thus $\Pr(S|b = 0) \leq e^{\varepsilon}\Pr(S|b = 1) \Rightarrow \Pr(b = 0|S) \leq e^{\varepsilon}\Pr(b = 1|S) = e^{\varepsilon}(1 - \Pr(b = 0|S)) \Rightarrow \Pr(b = 0|S) \leq \frac{e^{\varepsilon}}{1+e^{\varepsilon}}$. We conclude that $\mathrm{adv}_{\mathcal{A}} = 2\Pr(0|S) - 1 \leq \frac{e^{\varepsilon}}{1+e^{\varepsilon}} - 1 = \frac{e^{\varepsilon}-1}{1+e^{\varepsilon}}$.

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